CRANFIELD UNIVERSITY

Partha Priya Datta

A complex system, agent based model for studying and improving the resilience of production and distribution networks

Cranfield School of Management

Submitted for the degree of Doctor of Philosophy

CRANFIELD UNIVERSITY

SCHOOL OF MANAGEMENT

PhD THESIS

PARTHA PRIYA DATTA

A complex system, agent based model for studying and improving the resilience of production and distribution networks

Supervisors:

Professor P.M. Allen
Professor M. Christopher

March 2007

ABSTRACT

The very complexity and the extended reach of today's globe-spanning supply chain networks, the low inventory levels and lack of redundancies required to achieve efficient operations expose businesses to a huge range of unexpected disruptions. This calls for building resilience in supply chains, which is not just recovery from the mishaps, but is a proactive, structured and integrated exploration of capabilities within the supply chain to resist and win against unforeseen happenings. Literature on supply chain and organisational resilience are informative in identifying resilience enhancing strategies and capabilities, but a detailed dynamic analysis of behaviour of the supply chain to understand the suitability of different resilience capabilities over time and under different scenarios is not carried out. The thesis addresses this gap by studying the internal decision making mechanisms, rules and control procedures through development of an agent-based model and its application to a paper tissue manufacturing supply chain.

The model with a decentralised informational structure with informed and intelligent combination of push or pull type of replenishment strategy, flexibility, agility, redundancy and efficiency is found to enhance the resilience of the actual supply network in the face of large deviation of demand from forecasts. The effects of adopting several resilience improvement strategies in tandem or in isolation and the impact of applying different behavioural rules by different agents are studied in this thesis by carrying out numerical experimentation. The findings from the experiments suggest that, however flexible the resources are, however well-informed the different members are, however well-integrated the members are through coordination and communication, however well-equipped a supply chain is with mitigation and recovery capabilities the individual managerial judgements that can obtain a balance between various dimensions of performance (both global and local efficiency, quality and speed of responding to customer orders) and resilience (speedy reaction, maintaining buffers, flexibility in resource management) play the most important role in improving the resilience of the entire network.

An important contribution of this thesis is to produce a conceptual framework for supply chain resilience. This framework is used to test the appropriateness of different resilience enhancement procedures. Another significant contribution of this thesis is to provide a theoretical template for further research in supply chain resilience. The template will guide development of effective procedures for managing different situations of uncertainty. By using complex systems modelling methods, such as multi-agent models described in the thesis, outcomes of the system under a significant range of possible agent behavioural rules and environmental events can be explored, and improved levels of functioning and of resilience can be found. Building such models as a means to understand and improve resilience of supply networks is a significant contribution.

ACKNOWLEDGEMENTS

This thesis would not have come into being without the support and help from several persons and I would therefore like to thank all of them.

First of all, I wish to thank my supervisors Professor Peter Allen and Professor Martin Christopher for their guidance, support, inspiring and thoughtful comments throughout the program.

I am also grateful to the staff in Cranfield School of Management for their prompt administrative support and help in need. I also wish to thank the paper tissue manufacturing organisation for giving me the opportunity to use their supply chain as a case study for the PhD and providing me with all the necessary data.

My heartfelt thanks go to my parents, Dr. Nilkanta Datta and Mrs. Manjusri Datta, and my sister, Mrs. Rupanjana Datta, for always being there for me. Finally, I would like to thank my wife, Sanjukta, for providing endless and necessary support, understanding and love. Last but not the least, I would like to mention the name of my daughter Priyadarshini for being the source of constant joy and inspiration.

TABLE OF CONTENTS

TABLE OF FIGURES

NOTATIONS

Indices:
c: customer index, c=1…C
dc: Distribution Centre, dc= 1…DC
h: product currently being produced, $h \in [1....P]$
i: Product Types, i= 1…P
p: Pallet Types, p=E3,E5,S2
s: supplier index, s=1…S
t: time period index

Parameters:
$co_{t,i,i+1}$*: changeover time between products i and i+1 at time unit t, $i,i+1 \in [1....P]$*
k: safety factor corresponding to fixed target customer service level
PR_i*: Fixed production capacity for product i in units per unit of time*
T_{max}*: Maximum Transport Lead time from Central Warehouse to distribution centres*
T_d*: Transport Lead Time from distribution centres to customers*
T_{review}*: Inventory Review Period*
TAF_i*: Total fixed Annual Forecast of Product i*
TWD: Total number of working days in a year

Variables:
α_c*: Importance of customer c*
α_{dc}*: Importance of distribution centre dc*
AP_i*: Total Amount produced for product i*
$ATAF_{,t,i}$*: Adjusted Total Annual Forecast for product i at time unit t*
$b_{c,t,i}$*: Customer c's Sales backlog for product i at time unit t*
$B_{t,i}$*: Total Sales Backlog of product i at time unit t*
$B_{dc,t,i}$*: Sales Backlog at distribution centre dc in product i at time t*
CO: Total changeover time
$d_{c,t,i}$*: demand from customer c at time t for product i*
$D_{t,i}$*: demand aggregated over all customers for product i at time unit t*
$D_{dc,t,i}$*: Total aggregate demand of product i at time t for product i in distribution centre dc*
$\hat{D}_{t,i}$*: standard deviation of demand for product i at time unit t*
$\overline{D}_{t,i}$*: Average Demand of product i at time unit t over the lead time period, T_{max}*
$DFF_{t,i}$*: Forecast of product i directly sold from central warehouse at time t*
$DFS_{t,i}$*: Sales of product i directly sold from central warehouse at time t*
$f_{c,t,i}$*: forecast of demand at time unit t from customer c for product i*
$fd_{c,t,i,p}$*: demand at time unit t from customer c for product I to be stacked in pallet type p*
$ff_{c,t,i,p}$*: forecast of demand at time unit t from customer c for product i to be stacked in pallet type p*
$F_{t,i}$*: forecast aggregated over all customers for product i at time unit t*
$F_{dc,t,i}$*: Sales Forecast at distribution centre dc in product i at time t*
$FETS_{t,i}$*: Forecast Error Tracking Signal at time t for product i*
$FI_{t,i}$*: Finished goods inventory for product i at time unit t at the central warehouse, after production at factory*

$FI_{t,i}$*: *Target level for finished goods inventory for product i at time t at central warehouse*
$FB_{t,i}$: *Total finished goods sales backlog at time t for product i at the central warehouse*
$FSS_{t,i}$: *Finished goods safety stock at Central Warehouse for product i at time t*
$FF_{t,i}$: *Total forecast of product i at time t at all successive downstream stock-points to which the central warehouse is a supplier*
$FF_{t,i,p}$: *Total forecast of product i in pallet type p at time t at all successive downstream stock-points to which the central warehouse is a supplier*
$FC_{t,i}$: *Forward cover at time t of i in terms of days of stock in the central warehouse to meet forecasted demand during that period*
$FC_{dc,t,i}$: *Forward cover at time t in terms of days of stock in the downstream distribution centres to meet their respective product i's forecasted demand during that period*
$FD_{t,i}$: *Total demand of product i at time t at all successive downstream stock-points to which the central warehouse is a supplier*
$FD_{t,i,p}$: *Total demand of product i in pallet type p at time t at all successive downstream stock-points to which the central warehouse is a supplier*
$I_{t,i}$: *Total Inventory of product i at time unit t*
$I_{dc,t,i}$: *Total Inventory of product i at time unit t in distribution centre dc*
$I^*_{t,i}$: *Target Inventory of product i at time unit t*
$IP_{t,i}$: *Inventory Position of product i at time unit t*
$IP_{dc,t,i}$: *Inventory Position of product i at time unit t in distribution centre dc*
$IO_{s,t,i}$: *Total incoming orders from supplier s in product i at time unit t*
$IT_{s,t,i}$: *Total in-transit stock from suppliers s in product i at time unit t*
$o_{dc,t,i}$: *Distribution centre dc's replenishment order for product i at time unit t*
$O_{t,i}$: *Total replenishment order for product i at time unit t*
$pb_{dc,t,i}$: *Distribution Centre dc's production backorder for product i at time unit t*
$PB_{t,i}$: *Total Production Backorder of product i at time unit t*
$q_{t,i}$: *Order raised by any distribution centre for product i at time unit t*
$\tilde{q}_{dc,t,i}$: *Orders to be placed by distribution centre dc for product i at time t*
$r_{t,i}$: *Reorder point for any distribution centre for product i at time unit t*
$Rank_i$: *Rank of product i used for determining production sequencing*

$SS_{t,i}$: *Safety Stock level for product i at time unit t*
$\bar{t}$: *Average time of production across all products*
t_i: *time to produce product i (defined as the amount of time a product is produced continuously on the machine)*
t_{iL}:*Lower limit for time of production of product i*
t_{iU}:*Upper limit for time of production of product i*
T_0: *current time*
T_i: *Approximate production cycle time for product i, time between successive runs of production of i*
$THol_t$: *Total number of holidays until time unit t*
$TICF_{t,i}$: *Time increment contingency factor at time t for product i*
$y_{c,t,i}$: *product i delivery to customer c at time unit t*
$y_{dc,t,i}$: *product i delivery to distribution centre dc at time unit t*
$Y_{t,i}$: *Total Customer Supply of product i at time unit t*

[page intentionally left blank]

Chapter 1

Introduction

"It is not the strongest of the species that survive, not the most intelligent, but the ones most responsive to change." – Charles Darwin (cited in , p19, Chapter 3, Ayre, J., 2004, *Supply chain project management* – A structured collaborative and measurable approach, London, CRC Press)

1.1 Business Resilience

Business often feels like a highly competitive contact sport. Competitors want to rough each other up, blitz each other with unexpected new products, undercut each other's prices, gang up on each other via alliances or mergers and hammer away at each other's stock price. The important thing is a company's ability to minimise the damage, recover fast and quickly get back in the game with new strategies, business models and products. That's what business *"resilience"* is all about. The capacity to adapt and hence to survive becomes one of the central questions about resilience – because the stability of the environment cannot be taken for granted (McDonald, 2006).

Resilience is something that even the best companies will need to perfect as we proceed into an already turbulent 21st century. The ultimate goal of resilience, write Hamel and Valikangas (2003), is creating *"a company where revolutionary change happens in lightning-quick, evolutionary steps—with no calamitous surprises, no convulsive reorganisations, no colossal write-offs and no indiscriminate, across-the-board layoffs"* (p. 54). They argue that, resilience is not only concerned with recovery, flexibility or crisis preparedness, it implies something more and *"refers to a capacity for continuous reconstruction, It requires innovation…Any company that can make sense of its environment, generate strategic options and realign its resources faster than its rivals will enjoy a decisive advantage. This is the essence of resilience."* (p55, 63)

1.2 Growing Importance of Supply Chain Resilience – Motivation for this research

Over the last few decades, business environments have been changing from mass-production to customisation, and from technology and product-driven to market and customer-driven. Providing distinctive customer value has become one of the main business drivers for companies. However, a single company often cannot satisfy all customer requirements, including fast-developing technologies, a variety of product and service requirements, and shortened product lifecycles. Such developing new business environments have made companies look to the supply chain as an 'extended enterprise', to meet the expectations of end-customers. Christopher (1998) argued that real competition in the marketplace now exists between supply chains, not between companies. This implies that an organisation can no longer act as an isolated and independent entity in competition, but the fully-integrated supply chain can provide competitive advantages in the market. So to stay ahead of competition in today's dynamic business environment, resilient organisations need to build resilient supply chains.

Modern supply chains are very complex, and recent lean practices have resulted in these networks becoming more vulnerable. Managers optimised their supply chain designs by reducing inventory, outsourcing noncore activities, trimming the number of suppliers and sourcing globally, on the assumption that, the world is a relatively stable and predictable place (ATKearney, 2003). But in reality it is not. Firms increasingly depend on a complicated network of global suppliers and partners to deliver products in the right quantity and at the right place and time in increasingly volatile markets and under persistent cost pressures. The very complexity and the global reach of today's globe-spanning supply chain networks, the low inventory levels and lack of redundancies required to achieve efficient operations expose businesses to a huge range of unexpected disruptions.

The risk of supply chain disruptions—an indication of a firm's inability to match demand and supply—is receiving increased attention in the business as well as the academic press (Kilgore 2003; Radjou 2002; Billington et al. 2002; Lee et al. 1997; Fisher 1997). Hendricks and Singhal (2003, 2005) analysed announced shipping delays and other supply chain disruptions reported in the *Wall Street Journal* during the 1990s and showed, based on matched sample comparisons, that companies experiencing such disruptions under-perform their peers significantly in stock performance as well as in operating performance as reflected in costs, sales, and profits. As reported in Kleindorfer et al. (2003), disruptions from accidents in the chemical industry have led to huge economic losses and environmental damages, from the Bhopal and Exxon Valdez disasters, to the hundreds of lesser events that continue to occur on a yearly basis. There seems to be widespread recognition that such disruptions have the potential to cause significant negative economic impacts. These results along with 9/11 events have pushed the issue of supply chain resilience higher than ever before up corporate and political agendas. The growing importance of the field of supply chain resilience is the motivation for this research.

MIT research (2003, p30) defines resilience as, *"the ability to react to unexpected disruption and restore normal supply network operations."* Christopher and Peck (2004) defined supply chain resilience as the ability of the supply chain to return to its original state or move to a new, more desirable state after being disturbed. In this thesis supply chain resilience is defined as not only the ability to maintain control over performance variability in the face of disturbance but also a property of being adaptive and capable of sustained response to sudden and significant shifts in the environment in the form of uncertain demands. The challenge is to make supply chains resilient enough not only to survive in this risky business environment, but also to turn resilience into a distinctive competitive advantage by balancing the benefits and risks associated with the several resilience enhancing strategies.

1.3 Research Questions

Many recent articles (Lee and Wolfe, 2003; Rice and Caniato, 2003; Starr et al, 2003; Christopher, 2004; Christopher and Lee, 2004; Kleindorfer and Saad, 2005; Sheffi and Rice, 2005; Tang, 2006) come up with a list of recommendations for designing resilient supply networks. But none have mentioned the effects of adopting multiple resilience building strategies or which strategies are the most suitable to help firms protect from disruption risks without hampering its competitive advantage in terms of several performance metrics. Although the literature related to supply chain resilience is informative, it has primarily focused on supply chain disruptions from a general or high-level view of the phenomenon (Haywood and Peck, 2003; Sheffi 2001; Rice and Caniato, 2003; Christopher and Lee, 2001; Christopher et al, 2002; Sheffi et al, 2003). This perspective has guided to a fairly good understanding of the ‘big picture’, but deters the researcher from ‘drilling down’ to the key variables, the relationships among them and methodologies to manage these key issues (Blackhurst et al, 2005). This in turn reduces the practical utility of such studies since in any real application the detailed decision rules, controls, procedures and circumstances must be dealt with.

Designing resilient supply chains in this environment is a challenging task in cases of multi-product, multi-national supply networks, where different products with very different demand patterns (which are often unpredictable) share common resources, specifically production and distribution facilities. Current literature on supply chain resilience does not emphasise resilience build-up through effectively responding to disturbances without adversely affecting the performance by accumulation of excessive inventory or deterioration of production performance. Disturbance here refers to any unwanted event that adversely affects the performance of supply chain networks. Disturbances can arise from faulty processes and uncertainties within an individual organisation, from interaction between different partners (internal disturbances) or could be at a higher industry or environment-level that causes uncertainty in demand (external disturbances). Although most researchers would agree that disturbances are present in all supply chains, there is a limited amount of information on how to deal with them from a practical perspective in both the short and long term to improve resilience. So the questions addressed in this research are focused on improving resilience by management of both internal and external disturbances described above. The first research question describes the process of reacting to external disturbances in the form of major deviation of orders from forecasts. The second and third research question aims at mitigating disturbances arising from internal rules, procedures and control systems by focusing on the interconnecting linkages between different supply chain members. The research questions addressed in this research are:

a) How best to respond to external disturbances and improve supply chain's resilience?
b) Can we find rules, procedures and control systems used in managing complex supply chains systems that are not a potential source of disturbance?
c) How can the system elements adaptively respond to any disturbances through interconnecting linkages and maintain the performance at the same time?

1.4 Methodology

In order to address the research questions, it is extremely important to consider the integrated behavioural dynamics of production and distribution functions. Understanding the behaviour of integrated supply chain under different scenarios is a major question in this research. There are no controlled experiments that can be done within a reasonable time period, involving the whole supply chain or even involving only a single large factory (Armbruster, et al., 2002). Simulation models will have to be developed that substitute for the real environment.

In order to build resilience against any disturbances or crisis situation, the entire supply chain needs to be modelled in an integrated manner. Combining the activities of material management (supporting the complete cycle of material flow from internal control of production material to the planning and control of work-in-process, to the warehousing, shipping and distribution of finished products) and physical distribution (encompassing all outbound logistics activities related to providing customer services) in a multi-product, multi-objective, multi-period model represents not only a linear chain of one-on-

one business relationships but a web of multiple relationships. A key realisation to tackle this problem is that supply chain network should be treated as a '*complex system*' [which *'is any system that has within itself a capacity to respond to its environment in more than one way, and which selects among these in some way'* (Allen, 2000)]. Choi et al (2001) emphasised a similar viewpoint and aimed to demonstrate how supply networks should be managed if they are to be recognised as complex adaptive systems.

1.4.1 Existing Approaches & Their shortcomings

There exists a large body of literature on models dealing with uncertainty. While the solutions are elegant in their simplicity, they fail to address the key features of realistic supply chain problems, namely, multiple products sharing the same production and distribution facility, with capacity constraints and demands originating from multiple customers, which vary widely from forecasts. There has been a considerable amount of analytical research examining supply chains under various coordination and information sharing schema (Aviv, 2002 ; Cachon and Fisher, 2000). Pyke and Cohen (1993), Altiok and Raghav (1995) used operational research techniques to model and study the dynamics of a supply chain network. However this analysis becomes extremely complicated very quickly as a greater number of parameters are introduced and the models converge towards the complex systems phenomena, which they represent. These approaches, as indicated by Kafoglis (1999), are technically insufficient in handling a high volume of what-if scenarios and it is very difficult to address a problem where more than two management issues are considered, especially exploring multiple strategies for building resilience. Few tools are currently available to model the integrated production/distribution system under conditions of uncertainty.

Forrester's (1961) work has been extensively researched and substantial empirical support for the theory has been provided (Coyle 1982, Towill 1992). Towill (1996) has shown the various ways in which industrial dynamics models may be built and exploited in supply chains using simulation techniques. However most of these papers were based on a steady state design principle. Complex production distribution systems with multiple products, multiple echelons can become exceedingly difficult to model with such approaches, especially under conditions of uncertainty. These works are more concerned with capturing the mode of behaviour of the whole system making extensive use of system level observables without addressing the individual behaviours of the elements that constitute the system. So these types of models are most naturally applied to systems that can be modelled centrally, and in which the dynamics are dominated by physical laws rather than information processing. But in improving the resilience of supply chains, such modelling approaches are not true representation of reality, since there is no explicit representation of the behaviours of the individuals. Existing approaches discussed above lack some capabilities, like the explicit modelling of decision making infrastructure, the linkages between different levels of decision making, the systems responsible for control, their activities and their mutual attuning with time to adapt to changes, and these capabilities are essential for successful supply chain simulation to improve resilience.

1.4.2 Need for a new modelling framework – Agent Based Simulation

The modelling approach has to account for the decision-making nature of the various elements comprising the supply chain. It also has to account for the time-varying nature of the behaviour of certain subsystems according to the changing objectives of the decision makers, based on their knowledge of other decision makers and the environment the supply chain is embedded in (Backx, et al., 1998). Ultimately, behaviour of the supply chain should be synthesised to meet given operational objectives reflecting the market demands. They say this would result in a robust structure of the supply chain together with the operational strategies of all its parts, if the dynamics of the supply chain, all its constituents and the couplings between them could be taken into account at high resolution. The new modelling framework should reveal and aim to integrate the material structure (flow of material), the information structure (transfer of status information through the system), the decision structure (flow of decision related information, which is a set-point or target to be enforced or a criterion, which is used in the decision making process) and the strategic structure (the operational policy of each decision maker and defines its knowledge or ignorance of the goals and operational policies of other decision makers).

So a need for a modelling framework is clear, which is bottom-up, and starts by identifying the most basic building blocks of the supply chain; identifies their individual behaviours, decision making and interactions; and specifies how these agents interact with each other and the external environment. Accordingly in such a model, the behaviour of the supply chain emerges as a result of behaviour of all its subsystems, connected with each other and with the environment the system is embedded in, giving rise to improved resilience.

Like any complex systems, the study of supply chains should involve a proper balance of simulation and theory. Agent based simulation modelling is regarded as one of the best candidates for addressing the research questions identified above. Agent based modelling provides a method of integrating the entire supply chain as a network system of independent echelons; different entities employ different decision making procedure in most cases (Gjerdrum et al, 2001).

The specific difference between agent based simulation models and conventional simulation models are summarised below (Paolucci and Sacile, 2005):

- Part of the system entities is associated with agents
- The entities that are modelled as agents can communicate with one another, perceive changes in the environment and show a proactive behaviour.
- The system model is intrinsically distributed because agents behave autonomously
- Such models make it possible to study the emergent behaviour of the system, i.e., the outcome of the simulation at the macro level derives from the evolution of the interaction of single or groups of agents at the micro level.

Agent based simulation (ABS) models are the best tools to analyse situations in which distributed entities with an autonomous behaviour are present. Parunak et al (1998) offer a general recommendation: ABS is appropriate for domains characterised by discrete decisions and composed of a high number of distributed local decision makers. Such situations occur increasingly more frequently in integrated production-distribution systems, where distributed decision making has been labelled as a fundamental building block enabling agility (supply has to react quickly and flexibly to changing demand) (Christopher and Towill, 2000). Kornienko et al (2004) stated that because the activity of agents is a result of the group behaviour that is based on different forms of negotiations among agents, the problem solving (multi-period, multi-product resource allocation satisfying multiple objectives) in an agent based system has essentially more degrees of freedom than in traditional centralised systems. The interactive agent based framework becomes more flexible and more 'resilient' to different disturbances. In this thesis, I propose an agent based model to represent each entity in a complex supply chain, to capture non-linear decision making, allow implementation of a range of realistic operational and strategic policies and analyse the dynamic behaviour.

1.5 The Agent Based Model

Each member of the supply chain is modelled as an independent agent with autonomous decision making ability based on the available information on resources and demand. Hence the production facility is represented by a Factory Agent, which actually replicates the decisions made by Factory managers with respect to the physical flow of materials in and out of the factory and the information of strategic decisions taken by the organisation (for example, introduction of new products, new market entry etc.). Similarly, the distribution centres actually replicate the behaviour of individual regional sales manager's decisions based on country sales, forecast and organisation's strategic intent. The agent architecture is defined below. In order to make the agents a true representation of real business units, the agent structure is divided into two stages:

1. Functioning stage: This will describe the regular order fulfilment process, in which orders are received and goods dispatched and goods are produced. This level operates at a regular periodic interval according to a set of fixed difference

equations which depend on a certain number of fixed parameters and variable coefficients.

2. Decision-making stage: This part of the agent will monitor the different key performance indicators (KPI) identifying the states of different agents, the global supply chain network on the whole and itself, over time. This part of the agent will assess the performance of competing downstream elements, rank the products according to their urgency for manufacture and determine target inventory levels by adjusting safety stock levels, dispatching and replenishment policies to be used.

Such modelling framework has many desirable features (autonomy, intelligence and collaboration) for understanding supply chain behavioural dynamics under changing situations. This is because, first, there are multiple units as producers, distributors, and retailers. Secondly, these units are independently managed with independent decision making authority (autonomous); they are interdependent through exchange of information on customer demand, inventory levels, and exceptional events but there is no single authority to govern the whole chain collaboration. And thirdly, intelligent coordination is required for planning and scheduling of production and logistics in a dynamic market situation. This new software architecture for managing the supply chain views the supply chain as consisting of a set of intelligent agents, each responsible for one or more activities in the supply chain and each interacting with other agents in the planning and executing of their responsibilities (Gunasekaran et al, 2000). The notion of agents is naturally associated with the modelling of control structures, that is, the managers or systems deciding on the use of supply chain resources, their activities and the mutual attuning of these activities.

The application of the modelling framework is illustrated by studying the dynamics of the European supply chain of a multi-national paper tissue manufacturing company. The multi-product complex multi-country supply chain is subject to demand variability, production, transportation and distribution capacity constraints. The thesis then analyses the performance of the system under different scenarios, decision making rules, procedures, control systems and derives managerial insights for improving the system's resilience. The performance is analysed in terms of customer service level, network inventory level, production efficiency, reduction of bullwhip effects, response time to any unexpected events, number of stockout situations.

The relative effects of adopting several resilience improvement strategies in tandem or in isolation are also studied in this thesis by carrying out numerical experimentation. For example, use of centralised production planning based on sales forecasts or using real demand based dynamic production planning; use of adjustable stock policies or traditional theoretical stock replenishment policies; use of information sharing techniques across the supply network are studied under various conditions of uncertainty, such as demand spikes, unforeseen disruptions in production, huge demand-forecast mismatches. This would help to understand the dominant strategies needed to improve supply chain resilience. The behaviours of the different agents are also varied in the experiments to study the effects of adopting different behaviours on supply chain resilience.

First, the model is verified and validated with respect to the actual inventory level data collected over a year of operation of the real system. The different adaptive decision making strategies are implemented by the agent based model to provide improvements in supply chain resilience. Theoretical and empirical distributions are fitted to the sales data to generate replications for simulation of different experimental scenarios outlined above. In this way, the strategies for improving resilience and their effective implementation are investigated in this thesis.

1.6 Contribution

The main contribution of this research is to study and provide methods for improving the management of uncertainty and thereby improving resilience in complex multi-product, multi-country real-life production distribution system. This research, as depicted in the literature review section, addresses the gap in the study of complex production distribution systems in a stochastic environment. This research would provide some meaningful insights for supply chain managers to design more resilient supply chains in uncertain environments.

Above all, this research provides a generic agent-based computational framework for studying complex issues like supply chain resilience of complex production distribution systems that depend on multiple factors. The case of the paper tissue manufacturer depicted is used as an example of application of this framework. However, this framework can be applied to any complex production distribution system with any number of products with any demand profile, any forecast bias and errors and any number of distribution centres. The use of different attitudes of agents towards local or global performance improvement, information sharing or usage, balancing different strategies to improve resilience in a real supply chain using real data is novel in the field of supply chain management.

This research makes a number of contributions to supply chain management understanding, particularly in the area of supply chain resilience. One of them is to pinpoint the strategies to be adopted and adjusted and the parameters/measures to be monitored for improving the resilience of a complex supply chain. As has been stated in earlier section, the contemporary literature on supply chain resilience has recommended a plethora of possible ways of improving supply chain resilience, but none has analysed the effects of adopting all at once or balancing different strategies or different decision trade-offs stressing the time aspect of resilience. Another contribution to supply chain management is a broad, critical review of literature about the multi-faceted phenomenon of supply chain resilience and the use of agent based models in supply chain management. In this aspect, the thesis presents several qualitative and quantitative studies on resilience, supply chain resilience, risk management, vulnerability and modelling supply chain uncertainty. And a conceptual framework of supply chain resilience is introduced.

1.7 Chapter Layout

This thesis is organised in seven chapters.

Chapter 1 introduces the context of this research, the resilience in both business context and supply chain context. The reasons for this research are described after depicting the growing importance of the issue of supply chain resilience. An overview of different research in this subject is given first and the issues not addressed in contemporary literature are presented in the form of the research questions addressed in this dissertation. The methodology and its rationale are briefly described in this chapter after reviewing the existing methodologies and their shortcomings. After this, contributions for supply chain management and for wider audience in fields of modelling are summarised.

Chapter 2 reviews the literature on the background of this work. Different supply chain disturbances and problems are reviewed in this chapter. The review is synthesised in the form of a conceptual multidimensional framework for supply chain resilience and finally the research questions addressed in the thesis are presented.

Chapter 3 deals in detail the rationale for chosen methodology, describes and reviews agent based methodology, supply chain modelling techniques, presents supply chains as complex systems, describes different complex systems modelling techniques and application of agent based modelling in supply chain research.

Chapter 4 provides a detailed explanation of the agent based simulation model including description of the two stages of the agent architecture used in this research. Several possible examples, where such modelling framework can be applied are also provided.

Chapter 5 outlines an implementation of the model to a real world complex supply chain of a European paper tissue manufacturer. The model validation and verification with actual supply chain data, collection of data and the improvements in several performance measures under actual demand are discussed in this chapter.

Chapter 6 presents the series of experiments carried out with the model for the said example to identify the dominant strategies for improving supply chain resilience under different conditions of uncertainty. Several different configurations with application of different strategies either in isolation or in tandem for the supply chain are modelled. This chapter also analyses the results obtained from the different sets of experiments carried out and provides a comparison of the performance measures relating to supply chain resilience with respect to variation of strategies or parameters under different scenarios.

Chapter 7 summarises and interprets the findings from Chapters 5 and 6, to address the research questions. First, methods of improving supply chain resilience through management of disturbances are discussed. The different decision rules, control systems and procedures that are supposed to enhance resilience are investigated for not having any adverse influence on the functioning of the supply chain. This helps identifying procedures that are not potential sources of disturbances. Finally, the contribution and future scope of work are outlined.

Chapter 2

Literature Review

"Resiliency … resembles the elasticity of a spider web, a gull's skillful flow with the wind, the regenerating power of perennial grasses, the cooperation of an ant colony, and the persistence of a stream carving canyon rocks." - Ben Silliman (p.1, 1995, Resilient families: Qualities of families who survive and thrive, University of Wyoming Cooperative Extension Service, www.nc4h.org/greenlight/PDF/Wy1018.pdf)

2.1 Why Supply Chain Management is difficult?

Christopher (1998, p19) defines a supply chain as, *"a network of connected and interdependent organisations mutually and co-operatively working together to control, manage and improve the flow of material and information from suppliers to end users"*. Through the conceptualisation of a supply system as a network rather than a chain provides a more accurate and realistic view of inter-organisational relationships (Pfohl and Buse, 2000). More and more of the end-product value are delivered through a tier-structured supplier network with multiple connections to other value networks (Williams et al., 2002). As Nassimbeni (1998) convincingly argues, inside a network, firms enter into a complex set of interdependencies with other firms.

2.1.1 Different Conflicting Objectives

Companies do not make isolated decisions anymore. Since each company impacts on and is impacted by its partners in a supply network, any decision by a company to maximize its profits may disturb other companies, which may result in globally sub-optimal decisions, because organisations may have different conflicting objectives (Simchi-Levi et al., 2000, p3). Traditionally, the different supply chain functions, as purchasing, manufacturing, distribution and marketing have been operating independently; the consequences of their conflicting objectives are excessive costs and waste over the whole business line (Villa, 2002).

2.1.2 Supply networks are dynamic

Different entities in a supply chain operate subject to different sets of constraints and objectives and their performances are dependent on the performance of others (Swaminathan et al, 1998). The significant operational challenges presented by supply networks are driven by the dynamical behaviour of the supply chain as its members interact with one another (Parunak, 1998), and these interactions evolve over time making the supply networks a dynamic system. The changing demands of the marketplace, constant changes in product specifications, together with other continuous improvement initiatives within the organizations and the wider industry as a whole imply that the supply chains never actually reach a stable steady state (Haywood and Peck, 2004). Even supply chain structures should not be expected to be stable (Fine, 2000). In fact, as Fine (2000) shows, supply chain structures cycle between integral/vertical and horizontal/modular forms influenced by the pace of the industry.

2.1.3 Supply networks are complex

Modern supply chains are very complex with many parallel physical and information flows occurring in order to ensure that right products are delivered in the right quantity, at right place, at the right time, in a cost effective manner (Chapman et al, 2002). Deloitte Touche Tohmatsu research (2003) points to three critical trends that pull apart manufacturers' supply chains and make them more complex and difficult to manage:

- The unrelenting pressure to continually drive down supply chain costs from product concept to delivery
- The pursuit of new attractive markets and channels
- The quickening pace of product innovation.

Supply chain management literature has noted the causes for such complexity of supply chains. First, the material and information flows in supply networks can form a complex web of interlinked activity reaching across multiple suppliers, manufacturers and distributors (Lee and Billington, 1993; Lee and Whang, 1998). The supply chains are getting complex due to uncertainty present in customer demand, capacity, transportation time, manufacturing time, costs, quality, due date, priority, missing information, ambiguous information and the bull-whip effect (Davis, 1993; Lee and Billington, 1993; Lee et al, 1997; Lee and Whang, 1999; Taylor and Brunt, 2001; Arns et al, 2002; Geary et al, 2002, Kouvelis and Milner, 2002). These parameters of uncertainty can propagate through a supply chain network (Van der Vorst and Beulens, 2002). Harland et al (2003) identify the following as what contribute to the complexity of the supply chain: scale, technological novelty, quantity of sub-system components, degree of customisation, quantity of alternative design and delivery path, number of feedback loops in the production and delivery system, variety of knowledge bases, number of actors in the network, and various stakeholders. Supply networks show emergent behaviour with all characteristics of a complex adaptive system (Choi et al., 2001; Chung et al., 2004. Surana et al, 2005), and therefore their management is difficult, especially if information delays exist and lead times are long and variable. Braithwaite and Hall (1999) point out, inherently complex nature of supply networks makes it difficult for single organisations to monitor and control completely.

2.1.4 Supply networks are more vulnerable to disturbances

Supply chains are constantly subject to disturbances. Disturbances are unpredictable events that can influence the supply chain's ability to achieve its performance objectives adversely. Disturbances can arise from various sources either internal or external to the supply chains. Saad and Gindy (1998) classified disturbances into two broad categories – internal and external depending on their sources. Internal disturbances arise due to faulty processes and uncertainties within an individual company in the supply chain. Sometimes processes employed for improving supply chain performance can act as sources of disturbances. The drive towards more efficient supply networks during the recent years (lean concepts and TQM) has resulted in firms pushing towards zero or near zero inventory system. Thus, there often tends to be little or no inventory in the system to buffer the interruptions in supply. Owing to the close interrelationships between many supply chains in a supply network, the impact of such disruption can be far reaching (Chapman et al, 2002). As highlighted by Lee (2004), cost efficiency comes with a huge hidden cost should a major disruption occur. Even when there is a strong partnership among logistics nodes, there are in practice, evident risks of potential conflict areas, such as local versus global interests (Naish, 1994; Kahn, 1987) as well as strong reluctance of sharing common information (McCullen and Towill, 2002; Loughman et al, 2000; O'Donnell et al, 2006). In fact, in many real world supply chains the bull-whip effect increases dramatically as companies start to cooperate more closely (Van der Vorst et al, 1998). Another disturbing finding from experiments (Wilding, 1998), is that corrective actions (such as increasing stock levels or reducing lead-times) have conflicting results on overall performance.

Saad and Gindy (1998) classified external disturbance sources into demand and supply related sources. The demand related disturbances include unexpected large order spikes, expected orders with time delay, expected orders arriving early, changes in order priority and quantity variation in comparison to planned/forecasted quantities. The supply related external disturbances include delivery at the wrong time and failure to deliver the right products. Sheffi and Rice (2005) point out that, the primary source of supply chain risks is the uncertainty in the demand for products, uncertainty that has grown recently due to increased global competition, augmented customer expectations and greater product variety with shorter product life cycles. Such demand uncertainty can give rise to over- or under-production, with resultant excess inventories or inability to meet customer needs, respectively. Surplus inventory incurs excessive holding costs, while the failure to meet the customer needs results in both losses of profit and potentially, the long term loss of customers (Jung et al, 2004). In addition, supply chain managers must deal with the conventional disruptions of supply variability, capacity constraints, manufacturing yields, quality problems. On top of that, there are unwarranted disruptions such as natural disasters, strikes, accidents and terrorism (Chapman et al, 2002; Mitroff and Alpasan, 2003).

Among all these disturbances, the external disturbances resulting from deviation of sales from forecasts are more frequent and also results in huge long-term losses in the form of lost customer trust and costly bullwhip effects that affect the performance of the entire supply chain adversely. In fact, some internal disturbances resulting from internal decision making processes and rules can cascade into large magnitudes. All other forms of disturbances occur less frequently.

2.1.5 Summary

Hence from the above literature, it can be summarised that, supply chains are becoming increasingly difficult to manage due to:

- Large network of interlinked entities including suppliers, manufacturers and distributors across multiple organisations across the globe
- Each of these members may have conflicting objectives
- Dynamic and uncertain nature of the supply chain

Since supply networks often display unpredictable behaviour, they can never be completely controlled through top-down planning, however collaborative it might be (McCarthy and Tan, 2000; Radjou, 2002 and Lawrie, 2003). Also since supply networks are ever changing dynamic webs of linkages, it is pointless for each individual entity to optimise their functions by reducing or simply disregarding the interactions by assuming linearity. First of all, the space of possibility will be too large and secondly, there is no practical way to find an optimum as every moment the situation changes in today's dynamic environment (Holland, 1992). Firms increasingly depend on a complicated network of global suppliers and partners boosting the risk of system failure.

This new operating environment calls for a supply network structure design that is resilient enough to respond to unexpected disruptions and restore normal supply network operations (Rice and Caniato, 2003). This would involve developing "robust" strategies that serve dual purposes (Tang, 2006). First, these strategies should be able to help a firm to reduce cost and/or improve customer satisfaction under normal circumstances. Second, the same strategies should enable a firm to sustain its operations during and after a major disruption. Supply chain resilience has become a highly important strategic function in today's dynamic business world. Haapaniemi (2003) stated that, while the need for supply chain adaptability may be clear, but becoming one requires substantial change in strategy, processes and attitudes.

In order to justify the need for resilient supply network formation, one needs to have an understanding and clear definition of resilience, how it can be measured and most importantly, how it can be maintained and enhanced in the context of a supply chain network.

2.2 What is Resilience?

The Oxford English Dictionary defines resilience as (i) the act of rebounding or springing back and (ii) elasticity. The origin of the word is in Latin, where *resilio* means to jump back. The concept of resilience can be sourced from strengths of materials principles in engineering and the relationship dynamics of complex ecosystems. In a purely mechanical sense, the resilience of a material is the quality of being able to store strain energy and deflect elastically under a load without breaking or being deformed (Gordon, 1978). Both the areas of materials science and ecosystems dynamics focus attention on the internal elastic properties that allow systems to bend, flex, adapt and mould to continuous changes in external forces or environmental conditions thus counteracting other resistant forces that would drive the system to permanent deformation. The properties of systems to dynamically reshape themselves are a central premise of resilience.

2.2.1 View from Ecology & Social Science – Is adaptation enough?

Equilibrium view

Holling (1973) coins the word resilience for ecosystems as a measure of the ability of these systems to absorb changes and still persist. Many alternative definitions (Pimm, 1984; Perrings, 1994) have been provided focusing on different system properties since the seminal work by Holling (1973, 1986), but there have been constant challenges towards the core assumption of an equilibrium state to which systems return after experiencing a given level of disturbance, that underpins the concept of resilience.

Adaptive Capacity, Pliability, Flexibility

In spite of the relative lack of specificity with which resilience has been defined in ecology, the concept has also gained ground in social science, where it is applied to describe the behavioural response of communities, institutions and economies. Timmerman (1981) was one of the first to define resilience of a society as the measure of a system's or part of a system's capacity to absorb and recover from the occurrence of a hazardous event. Carpenter et al (2001, p766) defined the three properties of resilience:

'(a) amount of change the system can undergo (and implicitly, therefore, the amount of extrinsic force the system can sustain) and still remain within the same domain of attraction (i.e., retain the same controls on structure and function);

(b) the degree to which the system is capable of self-organization…

(c) the degree to which system can build and increase the capacity to learn and adapt.'

Adaptive capacity is therefore a component of resilience that reflects the learning aspect of system behaviour in response to disturbance (Gunderson, 2000). Dovers and Handmer (1992) stress the importance of this adaptive capacity while describing proactive resilience that accepts inevitability of change and tries to create a system that is capable of adapting to new conditions and imperatives.

After reviewing the definition of resilience in literature, it can be said, the degree of resilience is linked to the ability of the system's components to explore and develop mutually beneficial strategies and behaviours, which will permit them to change and adapt in response to disturbance (Clark, Trejo and Allen, 1995).

Summary – Resilience as a dynamic process

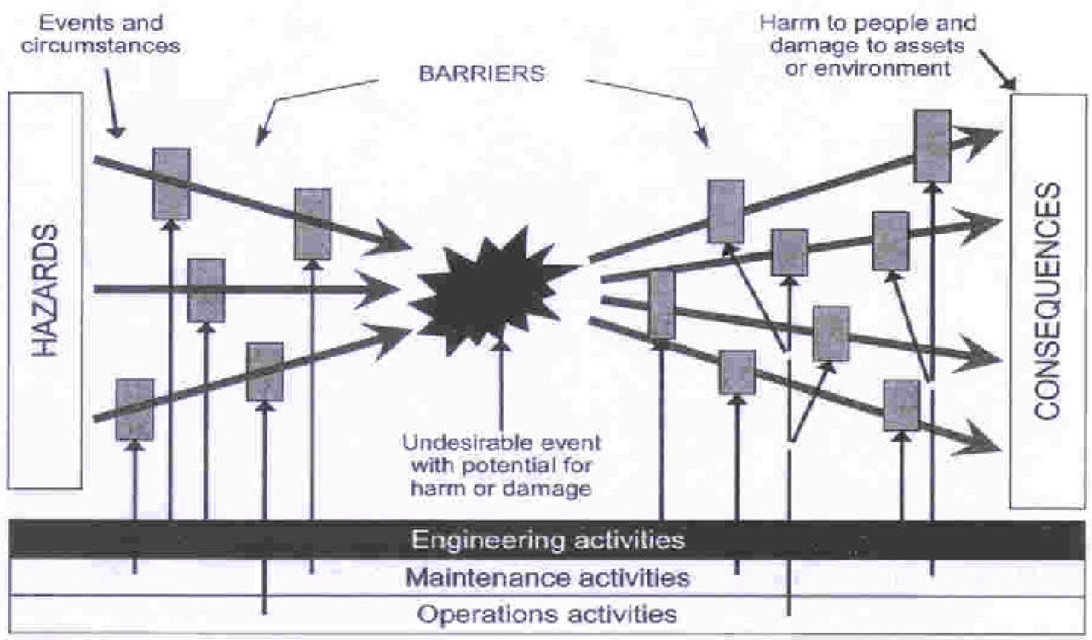


Figure 2.1: Bowtie model

So resilience, on one hand is the system's ability to efficiently adjust to harmful influences rather than to shun or resist them and on the other, it is also the ability to maintain effective barriers that can withstand the impact of harmful influences and the erosions caused by latent conditions thus linking resilience to planning for and adapting to hazards. If resilience needs to be expressed in a pictorial form, the bowtie model of accident scenarios (fig.2.1 adapted from Visser, 1998) can be used as a representation where resilience is not only located on the right-hand side of the centre event, but also on the left. And the barriers result from the different activities carried out by the system.

However, there is one problem with the concept of adaptation, planning and learning in the context of resilience. Since the change or adaptation deemed to be necessary at a particular environment may be sufficient for providing stability, but there is potentially large risk that this stability is not sustainable and could lead to collapse if the society cannot make changes necessary for survival at the right time (Handmer and Dovers, 1996). Moreover, uncertainty surrounding the impacts of environment changes will make planning particularly difficult (Klein et al, 2003). As a way to explain this, the above literature recognises that real systems are complex systems, exist in a state of dynamic stability, consist of multiple equilibria (Perrings, 1994; Holling, 1986) and must be able to adjust their performance to the conditions. Also, these systems must be dynamically constrained so that the adjustments do not get out of hand but at all times remain under control. Hence the essence of resilience is therefore the ability of a system to maintain or regain dynamically stable state, which allows it to continue operations after a potentially destabilising disturbance and/or in the presence of continuous stress. Resilience is a dynamic process of steering the actions so that the system always stays out of danger zone, and if the event occurs, resilience implies initiating a very rapid and efficient response to minimise the consequences. So resilience is not a static state, but has to be worked at continuously (Hale and Heijer, 2006). In words of Timmerman (1986, p444): *'Equilibrium myths are way of picturing nature as natura naturata – i.e., nature as object, fixed or fixable. The myth of resilience, on the other hand, sees nature as natura naturans – i.e., nature actively altering and responding in various ways to predictable or unpredictable stresses.'*

2.2.2 Resilience from an organisational perspective

Preparedness, Flexibility and Recovery – In organisational science, resilience refers to (a) the maintenance of positive adjustment under challenging conditions (Weick et al, 1999; Worline et al, 2004), (b) the ability to bounce back from untoward events (Sutcliffe and Vogus, 2003) and (c) the capacity to maintain desirable functions and outcomes in the midst of strain (Bunderson & Sutcliffe, 2002; Edmondson, 1999). Resilience is a dynamic capacity of organisational adaptability that grows and develops over time (Wildavsky, 1988). It is not a static attribute that organisations do or do not possess. Rather, it results from processes that help organisations retain resources in a form sufficiently flexible, storable, convertible and malleable to avert maladaptive tendencies and cope positively with the unexpected (Sutcliffe and Vogus, 2003; Worline et al, 2004). Resilient organizations are 'crisis prepared (or proactive)' encounter fewer disasters and recover better from hardship. (Mitroff and Alpasan, 2003). Anderson (2003) notes that, resilience is different than just recovery, it implies being flexible enough to adapt to both positive and negative influences. *"Resilience is a reflex, a way of facing and understanding the world. It is … the ability to bend and bounce back from hardship"* (Coutu, 2002, p 55).

Source for Competitive Advantage

Resilience is not only concerned with recovery, flexibility or crisis preparedness, it is a distinct source of sustainable competitive advantage (Hamel and Valikangas, 2003). Resilience is a critical capability for success (Coutu, 2002, p55). Focusing on resilience as a distinctive capability, Stoltz (2004, p17) states that, *'Resilience is the only sustainable, portable strategic plan. Resilient individuals, teams, and organizations consistently outlast, outmanoeuvre and outperform their less resilient competitors'*. Horne (1997, p28) expressed organizational resilience as the hallmark of corporate stardom in 21st century that reflects the organizations' *'ability to combine information with a range of other factors to flex, mould, adapt and redefine themselves to face ever-changing conditions.'*

Withstanding stresses without self-stressing

Horne (1997) defines organisational resilience as the ability to withstand the stresses of environmental loading based on the composition of the comprising elements, their structural inter-linkages and the way environmental change spreads and transmits through the organisation. He corroborates the views on resilience from ecosystems that, resilience allows a positive response to significant change that disrupts the expected pattern of events without resulting in unproductive behaviour. Mallak (1998) defines resilience *'as the ability of an individual or organization to expeditiously design and implement positive adaptive behaviors matched to the immediate situation, while enduring minimal stress'* (p148). A resilient organisation must, not only be able to change from one state to a more appropriate one in time, but also be able to return to normal functioning when the alerting of unusual conditions are over. This does not necessarily mean that it should go back to what were normal procedures before the events, since the world may have changed (Hollnagel and Sundstrom, 2006). But it means that it should be able to resume durable and sustainable performance, in the sense of attaining at least the same quantity and quality of whatever it produces, as it did before the disrupting events.

A Balance between Routinisation & Flexibility

In the context of organisational systems, resilience would seem, on the one hand, to depend on increasing standardisation. McDonald (2006) provides some examples of such tendencies, which are supported by other organisational resilience researchers as well:

- Stronger coordination of processes by routinisation of procedures in operations and organizational systems; this is stressed in organisational adaptation literature as a reflection of organizational memory and a presentation of a set of possible actions to respond to given situations (Nelson and Winter, 1982; Pentland and Reuter, 1994; Boisot and Child, 1999). Lengnick-Hall and Beck (2005) also supported the view that a resilient firm develops a broad and varied inventory of routines for responding to uncertain situations.
- Increased reliability through the removal of variance due to individual skills and ensuring substitutability of different people, through standardised selection and training (Mallak, 1998);
- Ensuring, through supervision, inspection, auditing, etc. that standardisation of the work-process does control the actual flow of work; Stoltz (2004) highlighted the need of leadership in developing resilience. Mallak (1998) stated the importance of goal-directed solution seeking as a key dimension of organizational resilience, which again necessitates the use of control procedures.
- Better standardisation of the outputs of the process is made possible through better monitoring, recording of those outputs; sensing and interpreting the outputs through appropriate measures is essential for building resilience (Haeckel, 1999; Thomas et al, 1993; Weick and Sutcliffe, 2001).
- Automation of routine or complex functions (Rasmussen, 1997; Reason, 1997).

On the other hand, resilience seems also to require certain flexibility and capacity to adapt to circumstances. Morgan (1986) pointed out that mechanistically structured organisations, designed for efficiently achieving predetermined goals, have great difficulty adapting to changing circumstances, which require different kinds of response and action. Resilience capacity is a multidimensional, organisational attribute that results from the interaction of three organisational properties: cognitive resilience, behavioural resilience, and contextual resilience (Lengnick-Hall & Beck, 2003, 2005). Firms with cognitive resilience encourage ingenuity and look for opportunities to develop new skills rather than emphasize standardization and need for control. In this context, Weick (1993) identified four sources of resilience as *improvisation* (swift replacement of the old order), *virtual role systems* (each member of the group *'can run the group in their head and use it for continued guidance of their own individual action'*, (p640)), wisdom (accepting ambiguity and lack of understanding in certain circumstances) and *communication* (sharing information about options and strategic directions in advance of change to attune the system to opportunities). These all require the members of organisations and the organisation as a whole to operate without following official rules and procedures, but using own knowledge and experience in the most judicious but effective way. Mallak (1998) wrote about implementing organisational resilience in a more general sense. He stated (p10-12) *'positive perception of painful organisational experiences, positive adaptive response to crises, external resource adequacy, expanded decision-making boundaries across the organisation, ability to improvise a solution on the spot (bricolage), tolerance for uncertainty, knowledge of each other's role'* – all act together as a first step in building resilience in organisations. Common organisational forms of this are (Deevy, 1995; Haeckel, 1999; McDonald, 2006):

- Informal work practices based on strong mutual understanding seen in Weick's (2001) analysis of high reliability organisation.
- Distributed decision systems with local autonomy; Wheatley and Rogers (1996) viewed organisations as living systems that thrive on chaos and disequilibria and have the built-in ability to adapt to changes in the environment by organising themselves into adaptive patterns and structures without any externally imposed plans or directions.
- Flexible/Agile manufacturing systems which can adjust to changing demand;

- Technologies that enable rather than constrain appropriate human action and modes of control;
- Organisational systems that can manage feedback, learning and improvement. William and Winfrey (1994) characterized the critical success factors in the continued resilience of organizations, as shared sense of organizational purpose/mission and interactive planning. This implies, organizations need to rapidly know its challenges, the competencies/resources it has or needs to meet them. Resilient organizations need to be very cohesive entities.

Resilience, therefore, is a function of the way in which organisations approach and manage the contradictory requirements of, on one hand, good proceduralisation and good planning, and on the other hand, appropriate flexibility to meet the challenges of uncertainty.

Management of Risks & Vulnerability

Several essential elements of organisational risk management are described below.

Notice of 'Latent Pathogens' & 'Incubation' –

The concept of management of risks, in organisational terms, was introduced in the pioneering work of both Turner (1976, 1978, 1994) and Reason (1987, 1990a, b, 1995, 1997). Turner introduced the concept of incubation in which the perceptions of senior managers within the organisation about the risks that they faced, would determine the control systems that would be put into place. However, often they fail to see the significance of the *"ways in which they do things"* in terms of their impact on crisis generation. In this *"crisis of management"* phase (Smith, 1990, 1995) the regular processes of management, especially around decision making, generate the conditions in which controls are by-passed and the conditions for incubation are established. The build-up to the crisis – what Turner referred to as "incubation" and Reason saw as the development of *"latent conditions"* or *"resident pathogens"* – very often passes unnoticed. Perrow (1999) stated, the nature of the organisation's design and systems causes a failure to escalate quickly and to do so in ways that were not considered to be particularly significant prior to the event. When the system is interactively complex, independent failure events can interact in ways that cannot be predicted by the designers and operators of the system. If the system is also tightly coupled, cascading events can quickly spiral out of control before operators are able to understand the situation and perform appropriate corrective actions. In such systems, apparently trivial incidents can cascade in unpredictable ways and with possibly severe consequences. So a notice of these latent harmful controls, decision rules is essential particularly in a tightly coupled and interactively complex organisation.

Organisational Slack – Pros & Cons

Building upon Turner's core ideas, Perrow (1999) considers redundancy as the primary engineering solution to risk increasing systems. Similarly, in a study of hospital responses to an unexpected doctors' strike, A.D.Meyer (1982) found that slack resources worked as "organisational shock absorbers" that buffered the impact of environmental jolts. Research on high reliability organisations (HROs) (LaPorte 1982; Roberts, 1990; Weick, 1987, 1993; LaPorte and Consolini, 1991; Rochlin et al, 1987) also suggests extensive use of redundancy to limit mishaps and improve performance (Sagan, 1993). Perrow correctly argues that redundancy introduces additional complexity and encourages risk taking therefore only making crises more likely. Hence the use of redundancy is not the only way to improve risk management capability.

Thoroughness and efficiency –

The essence of managerial capability in relation to risk management is the ability to deal with conflicts between risk and the primary performance goals of the organization. The individual approach to coping with complex goal environments can be seen as a trade-off between efficiency and thoroughness. On the one hand people genuinely try to do what they are supposed to do-or at least what they intend to do- with as much thoroughness as they believe is necessary. On the other hand they try to do this as efficiently as possible, which means that they try to do it without spending unnecessary efforts or wasting time

(Hollnagel, 1993). Rasmussen noted that organisations move toward the boundaries of safety under pressures to maintain economic performance and reduce workload (Rasmussen, 1997).

Integration –

Numerous examples illustrated the need for improved communication and coordination in order to reduce organisational risk by increased sense making of unpredictable environments (Berger and Bradac, 1982; Berger, 1987; Weick, 1979, 1990, 1993, 1996; LaPorte and Consolini, 1991). Disaster is more likely when organisations are not integrated because changes in systems or system designs made by one part of the organization may not be visible to other parts of the organization (Weick, 2004). This requirement for integration runs somewhat counter to the concept of organisational slack (Schulman, 1993).

Formalisation & Improvisation –

The effect of formalisation on risk is complex. On the one hand, procedures and rules are needed to ensure that information is not lost and that tasks are carried through (Robbins, 1992). On the other hand, formal hierarchies and job definitions can limit employees' willingness to identify problems and come forward with them (Gehman, 2003; Schulman, 1993).

Centralisation & Decentralisation –

Conventional managerial wisdom states that when the business environment is highly uncertain decentralisation is necessary in order to ensure flexibility of responses in the face of unexpected events (Weick, 1996, 1998). Centralisation limits decision-making about critical issues to employees who have a larger view of the system and should therefore be able better to assess the impact of decisions (Tucker and Edmondson, 2003).

Putting it all together – The Trade-offs

From the literature on organisational risk management, it can be inferred that resilience in organisational context is bound up with being able to successfully resolve apparent contradictions, such as:

- Formal procedures versus local autonomy of actions;
- Centralisation versus decentralisation of functions/knowledge/control;
- Maintaining system/organisation stability versus capacity to change;
- Maintain quality of product/service versus adjust product/service to demand or changing need;
- Maintaining a buffering capacity to absorb or adapt to the disruptions without a fundamental breakdown in performance or in system's structure.

Focusing on these tensions is difficult as efforts to improve or respond in one area are accompanied by greater squeezes in another area. More challenging is the dynamic resolution of these conflicts under changing environment needs, altering couplings across different parts of the organisation and changing economic pressures advancing the stringent performance goals of cost, quality, timeliness (cheaper, better, faster) (Woods, 2006). Also it is particularly challenging to make the trade-off decisions because the hindsight view will indicate that the sacrifice or relaxation in one area in order to improve upon other may have been unnecessary since ***"nothing happened".*** Hence a key component of organisational risk management is the judgment process in individuals and in organisations under uncertainty, to maintain a desired level of risk acceptance/risk averseness and the capability to recognise changing levels of risk acceptance/risk averseness. Lengnick-Hall and Beck (2005) pointed out, this capability provides a foundation for gathering information and insights from various sources to monitor the boundary between competence at designed for uncertainties and unanticipated perturbations (Carlson and Doyle, 2000; Csete and Doyle, 2002).

2.2.3 Summary

Resilience has been defined in terms of a productive tension between stability and change. The basic stability and integrity of the system is an important dimension, as is the capacity to absorb major disturbances from the operating environment and to recover from failure. The notion of adaptation to the requirements of the operational environment implies the capacity to adapt and change in order to survive in a changing environment. However, resilience is not just about being able to change on one hand or maintaining stability on the other. It is critically about the appropriateness of stability or change to the requirements of the environment or, more accurately, about the planning, enabling or accommodating of change to meet the requirements of the future environment (as anticipated and construed) in which the system operates. From the literature on resilience from general and organisational perspective, there is evidently lack of sound empirical evidence that is grounded in operational reality, is systemic (located in its technical and organisational context), dynamic (i.e., concerns stability and change over time) and ecological (i.e., concerns systems embedded in their environment). Unless this evidence gap is addressed, the concept of organisational resilience is in danger of remaining either a post-hoc ascription of success, or a loose analogy with the domain of the mechanical properties of physical objects under stress, which allows certain insights but falls short of a coherent explanation.

All these studies in organisational resilience suggest the complex construct of resilience. Unfortunately the majority of these references fail to provide any detailed explanation of this complex construct in its entirety. Resilience cannot simply be the adaptive capacity of a system but is a broader capability to recognise and adapt to handle unanticipated perturbations that call into question the model of competence and demand a shift of processes, strategies and coordination. It is a measure of an organisation's ability to interpret unfamiliar situations; to devise new ways of confronting these events and to mobilise people, resources and processes to transform these choices into reality (Kobasa et al, 1985). As resilience is a multi-dimensional phenomenon, it requires a lot of trade-offs to build a truly resilient organisation. Also, since resilience is a dynamic phenomenon, there is never a perfect model of resilience. Organisations need to adapt their policies to any changes on one hand and also build barriers to hazards through effective routines on the other.

2.3 Supply Chain Resilience

Supply chain resilience too, like organisational resilience, is a multi-dimensional phenomenon. Supply networks are becoming more complex, dynamically changing webs (Harland et al 1999). Wong et al (2002) stated a supply chain could be very lean and efficient; if it is unable to find an alternative route of delivery quickly, it will be susceptible to system shocks and disturbances. Many of the processes of supply chain management may unwittingly contribute to the creation of a system that, while responsive and efficient in the steady state, is so tightly coupled that it cannot prevent the escalation of threats and also has insufficient slack to cope with the demands of the event once it occurs (Smith, 2005).

Cranfield University research on supply chain resilience (2003, Christopher and Peck, 2004) notified the five broad elements of supply chain resilience – 1) Supply chain understanding implying knowledge about supply chain structures; 2) Supply base strategy, how many suppliers are the best; 3) Supply chain collaboration; 4) Agility with key component flexibility and 5) Creating supply chain risk management culture. MIT research group (2003, p30) defines resilience as, *"the ability to react to unexpected disruption and restore normal supply network operations."* Sheffi (2005b) examined the ways in which companies can recover from high-impact disruptions and focused on actions to lower vulnerability and increase resilience. These include: 1) reducing likelihood of disruptions through monitoring and detecting weakest signals, demand-responsive supply chains, supply-chain wide collaboration, redundancy; 2) operational flexibility through standardisation of parts facilitating interchangeability, postponement or mass customisation strategy to respond to unpredictable demand changes, customer and supplier relation management and multiple sourcing. Tang (2006) viewed resilience as a distinctive competitive advantage for supply chains and suggested developing robust strategies for mitigating supply chain disruption effects from supply and demand management perspectives. He suggested postponement, strategic stock investment, flexible supply base, economic supply incentives, multi-modal flexible transportation for improving supply management and dynamic pricing, dynamic assortment planning, silent product rollover for improving demand management. Christopher and Peck (2004) defined supply chain resilience as the ability of the supply chain to return to its original state or move to a new, more desirable state after being disturbed. So most of the definitions assume resilience as the ability to deal with unexpected events successfully after they have actually happened. None of the definitions have assumed resilience to be the ability to mitigate before the event actually happened. Now I will provide a detailed literature review of different key themes surrounding the construct of supply chain resilience.

2.3.1 Supply chain risk and management of risks

Supply chain risk has been defined as any risk to the information, material and product flow from original suppliers to the delivery of the final product (Christopher et al, 2003a, b). Christopher (2004, p18,19) suggested that for increasing resilience in the supply chains, *'Identification of 'pinch points' and 'critical paths' are important. Pinch points will often be characterised as bottlenecks where there is a limit of capacity and where alternative options might not be available, such as ports capable of taking large container vessels or central distribution facilities which, if they were to become inoperable, would place a heavy strain on the rest of the system.'* He states*, 'A high level of collaborative working across supply chains can help mitigate risk.' He also stated, 'supply chain risk assessment should be a formal part of the decision-making process at every level.'*

Johnson (2001) in context of toy industry provided some methods to manage supply chain risks. He stated managing supply chain risks requires focus on managing both supply and demand risks. Among the demand risk management strategies mentioned, the strategy of lean inventories to prevent obsolescence, matching channels to products speak of appropriate supply chain structures for different product varieties. And in speaking about supply side risk management, Johnson specifies outsourcing scale-dependent manufacturing operations (strategic sourcing of manufacturing), multiple sourcing, and risk diversification through multiple supplier sourcing, visibility of chain inventories as some specific risk management techniques which can be generalized to other supply chains. Zsidisin (2003) provided a grounded definition of supply risk based on case study data from seven purchasing organizations as (p222), '*supply risk is defined as the probability of an incident associated with inbound supply from individual supplier failures or the supply market occurring, in which its outcomes result in the inability of the purchasing firm to meet customer demand or cause threats to customer life and safety.*'

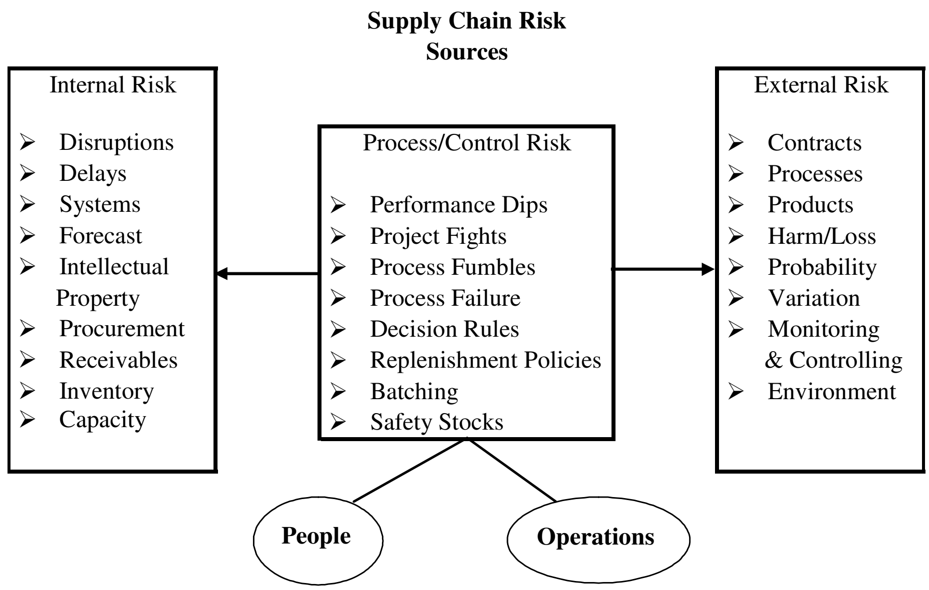


Figure 2.2: Supply chain risks arising from areas controlled internally, influenced externally and process alteration

Definitions of supply chain risk have been developed by several authors from their areas of origin. Chopra and Sodhi (2004) have categorized supply chain risk as arising from areas controlled internally by the organisation including manufacturing disruptions and delays, systems, forecast, intellectual property, procurement, receivables, inventory and capacity. Hutchins (2003) takes a view of supply chain risk coming from areas controlled externally to the organisation. These risks are defined as the supply chain partners' abilities to meet contract, process and product requirements, the possibility of harm or loss if requirements are not achieved, the probability of an event with undesirable consequences, and the variation away from a specified set of requirements and how this is monitored and controlled. In the context of changing a supply chain process, Buchanan and Connor (2001) categorise supply chain risk in four areas: performance dips, project fights, process fumbles, and process failures. Buchanan & Connor break down process risk further into a people risk category and an operations component. Figure 2.2 incorporates major risk sources that have been delineated by cited researchers.

Juttner et al (2003) stated that, a number of factors have increased the level of supply chain risk that includes: (1) a focus on efficiency rather than effectiveness; (2) the globalisation of supply chains; (3) focused factories and centralised distribution; (4) the trend to outsourcing; and (5) the reduction of the supplier base. All these arise from areas internally controlled by the organisation. They stated that risk management initiatives including the identification of the risk drivers are necessary to build a resilient supply chain. They discussed about managing various trade-off decisions as an essential part of supply chain risk management. Mason-Jones and Towill (1998a) suggested five overlapping categories of supply chain risk sources: environmental, demand, supply, process and control risk sources, which Juttner (2005) summed up to the major three sources of risk as depicted in Figure 2.2. She noted supply chain control mechanisms like decision rules and policies regarding order quantities, batch sizes and safety stocks can be potential sources of risk and hence need special attention in risk management. However she stressed upon the overlapping nature of all three sources of risk stating that each source can give rise to another source of risk, for example, environmental risks (fire, natural disasters etc) can give rise to supply or demand risks. Similarly, internal or process/control related risks (equipment failure, lack of integration etc.) can give rise to supply or demand disruptions at the time of environmental hazards. Christopher and Peck (2004) confirm this while analysing the resilient supply chain capabilities. Christopher et al (2002) in a vast research project on the global supply chain defined vulnerability as an exposure to serious disturbance, arising from risks within the supply chain as well as risks external to the supply chain; including all types of risks whether it is disruption, demand uncertainty or even 'internal risk' that arises from interaction between constituent organisations across the supply chain. MIT research (2003) has shown that firms usually focus on the type of disruption and not its source in order to know how to prepare against risks. What is important is the type of failure modes, the limited ways in which the disruption affects the supply chain. The research distinguishes six different types of failure modes, disruption in supply, transport, facilities, communications and demand; and freight breaches.

Just as there is an abundance of supply chain risk definitions, numerous techniques have been put forth to supply chain risk mitigation. Zsidisin, et al (2004) look at supply chain risk mitigation from the perspective of the purchasing organisation. Zsidisin et al discuss supply chain risk mitigation techniques in terms of tackling issues arising from processes external to the organisation including strengthening supplier quality, lessening the chance that supply disruptions will occur, and improving the process by which goods and services are supplied by vendors. Finch (2004) looks at supply chain risk management from the perspective of inter-organisational networking in pressing the need for companies to adequately plan for business continuity. This includes issues coming from processes external and internal to the organization. On an even more strategic basis, Christopher and Lee (2004) look at methods controlled internally including the need to improve supply chain confidence by improving end-to-end visibility across the supply chain as a mechanism for mitigating supply chain risk. An example of this is the sharing of demand forecasts in order to coordinate production and reduce the impact of demand amplification (bullwhip effect). Related to the issue of visibility is that of predictive analysis. Therefore tools are needed to assist in establishing a regular system of predictability (Blackhurst et al, 2005). Supply chain risk management is an integrated management approach along the whole chain (Adams *et al,* 2002) - with a view to managing "the exposure to serious business disruption, arising from risks within the supply chain as well as risks external to the supply chain." In this sense, the goal of supply chain risk management is "the ability to react quickly to ensure continuity" (Van Hoek, 2003; Rowbottom, 2004). Sinha et al (2004) presented a generic prescriptive methodology for mitigating risks in an aerospace supply chain and proposed five activities as 'identify risks, assess risks, plan and implement solutions, conduct failure modes and effects analysis (FMEA) and continuously improve'. This methodology, claimed by the authors, also provides a mechanism for various suppliers to minimise conflicting objectives in the aerospace industry. It differentiates between foreseen, perceived, controllable and uncontrollable risks and prioritises risks so that resources can be utilised efficiently. Based on theoretical foundation and empirical analysis Kleindorfer and Saad (2005) presented 2 key dimensions as fundamental in guiding management practice of disruption risk in supply chains. The first dimension consists of strategies and actions aiming at reducing the frequency and severity of risks faced, at both the firm level and across the supply chain. The second element focuses on increasing the capacity of supply chain partners to sustain or absorb more risk, without serious negative consequences or major operational disruptions. They formulated a set of 10 principles for managing disruption risks in supply chains mainly focusing on the internal policies of the organization and also the interconnections between the different supply chain elements: 1) internal supply chain integration and optimisation must precede any inter-firm interfaces; 2) diversification of facility locations, products, sourcing options, operating modes and processes; 3) identification of vulnerabilities across the entire supply network together with early warning and crisis management systems; 4) risk assessment and contingency planning must precede risk reduction; 5) managing tradeoff between robustness of supply chain to disruptions and the overall efficiency of the supply chain under normal operations; 6) redundancy and back-up; 7) cooperation, coordination and collaboration across supply chain partners; 8) embedding weak point measurement in on-going process management; 9) flexibility and mobility of resources, modular design, delayed differentiation and 10) applying total quality management (TQM) principles, e.g., six sigma approach reduces disruptive risks. An important recognition of this paper is (p.4-5), *"resilient supply chains are not inimical to efficiency and lean operations, but the dimensions of resilience and robustness to supply chain disruptions must be explicitly considered in the design process if they are to be captured."* But they mention, extreme leanness and efficiency may result in increasing level of vulnerability.

In supply base strategy, Christopher (2004) advised firms to balance the benefits and risks associated with multiple and single sourcing to achieve resilience. Anderson (2003) supported this in his study of organisational resilience in the form of building redundancy in the network to ward off effects of disaster. He mentions (p.1), *'Diversification pertains to the physical distribution of resources (hard assets and people) and the implementation of redundant/diverse networking capabilities to diffuse the impact of a disaster. The goal is to create an operational infrastructure that is physically distributed but capable of being managed as a single entity.'* Diversification was stressed by Holweg and Pil (2001, p80) as *'in the diversification strategy, companies use large, efficient but less flexible plants to satisfy the base demand and smaller potentially higher cost, but more flexible plants to meet low-volume demand and provide additional capacity if demand changes.'* Berger et al (2004) presented a useful way to think about the number of suppliers needed in the presence of risks. Lee and Wolfe (2003) suggested flexible sourcing strategy to mitigate supply risks and building supply chain resilience. Chopra and Sodhi (2004) contrast the traditional risk mitigation approaches to more sophisticated supply chain techniques. These include the following:

- Traditional Approaches
  - Excess Capacity
  - Additional Inventory
  - Redundant Suppliers

- Supply Chain Approaches
  - Increased Responsiveness
  - Increased Flexibility
  - Aggregated or Pooled Demand
  - Increased Capability
  - Added Customer Accounts

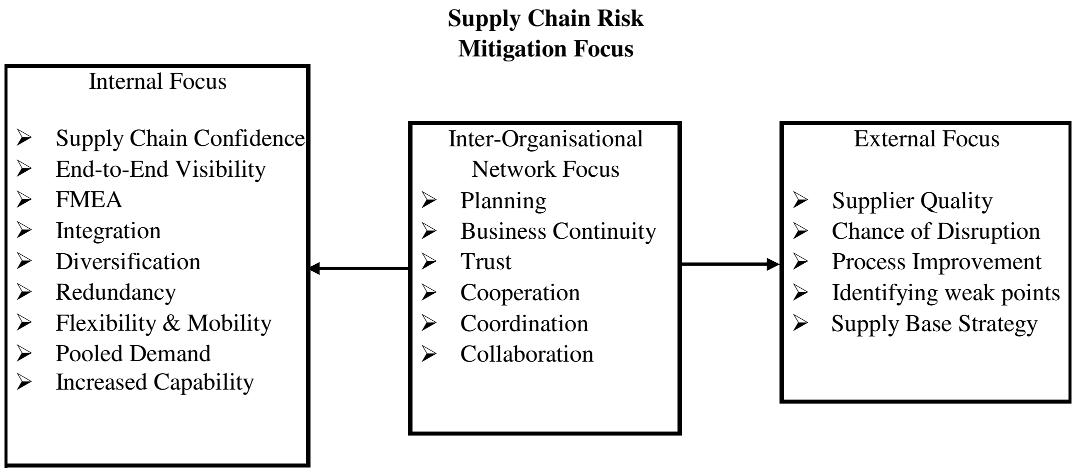


Figure 2.3: Supply chain risk mitigation focus

Oliver and Delbridge (2002), found out high performing supply chains are characterised by increased speed of material movement through tightly coordinated operations, stringent monitoring of schedule variability, greater proficiency in information exchange, communication across different members, higher levels of informal interaction and higher level of transparency. All these capabilities result in better customer service, better capacity utilisation and reduced inventory levels. Lack of trust is one of the major factors that contribute to supply chain risks (Sinha et al, 2004). In order to manage risks effectively in a supply chain, organisations are moving to adopt closer relationships with key suppliers (Giunipero and Eltantawy, 2004). Collaborative supply chain partnerships support the development of flexibility, responsiveness and low cost/low volume manufacturing skills thereby reducing risks (Hoyt and Huq, 2000). Also companies now collaborate readily with their supply chain partners in the areas of planning, forecasting and replenishment, which help in reducing risks (Handfield and Nichols, 1999; Peters and Hogensen, 1999). According to Chopra and Sodhi (2004), managers must do two things when they begin to construct a supply chain risk management strategy. First, they must create a shared, organization-wide understanding of supply chain risk and secondly, they must determine how to adapt general risk-mitigation approaches to the circumstances of their particular company. Figure 2.3 compiles focus areas for risk mitigation from the work of researchers noted above.

A qualitative empirical study conducted by Haywood and Peck (2003) identifies the drivers of risk and the methods of management of supply chain vulnerability in aerospace manufacturing. The results were interesting. The principal concerns of the respondents were not with the direct risks that characterize the impacts of unforeseen events or disasters or terror strikes. Instead they were more focused on the risk to their own areas of responsibility (on consequential risks to supply chain performance arising from other managerial practices and industry trends). The risks they identified provided highlighted tensions between individual process performance measures, the impact of strategic business decisions, constraints imposed by the complex safety-critical nature of the products and by industry or supply chain structures. They said (p129), '*The demands of the marketplace, constant changes in product specifications, together with other continuous improvement initiatives within the organizations and the wider industry as a whole meant that the supply chains never actually reached a stable steady state.'* Also most of the respondents stated that, due to product and supply chain complexity it is not possible to take an end-to-end supply chain perspective in supply chain risk management. The study suggested inter-organisational cooperation to reduce demand related forecasting and inventory management risk. The authors offered the basis of a cohesive process risk management tool kit arranged by class of supply chain activity (supply chain planning, supply chain change management and supply chain management) and the supply chain risk drivers (cost, quality, delivery and relationships). Although this study revealed the true dynamic nature of supply chains and hence the risks involved, but the recommendations suggested are not dynamic.

Often supply chain risk measures are based on managerial perceptions (Zsidisin, 2003) that are often static or are seldom updated. Since business environment is very dynamic and risks to supply chains change due to changes in environment, continual monitoring of risks is essential. The above risk mitigation methods consist of balancing routine procedures and informal flexible approaches; efficiency as well as redundancy. While the above approaches are beneficial in stable environmental conditions, dynamic measures of risk are necessary to decide proactively which risks are important to deal with and implement strategies to deal with those risks (Shtub et al, 1994). So building capability to adapt to changing environmental demands is essential for resilience.

2.3.2 Supply Chain Agility

Christopher (2004, p19) states, '*One of the most powerful ways of achieving resilience in the supply chain is to create networks, which are capable of more rapid response to changed conditions. This is the idea of agility.*' It is a business-wide capability that embraces organisational structures, information systems, logistics processes and in particular, mindsets (Christopher and Towill, 2000). Companies can minimise inventory risks by working with a highly responsive supplier (Chopra and Sodhi, 2004). Supply chain agility is a key to inventory reduction, adapting to market variations more efficiently, enabling enterprises to respond to consumer demand more quickly and integrating with suppliers more effectively (Faisal et al, 2006).

Christopher (2000) discussed the different elements of supply chain agility and said that the choice of lean or agile supply chain strategy is dependent on product types, the characteristics of demand. Fisher (1997) identified functional and innovative products and the need for two totally different supply chain strategies, lean and agile. Moving a step further from agility, researchers (van-Hoek, 2000; Mason-Jones et al, 2000; Naylor et al, 1999) have discussed combining agility with leanness resulting in leagile supply chains. Leagility enables cost effectiveness of the upstream chain and high service levels in a volatile marketplace in the downstream chain.

Christopher (2000) pointed out the main elements of supply chain agility. A truly agile chain is obtained through market sensitivity (supply chain is capable of reading and responding to real demand), technology (the use of information technology to share data between buyers and suppliers). The key characteristic he mentioned is supply chain flexibility, which in turn is dependent on the close collaboration between supply chain partners (process integration, joint strategy determination, buyer-supplier teams, transparency of information, and even, open-book accounting), building trust (there can be no boundaries, and an ethos of trust and commitment must prevail) and relationship (outsourcing all activities requires a greater reliance on suppliers and alliance partners and hence a new style of relationship) across the chain. Christopher (2004) states 2 fundamental foundations of agility are velocity and visibility *(p19). 'Velocity requires shorter end-to-end pipelines which themselves are dependent on sourcing decisions as well as internal process improvement. Visibility impacts agility in a number of ways. First, it reduces uncertainty and enables the goal of a demand-driven supply chain to be achieved. Second, it reduces supply chain risk through shared information, both upstream and downstream of the firm's operations.'* According to Blackhurst et al (2005, p4072), *"A key component in effective supply-chain management is the real-time sharing of correct information from every node in the supply chain in order to maximize responsiveness and flexibility to be able to avoid and mitigate disruptions."* Rupp and Ristic (2000) find that lack of coordination and inaccurate information flows lead to inefficient production planning and control. Increasing the visibility of demand information across the supply chain reduces the risks (Chopra and Sodhi, 2004). Smith (2004) in describing the operational capabilities of resilient supply chains emphasised the creation of an integrated environment that provides end-to-end interaction of orders, inventory, transportation and distribution to facilitate transparency in the supply chain from the supplier to the end distribution point and all points in between.

2.3.3 Supply chain flexibility and redundancy

In supply chain literature, flexibility is seen as a reaction to environmental uncertainty (Giunipero et al, 2005). Vickery et al. (1999) define five major types of supply chain flexibility capabilities; 1) product, 2) volume, 3) launch, 4) access, and 5) responsiveness. Product flexibility is defined as the ability to handle difficult, nonstandard orders, to meet special customer specifications, and to produce products characterized by numerous features, options, sizes, and colours. Product flexibility is a value-adding attribute that is immediately visible to the customer. Volume flexibility is the ability to effectively increase or decrease aggregate production in response to customer demand. Launch flexibility is the ability to rapidly introduce many new products and product varieties that requires the integration of numerous value activities across the entire supply chain. Access flexibility is the ability to provide widespread or intensive distribution coverage and responsiveness flexibility captures the overall ability of the firm to respond to the needs of its target markets. Duclos et al (2003) provided a six dimensional conceptual model of supply chain flexibility encompassing the cross-functional, cross-business nature of supply chain management. The six components are: 1) operations system (ability to configure operations to emerging customer trends), 2) market (mass customisation ability and setting up close customer relationships to design and modify new products), 3) logistics (ability to cost effectively receive and deliver products as sources or destinations of supply change), 4) supply (ability to reconfigure the supply chain, altering the supply of product in line with customer demand), 5) organisation (ability to align labour force skills to needs of supply chain to meet varying customer demands), and 6) information systems (ability to align information systems architecture with changing needs of organization as it responds to changing customer demands).

Flexibility enables a manufacturer to respond quickly and efficiently to dynamic market changes (Swamidass and Newell, 1987). Increasing flexibility in logistic systems may be a strategic response to environmental uncertainties (Barad and Sapir, 2003). Jung et al (1999) found that a supplier who faces a smaller demand with high variation would invest more in flexible facilities. Das and Patel (2002) estimate the needed flexibility by linking it to the uncertainty experienced by the company's manufacturing operations. Sanchez and Perez (2005) carried out an empirical survey of Spanish automotive suppliers to explore the relationship between supply chain flexibility dimensions and firm performance. They found that companies use routing (product processing through varying routes by using alternative machines, material handling and transport), product, responsiveness, sourcing and postponement flexibility to respond to environmental uncertainties.

Rice and Caniato (2003) suggested a hybrid flexibility and redundancy approach for increasing supply chain resilience and security. In their opinion (p25,26), '*Flexibility entails creating capabilities within the organization to respond. These capabilities are mainly developed through investments in infrastructure and resources before they actually are needed. Redundancy, by contrast, entails maintaining capacity to respond to disruptions in the supply network, largely through investments in capital and capacity prior to the point of need.'* Lee and Wolfe (2003) argued that to improve resilience in supply chains, firms must promote measures that also increase supply chain flexibility. They suggest that firms need to increase the visibility in the relations with trading partners, formalised in a contract. Sheffi (2001, 2005a) explained how adding some redundancies in the supply chain (strategic emergency stock to cover risks of extraordinary events) could help to deal with the unexpected happenings. However determining the adequate level of stocks remains a tricky question. Martha and Subbakrishna (2002) proposed a series of measures and do so by looking at past disasters. These include, improving visibility, adding redundancies (referred to as flexibility with duplication of assets). However, they attack Sheffi's proposition by saying that, even minor adjustments to inventory can have a major impact on costs and they suggest companies to carefully assess alternate strategies to hedge risks with respect to inventory adjustments. They also suggested that firms could add flexibility without any duplication of assets to be able to respond to environmental changes. And this can be done by influencing demand, locking into forward supply contracts or redesigning product and process by means of postponement or delayed product differentiation.

Garavelli (2003) proposed a framework for the analysis of the supply chain flexibility. Based on a work-in-process and lead-time analysis, different supply chain configurations are analysed in order to support the selection of suitable flexibility degrees of the operations network. The supply chain flexibility addressed took into account 2 main aspects: process flexibility of each supply chain plant, concerning the number of product types that can be manufactured in each production site and the logistics flexibility related to the different logistics strategies which can be adopted either to release a product to a market or to procure a component from a supplier. Two extreme degrees of flexibility, *total* and *no* flexibility plus an intermediate degree of flexibility, *limited* flexibility, were defined. These degrees refer to possibility of processing a product or component in one, two or all the supply chain plants respectively. The results quantify the performance of the different configurations considering demand variability and plant reliability. Results suggested supply chains characterised by the limited flexibility of both assemblers and suppliers is over-performing in most cases. They found out, in cases of high demand peaks, configurations with focused plants perform better. The effects of different supply chain flexibility configuration on the response to uncertain situations signify the importance of flexibility in supply chain resilience.

2.3.4. Supply chain structure – Centralisation

Oliver and Delbridge (2002) studied and contrasted the characteristics of high and low performing supply chains in Japan, the US and Europe. An interesting finding of relevance is that, the high performance in supply chains stems from a combination of structural and processual factors. However they concluded saying (p72), *'the link between supply chain structure and performance is not clear cut as different supply chain structures are likely to evolve in different situations. …. aspects of supply chain structure such as the number of players at the second tier seemed to be linked to the product strategies pursued by the Japanese auto makers. This suggests that, like other aspects of organisational structure, the characteristics of supply chains may be usefully viewed as organisational responses to the context within which tasks are enacted.'*

Randall et al (2003) examined the association between product demand characteristics and the initial investment in a supply chain at the time of market entry. They characterised supply chains as responsive (distinguished by short production lead times, low set up costs and small batch sizes allowing quick adaptation to market demand at a higher unit cost) and efficient (distinguished by longer production lead-times, high set-up costs and larger batch sizes allowing to produce at a low unit cost). They commented (p442), *'Our results emphasize… firms do consider market characteristics – market* *growth rates, level of product variety, relative contribution margins and uncertainty – when making an initial supply chain investment.'* The results from a mountain bike industry showed that, as industry growth rate increases, firms tend to enter with an efficient supply chain. But when contribution margins from responsive products or the level of product variety increases, firms enter with a responsive supply chain. The study however partially supported the hypothesis that, when uncertainty exists, firms enter with a more responsive supply chain. This research though is a very special case study of a particular industry and considers supply chain choice at the time of market entry, yet it is a strong foundation that establishes supply chain structure as a crucial factor in firm success.

Randall and Ulrich (2001) used US bicycle industry to examine the relation among product variety, supply chain structure and firm performance. They found from the empirical research that, firms, which match supply chain structures with the type of product variety they offer, outperform others. They characterised supply chain structure along two fundamental dimensions, distance of production facilities from target markets and the degree to which production facilities reach minimum efficient scale. They showed that supply chain structures in turn affect the production and market mediation costs. They found from their study that production-dominant product variety is positively associated with scale-efficient/distant production pooling in all dispersed production facilities into one, while market mediation dominant variety of product is positively associated with scale-inefficient/local production. This study also establishes an importance of supply chain structure in supply chain performance increase.

Over a period of time, the structure of a supply network emerges (Choi et al., 2001) with no one firm deliberately orchestrating the exact shaping, just as the structure of an organization ultimately emerges regardless of the intended design (Mintzberg, 1979). Since structure of an organization is viewed as "the pattern of relationships among people" (Gerwin, 1984, p. 9), structure of a supply network can be viewed as the pattern of relationships among firms engaged in creating a sellable product. Further, regardless of the structure that will eventually emerge over time, the underlying purpose of structure is to "control" activities (Gibson et al., 1997; Miles, 1980), whether the controlling occurs globally throughout the system or locally within a system. The extant literature identifies three key dimensions to describe complex supply networks —vertical structure (number of stages), horizontal structure (number of channels), and location in the network (Harland, 1996; Lambert et al., 1998; Randall and Ulrich, 2001). For these interactions, goods and services flow in one direction; payments flow in the opposite direction; and information flows in both directions. Hong and Choi (2002) carried out a three-case analysis to frame supply chain structures in three dimensions of centralisation, formalisation and complexity to show how these dimensions interact and affect the network behaviour. Formalisation in the supply network context refers to the degree to which the supply network is controlled by explicit rules, procedures, and norms that prescribe the rights and obligations of the individual companies that populate it. In the context of the cases in the study, the authors describe centralisation as the amount of authority or power the final assembler exercises over the suppliers in the network. In a centralised supply network, decisions would be made by the final assembler; in a decentralised network, decisions would be made autonomously by individual suppliers. Complexity refers to the structural differentiation or variety that exists in the supply network. The study concluded that too much formalisation can lead to rigidity, and one often needs flexibility and informality for operational purposes. The analysis revealed that, cost considerations shape supply chain structure constructions through more elaborate formal procedures. Samaddar et al (2006) used the same set of cases to investigate the relationship between supply network structure design and information sharing. Coordination structure based on global information, location of the partner firms in the network and the degree of goal congruence are found to influence the nature of inter-organisational information sharing in specific supply network designs.

Information structure refers to the type of information available to the decision maker. Anand and Mendelson (1997) refer to the use of local and global information, or a hybrid of the two, for decision-making purposes within a supply network. A supply network with centralised authority is associated with the use of global information, while a decentralized one will rely on local information for decision-making, even though mismatches can occur, as studied by Anand and Mendelson (1997). According to Robbins (1990) the decision on the appropriate level of centralisation will depend on situational factors. In a decentralised supply network structure firms are able to respond quickly to changes at their individual location, which is an important capability to have when the local environment is susceptible to rapid changes and especially in a resilient supply chain. Such a structure offers opportunities for the decision maker to incorporate the local information when making decisions. A decentralised supply network structure is also more appropriate when there are characteristics that are unique to a particular location or firm, which need to be considered before making a decision. As such it cannot be easily captured in a centralised system owing to the specific (or tacit) nature of its knowledge. One of the drawbacks of a decentralised structure is the likelihood for misalignment between the interests of an individual firm and those of the network, which result in agency problems. Thus the costs incurred in inducing the firm to adjust its interest to match those of the network can be high (Anand and Mendelson, 1997). In contrast, the centralised structure is more appropriate when the decision maker needs to take actions that benefit the total network, rather than the special interests of individual firms. This structure is also more suitable when there are distinct economies of scale, or a need for using standard products and procedures.

The centralised structure also has its challenges, as it is costly to gather information that is tailored to meet the needs of individual firms. For instance a supplier may receive POS data from retailers but also needs to be told about a promotion that a retailer is planning to mount in the near future, so that the correct replenishment decision can be made (Aviv, 2002). It becomes especially difficult for single decision making authority to manage supply networks, if it becomes complex (Samaddar et al, 2006). So it becomes extremely important to understand the supply chain structure for designing resilient supply chains

2.3.5 Supply chain strategy

Lee (2002) stated (p118), *'demand and supply uncertainties can be used as a framework to devise the right supply chain strategy.'* He matched the supply chain strategies to supply and demand uncertainties through a two by two matrix. It is seen that agile supply chains utilize strategies aimed at being responsive and flexible to customer needs while the risks of supply shortages or disruptions are hedged by pooling inventory or other capacity resources. Responsive supply chains take care of changing and diverse needs of customers by using build-to-order and mass-customisation processes. Risk hedging supply chains take care of supply risks through multiple sourcing or safety stocks. And efficient supply chains use optimisation strategies to ensure the most efficient, accurate and cost effective transmission of information across the supply chain, when products have both low supply and demand uncertainties.

He provided several real world cases to demonstrate the applicability of suitable strategies for different product types. He stated, companies with innovative products with highly unpredictable demand should pursue responsive supply chain strategies. He commented that (p116), *'rather than focussing on accurate forecasting and inventory planning, companies with a very stable process and product technology can make use of the concept of postponement to pursue aggressive build-to-order strategies.'* And (p117), *'Companies with innovative products and evolving and unstable supply processes have to utilize the combination of risk-hedging and responsive strategies. The appropriate strategy here is to establish 'agile' supply chains.'* And companies with functional products and stable or evolving supply processes should adopt efficient or risk hedging supply chains respectively.

Li and O'Brien (2001) focused on a quantitative analysis to match types of products to supply chains based on a mathematical model. They conducted a sensitivity analysis using a multiple objective optimisation model to detect variance of performance in relation to three supply chain strategies (Manufacturing to order/MTO, manufacturing from stocks/MFS and manufacturing to stocks/MTS) and based on different product characteristics (value-adding and demand uncertainty). They found out that, when demand uncertainties of materials and finished products are at lower levels, the physical responsive strategy (MTS) always performs better than the other two and physically efficient process (MTO) is the last option. As demand uncertainties increase, the performance of MTO and MFS surpasses the performance of MTS process. Thus they found out the impacts from different operational conditions by quantitative modelling of the three commonly used strategies. Many other uncertainties could have been included in their study.

2.3.6 Supply chain complexity

Christopher (2000) suggests reduction of complexity through business process reengineering initiatives, where non-value adding operations can be eliminated. Vachon and Klassen (2002) carried out an exploratory study in manufacturing industry to find some empirical evidence that the complexity of the supply chain had an impact on delivery performance. They came up with a two-by-two conceptual framework for supply chain complexity using technology and information processing dimensions. Their study revealed evidence indicating that only process/product complicatedness (structural elements) and management systems uncertainty were significantly related to delivery speed and reliability. They suggested that practitioners must continue their efforts to reduce risk and impact associated with supply chain complexity by improving information flows, building supplier capabilities and by leveraging technological and organisational systems. The model however is limited to one dimension alone in terms of supply chain performance (delivery time) and that too at a single echelon in the supply chain.

2.3.7 Supply chain uncertainty reduction

Geary et al (2002), Van der Vorst and Beulens (2002) took a different view of improving supply chain resilience and that is through reduction of uncertainty. Van der Vorst and Beulens (2002) identified several sources of uncertainty, namely inherent (consisting of process, supply and demand uncertainty), supply chain configuration and organisation structure uncertainties, supply chain control uncertainties and information system uncertainty. Van der Vorst and Beulens (2002, p426) suggested that, *'sources of uncertainty were identified in the company culture and division of responsibilities and authority. Specific human behaviour in decision-making processes resulted in different outcomes because of cognitive or political influences.'* Geary et al (2002) stated how to reduce uncertainty in the supply chain. They suggested *'In a demand pull environment, the linkage between supply and demand is clear and control uncertainty is eliminated.'*

Geary et al (2002, p57) also suggested the use of integrated supply chains for reduction of uncertainty, *'Full supply chain integration is achieved by extending the scope of management outside the company to embrace the suppliers and customers. It embodies a change of orientation away from product to customer. A high level of integration with the customer organisation is involved in order to understand the products, culture, market and organisation. It also involves integration back down the supply chain to include supplier partners.*' This would reduce the inherent uncertainty induced by process, demand and supply uncertainties. Christopher and Lee (2001, p9) also supports this by saying, *'Synchronous supply requires transparency of demand and pipeline inventory in as close to real time as possible. It also requires a willingness on the part of all the members of the supply chain to work to a single supply chain plan.'*

Christopher and Lee (2001, p7) also said that, *'Throughout the supply chain, key operational metrics and status such as inventory, demand, forecasts, production and shipment plans, work in process, yields, capacities, backlogs, etc., are accessible easily by key members of the supply chain. Such information should be accurate and timely, rendering them useful for all parties for planning and re-planning purposes. Thus, it is important that the key indicators are tightly managed so that any updates are made as timely as possible. The accuracy of the data should be a source of confidence to the parties using the data.'* This is bound to reduce information systems uncertainty, as pointed out by Van der Vorst and Beulens (2002). Geary et al (2002) stated that supply uncertainty can be reduced by *'looking at supplier delivery performance, time series of* *orders placed or call-offs. And deliveries from customers, actual leadtimes, supplier quality reports'.*

Lee (2002) mapped the uncertainties in supply and demand processes and provided measures for reduction. He said (p108), '*Only through information sharing and tight coordination can one regain control of supply chain efficiency.'* Similarly (p110), *'Free exchanges of information – starting with the product development stage and continuing with the mature and end-of-life phases of the product life cycle – have been found to be highly effective in reducing the risks of supplier failure.'* He also mentioned early supplier collaboration, setting up of supplier hubs (to gain information about the inventory and customer needs, consumption patterns) as measures to reduce the supply risk.

Sorensen and Janssens (2001) studied a flow-line production system of '*n'* machines in series. A finite buffer separates each pair of subsequent machines. The machines work at deterministic speeds but are unreliable and can break down. The allocation of buffers improves the availability of the system. The problem of where to allocate buffer space in order to achieve a required availability is studied in this paper. Pagell et al (2000) used three case studies to show that companies use their strategic choices of flexibility and buffers as response to external and internal uncertainty. The case studies also suggested the long and short-term implications of buffer use. The studies are descriptive (stating buffers are used) rather than prescriptive (when or if buffers should ever be used). So the authors admitted this shortcoming of their paper and asked for studies in future to be prescriptive and helping organisations to optimise operations. Finally they concluded by noting that (p42), '*choices exist in dealing with uncertainty, but that no one has identified what factors determine the best mix or how to find it for a given situation.'*

2.3.8 A Conceptual Framework for Supply Chain Resilience

Supply chain resilience is the ability and capacity to withstand systemic discontinuities and adapt to new risk environments. So supply chain resilience can be defined as not only the ability to maintain control over performance variability in the face of disturbance but also a property of being adaptive and capable of sustained response to sudden and significant shifts in the environment.

Having explored different aspects of supply chain resilience, it would appear that the characteristics of resilient supply chains are (Triple-A supply chain as described by Lee, 2004):

- Agility, speedy reaction to sudden changes in demand or supply, in addition to speed and cost-effectiveness
- Adaptability over time as market structures and strategies evolve
- Alignment of interests of all firms or units in the supply network, so that individual members optimise the chain's performance when they maximize their own interests requiring:
    - Interactive planning across all units to rapidly know each other's challenges, the competencies/resources each has or needs to meet them
    - Informed coordinated decision making at all levels of the supply chain

Building resilience in the supply chains involves a lot of trade-offs. For example, building resilient supply chain has many benefits, however increasing redundancies and flexibilities in the supply chain often leads to increase complexity, which works against resilience. As complexity increases, uncertainties become more and more prominent and firms become more vulnerable. As a result it is necessary to find a trade-off between resilience and complexity. Single supplier might be risky but single supplier allows a better protection of company's intellectual property rights. Also trade-offs between cost-efficiency and risk must be assessed to build resilient supply networks. Therefore on one hand, when a decision is made to reduce cost it is necessary to check that risks have not been increased imprudently. Also on the other hand, firms need to determine if greater flexibility is worth extra cost.

Table 1 below summarises the literature reviewed in the field of resilience.

Table 1: Literature Review on the multi-dimensional characteristics of Resilience

Characteristics	Relevant research summary	Focus
Ecosystem & Social Science View		
Equilibrium Seeking	Ability to return to an equilibrium state after experiencing a given level of disturbance (Holling, 1973, 1986)	**Static**
Adaptability	Ability to absorb and recover from the occurrence of hazardous events (Timmerman, 1981; Carpenter, 2001)	**Recovery**
Learning & Planning for disasters	Proactive ability that accepts change and tries to create a system capable of adapting to new conditions by learning and planning (Gunderson, 2000; Dovers & Handmer, 1992)	**Mitigation Static**
Dynamic Process	Ability to maintain or regain dynamically stable state (Hale & Heijer, 2006; Klein et al, 2003; Handmer & Dovers, 1996)	**Mitigation Dynamic**
Organisational View		
Dynamic capacity	A dynamic capacity that maintains positive adjustment under challenging conditions, dynamic capacity that grows and develops with time (Weick et al, 1999; Worline et al, 2004; Sutcliffe & Vogus, 2003; Wildavsky, 1988; Teece et al, 1997)	**Dynamic**
Flexibility	Resilience implies being flexible enough to adapt to both positive and negative influences (Anderson,2003; Coutu, 2002; Sutcliffe & Vogus, 2003)	**Recovery Coping**
Routinisation	A resilient firm needs to develop a broad and varied inventory of routines for responding to uncertain situations (Nelson & Winter, 1982; Pentland & Reuter, 1994; Boisot & Child, 1999; Lengnick-Hall & Beck, 2005)	**Mitigation**
Foresight, leadership Goal directed solution	Supervision, auditing, leadership are key dimensions of resilience (Stocltz, 2004; Mallak, 1998)	**Mitigation**
Monitoring Awareness	Monitoring, recording of outputs, sensing and interpreting the outputs through appropriate measures (Haeckel, 1999; Thomas et al, 1993; Weick & Sutcliffe, 2001)	**Recovery Mitigation**
Distributed decision making - decentralisation	Decentralised systems with local autonomy adapt to changes better (Wheatley and Rogers, 1996; Weick, 1993, 2001)	**Recovery Mitigation**
Integration/Alignment Information Sharing	Resilient organisations are characterised by shared sense of organisational purpose (William & Winfrey, 1994; Weick, 2004)	**Recovery Mitigation**
Collaboration/coordination communication	Improved communication and coordination reduces risks by increased sense making of unpredictable environments (Berger & Bradac, 1982; Berger, 1987; Weick, 1979, 1990, 1993, 1996; La Porte & Consolini, 1991)	**Mitigation Recovery**
Improvisation	One important source of resilience (Weick, 1993; Gehman, 2003; Schulman, 1993)	**Recovery Coping**
Redundancy	Slackness is organisational shock absorber to environment jolts (Meyer, 1982; Perrow, 1999; Weick, 1987, 1993; Sagan, 1993)	**Mitigation**
Thoroughness	People try to be as thorough as possible to avoid exposure of risk (Hollnagel, 1993; Smith, 1990, 1995)	**Mitigation**
Trade-Offs	Formalisation (Robbins, 1992) Vs Improvisation (Gehman, 2003; Schulman, 1993) Slack Vs Integration (Perrow, 1999) Thoroughness Vs Efficiency (Rasmussen, 1993; Woods, 2006) Decentralisation (Weick, 1996, 1998) Vs Centralisation (Tucker & Edmondson, 2003) Resident Pathogens (Turner, 1976, 1978, 1994; Reason, 1987, 1990a, b, 1995, 1997)	**Judgment**

Table 1 (Continued)

Characteristics	Relevant research summary	Focus
Supply Chain View		
Visibility/Information Sharing	Improving end-to-end visibility and information sharing improves mitigation of risk and also helps in responding faster (Chopra & Sodhi, 2004; Christopher & Lee, 2004; Blackhurst et al, 2005; Smith, 2004; Lee, 2002)	**Mitigation Recovery**
Agility, Velocity	Rapid response to changed conditions (Christopher, 2000, 2004; Faisal et al, 2006)	**Recovery Coping**
Structure	A broad element of supply chain resilience is knowledge and understanding of supply chain structures - both physical and informational (Samaddar et al, 2006; Hong & Choi, 2002; Anand & Mendelson, 1997)	**Mitigation Recovery**
Flexibility	Increasing flexibility enables supply chain's ability to respond quickly and efficiently to market changes (Swamidass & Newell, 1987; Barad & Sapir, 2003; Das & Patel, 2002; Garavelli, 2003; Kleindorfer & Saad, 2005;Chopra & Sodhi, 2004)	**Recovery Coping**
Integration/ Collaboration	In order to manage risks effectively supply chains should adopt collaborative partnerships within members (Sinha et al, 2004; Giunipero & Eltantawy, 2004; Hoyt & Huq, 2000;Handfield & Nichols, 1999; Peters & Hogensen, 1999; Haywood & Peck, 2003; Geary et al, 2002;Van der Vorst & Beulens, 2002; Lee, 2004)	**Mitigation Recovery**
Redundancy	Adding some redundancies in supply chain can help to deal with unforeseen happenings (Sheffi, 2001, 2005a; Martha & Subbakrishna, 2002)	**Mitigation Recovery**
Diversification/ Added Capability	Multiple sourcing, augmentation of capability by providing additional resources diffuse impacts of disaster and also improves preparedness (Christopher, 2004; Anderson, 2003; Holweg & Pil, 2001; Berger et al, 2004; Lee & Wolfe, 2003; Vachon & Klassen, 2002)	**Mitigation Recovery**
Trade-offs	Focuses on combination of different capabilities (Juttner et al, 2003; Van Hoek, 2000; Mason Jones et al, 2000; Rice & Caniato, 2003;Pagell et al, 2000; Kleindorfer & Saad, 2005)	**Judgment**

So in developing a conceptual framework for supply chain resilience, from the summary of literature review on supply chain resilience, organisational resilience and resilience phenomenon in general (Table 1), it is important to note that resilience in all contexts is a dynamic characteristic and a source of sustainable competitive advantage for supply chains, individuals and organisations. Three different focus (mitigation, recovery and judgment) of the relevant research are identified. The literature is classified into these three broad categories to show that resilience apart from being a dynamic phenomenon, is a combination of capabilities required to mitigate the effects of unwarranted happenings, recover from hazards after they occur and make decisions to adopt a set of capabilities in response to changes in environment.

Resilience is not just recovery from the mishaps, but it is a proactive, structured and integrated exploration of capabilities within the supply chain to resist and win against unforeseen happenings. It is a catalyst to propel one's business forward while competition sits still. Resilience embeds the capability to map an event on the time horizon and builds capabilities to cope with it. It is also important that, the strategies or policies for improving resilience and avoiding or responding to any untoward events do not harm the normal performance level of all the members of the supply network. So a resilient supply chain should have enough slack to recover from any disruptions, but that slack should in no way harm the normal working efficiency; it should be watchful of and responsive to any faint signal of deviation or disturbances through continued monitoring of key performance indicators thus concentrating on the prevention of loss of control over risks. Also in case of occurrence of an event, depending on severity, resilience involves applying improvisation to existing rules and procedures to respond rapidly and effectively. Sometimes, the culture of an organisation might give rise to latent hazards in supply networks. For example, too much obsession with optimisation approaches might lead to risky situations of stock-outs in cases of unprecedented demand spikes. Hence the resilient supply chain should also be watchful enough to ensure that efficiency focus (leanness) do not wear out the capabilities to resist any unforeseen events when they happen.

As discussed above in a number of occasions, supply chain resilience is a conglomeration of multiple capabilities and requires certain crucial sacrificial judgments. A resilient supply chain should be adept at adjusting the proportion of different capabilities. The supply chain resilience conceptual framework proposed here (Figure 2.4) is based on three different foci of resilience literature: mitigation, coping with ongoing trouble/ recovery from events already happened and judgement. The fourth focus is the performance focus, which guides the resilience framework to keep it within a dynamically stable trajectory, so that in coping or preparing for stresses, the supply chain never over-stresses itself and deteriorates performance.

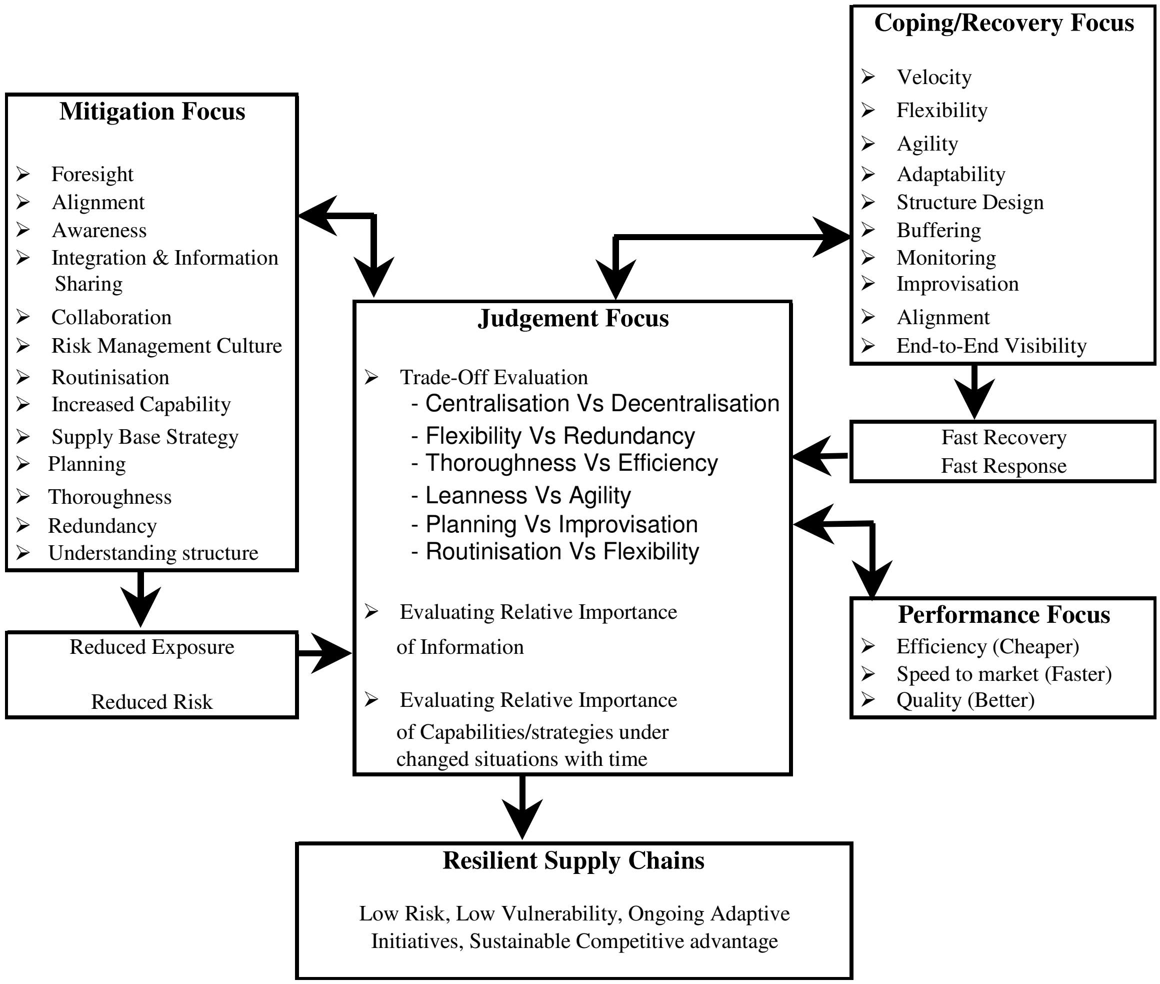


Figure 2.4: A conceptual framework for supply chain resilience

Figure 2.4 depicts a dynamic system, not necessarily one that is in balance. The arrows indicate important relationships between components of the system that must be understood, so that when one element changes, an appropriate response can be made to keep the system in some sort of dynamic equilibrium at that particular time interval. It is suggested that through these three interacting conceptual foci, concepts of resilient supply chains can be explored more fully.

In a broad context, it is through mitigation focus, the exposure and risks of supply chains are reduced. The risk mitigation focus of the supply chain resilience framework derived from relevant literature described above requires several capabilities. This requires foresight associated with experiential learning and processing faint signals of disruptions in the form of symptomatic events, suspected trends, gut feelings and intelligent speculation. High alignment of goals between supply chain members and awareness boost supply chain's capability to detect, compile and integrate diverse information and hence encourages proactive response to dangers that have not yet materialised. Cross-network collaboration, routinisation of standard tested procedures, standardisation of parts and rules, procedures help mitigating risks in supply networks. As has been seen from supply chain resilience literature, a detailed understanding of supply chain strategy and structure, use of slackness in resources, diversification of supply base, more attention towards thoroughness – all contribute to mitigating supply chain risks.

Coping with ongoing disruptions immediately raises the questions of defences and capabilities of the supply chain. The focus here is on the quick response to disturbances or the capability to redesign amidst trouble. The supply chain's flexibility, agility, visibility and buffering ability (safety stocks, multiple sourcing) help it to cope with the struggle. The ability to monitor what is happening in the supply chain members through global information sharing removes many underlying problems (latent pathogens as described before in literature review of organisational resilience). In case of totally unexpected one-off events, for which it is virtually impossible to learn any pre-planned response, improvisation, moving out of routines and procedures (through flexibility in transportation, production, distribution) is essential to cope and recover.

The third focus of supply chain resilience literature is the most important and is on the dynamic evaluation of different alternative strategies, policies and information based on situation. At this stage, the system continually receives feedback in the form of performance indicators (cost, quality and timeliness) from the implementation of different mitigation and recovery capabilities. This helps in dynamically balancing the different trade-offs to some extent, so that the system either stays out of danger or recovers fast without affecting the performance parameters adversely over a longer time horizon. For example, the benefits of visibility are judged depending on the operating environment of the supply chains, because otherwise it might affect the costs of the supply chains negatively. Again under certain environments, leanness might be preferred to redundancy as a risk mitigation strategy as it improves performance by reducing redundant and un-used capacity. This would require a dynamic evaluation of environment with time and evaluating the performance of different mitigation/recovery capabilities with respect to the performance parameters. Only through proper understanding of these trade-off decisions, resilient supply chains can be sources of sustainable competitive advantage for organisations. This framework actually shows that through dynamically adapting, integrating and reconfiguring the different capabilities, skills and procedures to match the changing environment, supply chains can improve resilience and become source of sustainable competitive advantage for the organisations. Most importantly, this framework is dynamic and the different trade-off decisions taken to restore stability at one time interval may be totally disastrous at another time interval as supply chains never operate at a static equilibrium state and every time interval the supply network behaviour changes due to the myriad interactions among different entities. The conceptual framework shows that, resilience is a dynamic capability of an organisation (Teece et al, 1997), that requires continuous renewal to achieve congruence with changes in business environment (either harmful or beneficial).

2.4 Research Questions

Although there have been several research targeted at understanding the risks, uncertainty, reliability or vulnerability of supply chains, yet none of them have addressed the issue of resilience. Neither has anybody attempted to model a resilient supply chain. All researches in a way have addressed one or other elements of resilience as flexibility, agility, reliability, but none has come up with a definite resilient supply chain that is capable of responding to changing customer requirements, at the same time capable of maintaining it in the face of several disruptions. Also, the concept of resilience studied in literature discussed is very narrow and does not include a broader vision, which sees supply chain resilience as a balancing function between satisfying today's customers, maintaining efficiency and responsiveness and at the same time focusing on changes in environment to adapt to meet tomorrow's demands. This needs to take a process view of resilience. This is not considered in the literature available so far.

Most of the supply chain resilience literature has come up with several recommendations for building resilient supply chains. But none have come up with a dynamic integrated view of resilience (described in the conceptual framework, Fig. 2.4). That is probably the reason, why none has mentioned that one resilience building strategy under certain circumstances might actually increase the vulnerability of the supply chains under some other circumstances. For example, almost all the authors are unanimous in recommending inter-organisational integration as a step to improve supply chain resilience. But as I have mentioned in the literature review on organisational resilience, extensive integration actually makes an organisation tightly coupled and thus making it more vulnerable to latent hazards. Also each member of the supply network must understand the dynamics of different trade-off decisions required to improve the entire supply chain's resilience. Although there are a plethora of methods to improve resilience, it is extremely difficult to get everything right in practice, as unforeseen aspects often come around in unexpected ways to create new possibilities for incidents. Each incident challenges the mindset of the team responsible for developing an appropriate response, disconfirming initial assumptions of what was necessary to solve the problem, and eventually involving the personnel directly finding an adequate solution going out of usual routine procedures (McDonald, 1999). Contemporary literature on supply chain resilience although stresses on the trade-offs but has not studied how these judgements can affect the resilience in a real world case study. Hence, the main challenge in building resilient supply chains is to study the decision making process of different elements that evaluates the different strategies recommended in supply chain resilience literature and applies them in accordance with changes in environment. Although, different authors have invented a plethora of practices essential for building resilient supply chains, none have mentioned the effects of adopting multiple resilience building strategies or which strategies are the most suitable to help firms protect from disruption risks without hampering its competitive advantage in terms of several performance metrics. Although the literature related to supply chain resilience is informative, it has primarily focused on supply chain disruptions from a general or high-level view of the phenomenon (e.g., supply chain uncertainty, risk perceptions, hazards) (Haywood and Peck, 2003; Sheffi 2001; Rice and Caniato, 2003; Christopher and Lee, 2001; Christopher et al, 2002; Sheffi et al, 2003). This perspective has guided to a fairly good understanding of the 'big picture', but deters the researcher from 'drilling down' to the key variables, the relationships among them and methodologies to manage these key issues (Blackhurst et al, 2005). This in turn reduces the practical utility of such studies since in any real application the detailed decision rules, controls, procedures and circumstances must be dealt with.

Apart from not identifying the key parameters or properly addressing the issues of trade-off judgements or the dynamic issue of supply chain resilience, the existing literature does not realise the importance of carrying out a dynamic analysis of behaviour of the supply chain to understand the suitability of different resilience capabilities over time and under different scenarios. Very few of the literature have attempted to address the issue of identifying rules or procedures, which can be adjusted in the face of uncertainty. Very few studies have attempted to explore how control systems established for reducing uncertainty can become sources of disturbance in the form of bull-whip effects. All these studies have mostly focused on the practices introduced to manage uncertainty (Wilding, 1998) or bull-whip effects (Van der Vorst et al, 1998) that can become sources of disturbances. Some studies (Saad and Kadirkamanathan, 2006; Saad and Gindy, 1998; Towill et al, 1992) have tried to understand the different rules, control systems for managing different types of disturbances discussed before. But all these studies are limited to inventory policies, lead time variation effects and other operational techniques. None of the above studies has investigated the effects of different resilience enhancement strategies or different decision rules or procedures taken by different members on the performance and resilience of the entire supply network. No study has ever attempted to study the effects of behaviour of the supply network elements on resilience. A detailed dynamic analysis of operating parameters, their adjustments, integrating with different members through information sharing, real time planning are not explored as a means of improving resilience in contemporary literature. In summary, a complete dynamic view of resilience is lacking in literature and this research aims at addressing this gap in literature. The research questions addressed in this research are:

a) How best to respond to the external disturbances and improve supply chain's resilience?
b) Can we find rules, procedures and control systems used in managing complex supply chains systems that are not a potential source of disturbance?
c) How can the system elements adaptively respond to any disturbances through interconnecting linkages and maintain the performance at the same time?

This thesis considers large unanticipated deviations of actual sales from forecasts as the primary disturbance to deal with. This is because, inspite of highly sophisticated forecast improvement techniques adopted by organisations, the forecasts are often found to be wrong. '*Despite the best of intentions, millions of dollars invested in technology, and several "world changing" collaboration initiatives, generating good forecasts is still difficult for even the best managed consumer goods companies*' (Shamir, 2007, p1). A natural adverse effect is the bullwhip effect, which has serious cost implications, for instance, the manufacturer incurs excess raw materials costs or material shortages due to poor product forecasting; additional manufacturing expenses created by excess capacity, inefficient utilisation and overtime; and mostly excess warehousing expenses due to high stock levels (Towill, 1996, Lee et al, 1997). Holmstrom (1997) reports that, the bullwhip effect in European grocery chains can increase order levels by 200% at the factory level. This thesis actually looks at improving the resilience of a supply network by studying the decision making rules, control procedures for responding to disturbances caused by poor demand forecasting.

Chapter 3

Methodology

3.1 Rationale for Chosen Methodology

In order to address the research questions identified in the literature review section, it is extremely important to consider the integrated behavioural dynamics of production and distribution functions. *'Because of the complexities in supply chains, the representation of inter-organisation relationships, the alignment of processes and the synergy of supply chains are very challenging. As the patterns between partners might be different due to diversities of products and the morphology is dynamic over time, the process of producing comprehensive or rigorous maps of the network is clearly a challenge'* (Li, et al, 2002, p551). Obviously there are no controlled experiments that can be done involving the whole supply chain or even involving only a single large factory to understand the behavioural dynamics (Armbruster, et al, 2002). Hence simulation models will have to be developed that substitute for the real environment. Researchers in the past have used various types of modelling techniques for analysing different aspects of supply chain networks. The focus on optimizing the flow in a supply chain network limits the use of these approaches for studying the behavioural based dynamics (Riddalls et al. 2000). Due to the dynamic and evolving nature of the supply chain networks (Parunak et al. 1998), an approach is needed that is non-deterministic in nature, is rich enough to capture the dynamical behaviour. A 1999 review by Sarimento and Nagi listed no papers that dealt with coordinated production/distribution/transport decision problems in a nonstationary stochastic environment. Within the context of manufacturing, Pratt et al (1994) found that decision makers, control rules and their interactions are mostly hidden. A reason for this may be the analyst's choice of building blocks, which does not appeal to supply chain partners. Further, control elements may be dispersed throughout the model – being associated with various building blocks or with time-indexed scheduling of events. These may simply not be visible. Consequently, not only realism but also modelling flexibility and modularity are harmed (Karacel and Mize, 1996). The intrinsic dynamics of the supply chain elements are not adequately covered by existing modelling approaches (hybrid discrete-continuous industrial dynamics models originally introduced by Forrester, 1961, discrete time models with delays (e.g., Tzafestas and Kapsiotis, 1994)), though academics and practitioners have dedicated considerable resources to the understanding of supply chains and their dynamics. Review of supply chain resilience literature showed that no papers have addressed the modelling of integrated decision making across different functions to improve supply chain resilience.

The next section reviews the existing modelling techniques used in supply chain modelling and justifies their unsuitability in application in current research. Next, the methodology adopted in this research is described in detail and justifications are provided why it is the most suitable technique to address the current research questions. Then several applications of the methodology are highlighted in the subsequent section.

3.1.1 A review of existing supply chain modelling methods

Riddalls, et al (2000) did a review of the various mathematical methods used to model and analyse supply chains and categorised them as continuous time differential equation models, discrete time difference equation models, discrete event simulation models and operational research techniques. They observed that, different methods are suited to different problems. According to them (p975), *'OR tools have their place at a tactical level in the design of supply chains. They constitute the only analytical approach … to solve batch sizing and job sequencing problems. Yet they fail to throw much light on the dynamic behaviour of the supply chain as a whole. Qualitative phenomena like demand amplification can only be investigated and hence combated by methods based on the dynamics of the system. Further, implications of strategic design on supply chain performance can only be discovered by using broadbrush simulations based on the dynamics of the system.'* They concluded that, while OR techniques are useful in providing solutions to local tactical problems, the impact of these solutions on the global behaviours of the whole supply chain can only be assessed using dynamic simulation.

Li, et al. (2002) stated (p551), '*The main motivations for supply chain modelling are:*

- *Capturing supply chain complexities by better understanding and uniform representation of the supply chain;*
- *Design supply chain process to manage supply chain interdependencies;*
- *Establish the vision to be shared by supply chain partners, and provide the basis for Internet-enabled supply chain coordination and integration;*
- *Reduce supply chain dynamics at supply chain design phases.'*

They actually emphasised the need for further research in supply chain modelling to produce comprehensive representation of inter-organisational relationships, the alignment of processes and the synergy of supply chains, which might be different due to the diversities of products and dynamic morphology. Min and Zhou (2002) in their evaluation of supply chain modelling techniques, stated (p245), *'the supply chain concept represents new management thinking with heavy emphasis on customer service. Such a paradigm shift necessitates a new mindset that defies the preconceived importance of functional excellence. In other words, reinventing traditional analytical tools will not be the answer for many managerial issues involving real world supply chain problems. Those issues may include organisational resistance to change, inter-functional or inter-organisational conflicts, joint production planning, dynamic demand forecasting, profit sharing, team-oriented performance measures, channel power shift, customer relationship management, information sharing…. Since many of these issues are perceived 'soft' (e.g., ill-structured, strategic, behavioural), these are not necessarily 'hard' (e.g., structured, operational, technical) issues commonly addressed by analytical tools such as mathematical programming tools.'*

The significance of supply chain modelling lies in capturing supply chain complexities by better understanding and uniform representation of the supply chain (Li, et al, 2002). Modelling of supply networks is essential for robust strategy designs and understanding the dynamic behaviour of supply network structures (Forrester, 1961, Sterman, 2000).

Supply networks are complex bi-directed networks, having parallel and lateral links, loops, bi-directional exchanges of material money and information, encompassing a 'broad strategic view of resource acquisition, development, management and transformation' (Harland et al, 2002). Researchers in the past have used various types of modelling techniques for analysing supply chain networks. Pyke and Cohen (1993), Altiok and Raghav (1995) used operational research techniques to model and study the dynamics of a supply chain network. System dynamics research has been widely acknowledged since the seminal work of Jay W. Forrester and J.L. Burbidge in the 1950s and 1960s. Forrester (1961) examined how production and distribution procedures in a supply chain may result in an inaccurate assessment of perceived demand. He used a system dynamics approach; integrating systems of ordinary differential equations over time to study and analyse the dynamics of the supply chain network. The Forrester effect, also known as 'demand amplification', has been shown to affect logistical information such as order forecasts and inventory control. Burbidge (1961) studied similar demand amplification effects arising from forecasting inaccuracies in a shop floor control system; they later became known as 'the Burbidge Effect.' He described the amplification phenomenon using simple filter theory and a graphical representation. Forrester's work has been extensively researched and substantial empirical support for the theory has been provided (Coyle 1982, Towill 1992). Towill (1991) improved upon Forrester's work by considering tiered structures in supply chains. Towill (1996) has shown various ways in which industrial dynamics models may be built and exploited in supply chains using simulation techniques. By considering supply chains as an integrated operation, he found that the effect of poor decision-making within the chain is multiplicative, not additive (Towill and Naim 1993). Towill (1997) used feedback control block diagrams to represent the supply chain, and difference equations to describe chain dynamic behaviour. These studies suggest improving chain performance through modifications of the chain such as through removal of one layer of the chain, information integration, reduction in lead time and modification of ordering rules as well as combinations of these. However most of these papers, although addressing the specific objective of maximising customer service levels while at the same time minimising finished goods stock levels, were based on a steady state design principle. Even if multi-time simulation is performed (Evans et al, 1998; Dejonckheere et al, 2004), they are based on the assumption of standard normal distributions for the uncertain demand or step demand in some cases (Mason-Jones et al, 1997), which is quite far from real supply chain demand. Perea-Lopez et al (2001) proposed a dynamic modelling approach from the Process Systems Engineering viewpoint, using the balance of inventory and orders in terms of ordinary differential equations, together with the definition of shipping rates to the downstream product-nodes, subject to some physical bounds and initial conditions for the inventory and order values. Perturbations to the system are the fluctuating demands from the customers and the changes in yields that the system might experience. But the model does not say anything about the implementation of a feed-forward action to the system over time, so that the supply chain can react ahead of time to perturbations. Bose and Peckny (2000) proposed the use of model predictive control for planning and scheduling of a generic supply chain. They also studied the effect of varying co-ordination structures and other parameters on the overall customer service level. A shortcoming in all the above models is the use of continuous material and order flows. In reality, flows are often discrete. In conclusion, the issue of parameter sensitivity, still applicable to these models, has not been resolved. To our knowledge, no sensitivity analysis has been carried out on these models. Also complex production-distribution systems with multiple products, multiple echelons can become exceedingly difficult to model with such approaches, especially under conditions of uncertainty.

Forrester's approach developed into the 'system dynamics' modelling technique and has been used by Sterman (2000) as a simulation methodology to understand the supply chain dynamics of a major computer firm. Anderson Jr et al. (2000) used system dynamics techniques to investigate 'demand amplification effects' in the machine tool industry. They replicated the supply chain model by creating two dynamical sources: 'Bullwhip effects' (Lee et al. 1997a) and the investment accelerator (Samuelson, 1939). Unlike other modelling work which concentrates on logistical decisions, these authors investigate the effect of external factors such as work force learning on supply chain dynamics. A system dynamics approach, in which levels of variables are controlled by the rates of change of other variables, is very useful is simulating many systems. Yet, such a system will ultimately fail when attempting to tackle the myriad interactions that comprise a real-life complex production distribution system under changed environments. The system dynamics community then extended the general model of stocks and flow for understanding the qualitative behaviour of supply chains (Parunak and Van der Bok, 1998, Riddalls et al, 2000). There have been a large number of pilot studies of supply chain dynamics (for instance, Saporito, 1997; Alber and Walker, 1997) that verify the predicted demand amplification and information distortion. Porter and Bradshaw (1974) and several other researchers (Bradshaw and Daintith, 1976; Burns and Sivazlian, 1978) used discrete time difference equations based modelling approaches for analysing a supply chain. Naim and Towill (1994) defined a supply chain engineering lifecycle framework by which supply chain dynamics may be detected, understood and documented requiring a holistic approach to supply chain engineering bringing together different strands of systems theory. Naim, et al. (2003) pointed out the suitability of systems approach in the analysis of supply chains in dynamic and complex environment considering interrelationships among subsystems as well as interactions between the system and its suprasystem. However they also stated the issues of boundary definition, sub-optimality, environmental interaction and goal alignment in such models. Systems change and steady state models only provide partial representation of reality (Rigby et al, 2000). Even soft systems methodology, where a realisation of the human element is made, cannot capture the essential essence necessary to fully describe the dynamic aspects of supply networks.

Principal limitations of these techniques are that they are unable to model behavioural based dynamics of a supply chain and the analysis can become quite complex for dynamic supply chains. Moreover all these approaches assume a relatively static supply chain network structure and try to optimise the flow in the network making them unsuitable to understand the dynamic aspect of supply chains. These works are more concerned with capturing the mode of behaviour of the whole system making extensive use of system level observables without addressing the individual agent behaviours that constitute the system. So these types of models are most naturally applied to systems that can be modelled centrally, and in which the dynamics are dominated by physical laws rather than information processing. But in understanding and hence improving the resilience of supply chains, such modelling approaches are not true representation of reality, since there is no explicit representation of the behaviours of the individuals.

Another group of research in supply chain modelling, and probably the largest one can be classified as supply chain optimisation. Supply chain optimisation can be roughly clustered into two main groups. The first group is concerned with multi-echelon inventory systems and focuses research on cost and service optimisation of warehousing policies at different levels of a supply chain. In turn, these may use a decentralised view (when ordering is triggered solely by inventory position at each stock-point, or *installation stock policy*) or a centralised view. The latter is called *echelon stock policy* and in this case ordering is triggered by the echelon inventory position, that is, the sum of all stock in transit to this stock-point plus its physical stock plus that in transit to or on hand at its downstream stock-points minus back orders at its end stock-points. In 1968 Sherbrooke formulated the well known METRIC (Multi Echelon Technique for Recoverable Item Control) model for a two-echelon inventory system consisting of a set of bases and a supporting depot. The items stocked in the system are called recoverable items, that is, they are subject to repair when they fail. Sherbrooke has proposed a variety of algorithms for determining optimal base and depot stock levels. A substantial portion of the computational requirement associated with each of the algorithms is related to the search for the optimal depot stock level. A literature review of optimal multi-echelon problems from a service level perspective was given by Diks et al. (1996). Most work dealt with one distribution centre and N retailers (e.g. Axsater and Zhang, 1999; Cachon and Zipkin, 1999; Seo et al., 2002; Svoronos and Zipkin, 1988). Tempelmeier (2000) developed a procedure for estimating the probability distribution of the order waiting time in a discrete time periodic (s, S)-inventory system, which is particularly useful for determination of inventory location that serves downstream nodes (e.g. production processes, regional warehouses or customers) in a supply chain. Among these papers, very few deal with optimal solution methods for systems of more than two-echelons, apart from the work of Diks and de Kok (1998, 1999) who developed a model for divergent multi-echelon systems and tested it using a decomposition approach. However, the models become mathematically intractable with increase in the number of echelons and incorporation of other real world parameters (demand patterns, member interactions).

The second group includes mainly those that use classic operations research methods and consider more than one of the following aspects of supply chain management: plant design, production scheduling, logistics of distribution and inventory management (e.g., Chandra and Fisher, 1994; Haq et al., 1991). General literature reviews have been made by Thomas and Griffin (1996) and Maloni and Benton (1997). The review by Vidal and Goetschalckx (1997) paid special attention to mixed-integer programming models of production-distribution problems. Baita et al. (1998) reviewed dynamic routing and inventory problems. Bok et al. (2000) proposed a multi-period optimisation model that considers inventory profiles, process operating modes and product sales. Zhou et al. (2000) used goal programming to optimise a continuous chemical plant with a multi-objective function. Gjerdrum et al. (2001) modelled multi-enterprise supply chains assuming fair profit distribution as a mixed-integer non-linear program. Timpe and Kallrath (2000) modelled a chemical supply chain considering production and distribution using a MILP approach. Kallrath (2002) presented a comprehensive review of literature on planning and scheduling of batch and continuous process plants. Other works studied sub-optimal solutions using commonly applied policies, as for example Agrawal and Cohen (2001), who analysed the effect of a fair share policy in a production-inventory problem over service level. An interesting method for coordinating information and materials flows in a supply chain using optimisation models was presented by Haehling von Lanzenauer and Pilz-Glombik (2002) and applied to a modified version of MIT's Beer Distribution Game. It demonstrated enormous potential for performance improvement using analytical decision support over human decision making. In supply chains, optimisation using mathematical programming is probably the most widely studied approach. However, this approach also has some limitations. For example, as indicated by Kafoglis (1999), it is technically insufficient in handling a high volume of what-if scenarios, and it is very difficult to solve a problem where more than two management issues (minimisation of costs or maximisation of profits) are considered. Based on the study of networked batch plants with interdependent production schedules, multi-stage production at multi-purpose facilities and chain production, Berning et al. (2002) also addressed the insufficiency of pure mathematical models for scheduling and proposed an integrated framework that consists of three layers, i.e. an optimiser for scheduling solution, a mechanism for collaborative planning among the involved plants, and a tool for manual updates and scheme changes.

Thomas and Griffin (1996) reviewed the research done in the coordinated planning between procurement, production and distribution stages of the supply chain. They found that, most of the models are based on mixed integer programming (MIP) and have the sole objective of cost reduction or customer service level improvement. Beamon (1998) provided a focused review of literature in the multistage supply chain modelling and found that the majority of models used inventory level as a decision variable and cost as a performance measure. Very few studies actually considered the case of multiple products. A 1999 review on integrated analysis of production and distribution system by Sarimento and Nagi revealed that no papers dealt with coordinated production/ distribution/ transport decision problems in a non-stationary stochastic environment. Erenguc et al (1999) gave a taxonomical framework for analysing supply networks from an operational perspective. They classified the entire network into three stages: supplier, plant and distribution. They found that researchers have yet to identify consistently efficient solution procedures to solve multiple stage inventory problems taking an integrative view of supply chain management. Researchers considered issues such as capacity, commonality, schedule stability and lead-time uncertainty as internal factors within a single facility. Ganeshan et al (1999) presented a broad taxonomy for understanding supply chain management research and concluded that, successful supply chain management requires heavy emphasis on integration of activities, cooperation, coordination and information sharing throughout the entire supply chain. Min and Zhou (2002) synthesised the past supply chain modelling efforts and identified key challenges and opportunities associated with supply chain modelling. They pointed out the scarcity of tools to study integrated supply chain concepts because of the inherent complexity in integrated modelling. The authors observed that the supply chain is a complex network of organisations with conflicting objectives. Bilgen and Ozkarahan (2004) recently reviewed the supply chain models developed for production and distribution problem at strategic, tactical and operational levels. They observed that the vast majority of publications until now included a single performance measure and were limited to deterministic models. There is one clear shortcoming in all of these works. In order to develop models that are mathematically tractable, there are a number of assumptions that must be made to simplify the problems. Thus multiple buyers or suppliers may be abstracted to one or layers are reduced. The abstractions and the assumptions limit the extent to which the models reflect the reality of the complex inter-organisational relationships, which exist in modern day supply networks composed of many interdependent elements.

Even though certain models researched in the above reviews considered multiple conflicting objectives, they were deterministic and did not consider multi-period model characteristics, capacity constraints and uncertainty factors. Most models were not based on industry data and mostly considered hypothetical situations, which have very little relationship with reality. Such models may produce an optimal solution for a static point in time, but these solutions may not prove to be robust in dynamic environments (Blackhurst et al, 2005). These approaches are static and can be unsuitable to the dynamic nature of the supply chains. In other words, as a disturbance occurs, the optimisation model is no longer valid – 'it is a brittle model' (Davidsson and Wernstedt, 2002). For years, studies have mainly investigated various supply chain activities in an isolated way, without considering the complex interactions between production and distribution activities (Lim et al, 2006). These activities in reality have conflicting objectives; for example, a manufacturing factory aims to maximise throughput and minimise idle time without considering the impact on inventory levels and distribution capabilities. So a model to research supply chain resilience and address the research questions in this thesis should include multi-objective, multi-period, multi-product treatments of joint procurement, production and inventory decisions explicitly considering different disturbances, capacity constraints, trade-offs among total cost, customer service and lead time and most importantly representing reality.

The modelling approach for addressing the research questions identified in Chapter 2 has to account for the time varying nature of the behaviour of certain subsystems of the supply chain largely driven by dynamically changing supply chain environment (Backx, et al. 1998). Capturing the overall dynamics of the supply chain constituents in a black box fashion does not allow for a sound integration of the overall supply chain with the intrinsic dynamics and the operation, decision making of its subsystems (Backx, et al. 1998). Ultimately, structure and behaviour of the supply chain should be synthesised to meet given operational objectives reflecting the market demands (Backx, et al. 1998). Existing approaches discussed above lack some capabilities that are required for successful supply chain simulation that would help in understanding and improving resilience. The inability to explicitly model the decision making infrastructure, the linkages between different levels of decision making, the systems responsible for control, their activities and their mutual attuning with time to adapt to changes are considered as intrinsic weakness of the existing tools. Mostly, the existing models strongly focus on physical transactions, leaving the definition of control structures largely to the analyst.

The modelling framework required for addressing the research questions should reveal and aim to integrate the material structure (flow of material), the information structure (transfer of status information through the system), the decision structure (flow of decision related information, which is a set-point or target to be enforced or a criterion, which is used in the decision making process) and the strategic structure (the operational policy of each decision maker and defines its knowledge or ignorance of the goals and operational policies of other decision makers). It will also require the modelling of market mechanisms, of decision-making agents outside the supply chain and of phenomena occurring outside the supply chain but affecting the various mechanisms within the supply chain.

So a need for a modelling framework is felt, which is bottom-up, starts by identifying the most basic building blocks (agents) of the supply chain; identifies their individual behaviours, decision making and interactions; and specifies how these agents interact with each other and the external environment. Accordingly in such a model, the structure of the supply chain is determined by all its elements and their aggregation to more complex systems across a number of hierarchical levels. And the behaviour of the overall supply chain emerges as a result of behaviour of all its subsystems, connected with each other and with the environment the system is embedded in, giving rise to improved resilience. A key realisation to tackle this problem is that supply chain networks should be treated as '*complex systems*' [which are systems that have within themselves a capacity to respond to its environment in more than one way, and which select among these in some way (Allen, 2000)]. Choi et al (2001) emphasised a similar viewpoint and aimed to demonstrate how supply networks should be managed if they are to be recognised as complex adaptive systems. The next few sections briefly describe complex systems modelling, supply chain networks as complex systems and the appropriate modelling technique for addressing the research questions identified in this research.

3.1.2 Complex Systems Modelling

Complexity science is the science of evolution, of changing organisational forms and structures, and of emergent capabilities and features. However, complexity science views such organisational evolution as resulting from the interaction of individuals. Simon (1996) defined a complex system as one made up of a large number of individual parts that have many interactions. Thompson (1967, p6) described a complex organisation as a set of interdependent parts, which together make up a whole that is interdependent with some larger environment. This is not simply a reductionist view because the individuals are changed internally by their interactions, and therefore give rise to genuine emergent, collective effects. It is also a view in contrast to that in which organisations are viewed as functional from a top-down perspective. It cannot be assumed that the interaction of the individuals will necessarily lead to the successful functioning of the organisation, or that there is any scientific principle that ensures the functioning will be optimal, or indeed even maintained. Instead, complexity science sees an organisation that is operating as being the result of a historical pathway of local experimentation that has led to a system that works well enough to have survived until now. Its operation affords no simple guarantee about future survival. Complexity science is cognizant of the whole system in qualitative, holistic ways (McKelvey, 1997), recognising that interactions in real systems exhibit non-linearity, and that this is the mechanism by which small causes and fluctuations at a lower level can generate disproportionate, structural evolution at a higher level above. Daft and Lewin (1990) meant behaviour of complex systems is surprising and is hard to predict because it is nonlinear (Casti, 1994). In nonlinear systems, intervening to change one or two parameters a small amount can drastically change the behaviour of the whole system and the whole can be very different from the parts. It is sometimes called the butterfly effect (Lorenz, 1963), wherein a tiny effect of a butterfly flapping its wings could potentially change the emergent pattern of the large-scale atmospheric dynamics. In general, complexity recognises that structural evolution, emergent properties and capabilities are driven by the dialogue between the microscopic and the macroscopic levels of description of a system. In this way, Complexity Science also recognises that history – luck, contingency, particular circumstances – really matters, since this evolutionary dialogue is path-dependent and is not reversible. The co-evolution of the agents within complex systems means that together their learning and adaptation trace a particular pathway into the future rather than a convergent one to some generic equilibrium structure. The system is sensitive to initial conditions as well as to events and circumstances along the way with an irreversibility expressing the 'arrow of time'. These characteristics of organisations, as complex systems, need to be recognised in order for managers to recognise the constraints and opportunities to influence the evolution of their organisations. A complex system does not exist in isolation. It both competes and collaborates with other organisations for resources and customers, at many layers within the organisation, for example individuals, teams, departments. Coevolution occurs when the direct or indirect interaction of two or more evolving units produces an evolutionary response in each other (Van Valen, 1973). The relevance of co-evolution is that regardless of the dimensions that each agent perceives at a given time, these dimensions will change over time, sometimes incrementally and sometimes suddenly as the consequence of a phase transition. Because of this, looking at the variables, parameters and factors in reality (ontology) evolutionary change is made in the understanding and knowledge (epistemology) of what is happening, as well as the aims and goals (axiology) of the elements with respect to this domain.

Deconstructing complexity

In a series of papers (Allen, 1976, 1994; Allen and McGlade, 1987), the essential driving force of evolution and of complex systems was shown to be the micro-diversity (heterogeneous and idiosyncratic individuals) that exists below any chosen level of description of real systems. It was shown that micro-diversity provides an internal pool of adaptive and creative behaviours that drives the evolution of the system as a whole, through successive structures and organisations, changing both the macro-structure and also the internal beliefs, criteria and aims that underlie individual behavioural responses. In this way, the internal beliefs and views held by agents of a given kind are shaped by their experiences that in turn result from the organisation and structures that they inhabit. These are, in their turn, also formed by the behaviour and interactions of the individual agents. This is a circular system that either is self-reinforcing, marking a period of stability, or is not, marking the occurrence of instability. The complex system that represents organisational evolution is therefore about periods of structural stability, when rational analysis and knowledge can exist, separated by instabilities, when new variables and aspects invade the system, and rational decision making is impossible. This can be understood by studying the assumptions and approximations made in arriving at a mechanical description or model of any evolved, and hence complex, part of reality. There are five assumptions:

1. There is a system boundary, with the environment outside and the “ system ” inside.

2. That we can define and classify the content of the system – the variables, mechanisms, processes, elements and their interactions – and we see that over time these have changed qualitatively.

3. That we can describe the system in terms of average types.

4. That we need consider only most probable (average) micro-events.

5. That the system has run to equilibrium.

This is illustrated in Figure 3.1 in which the different types of model are seen and epistemology that arise as successively more constraining, simplifying assumptions are made.

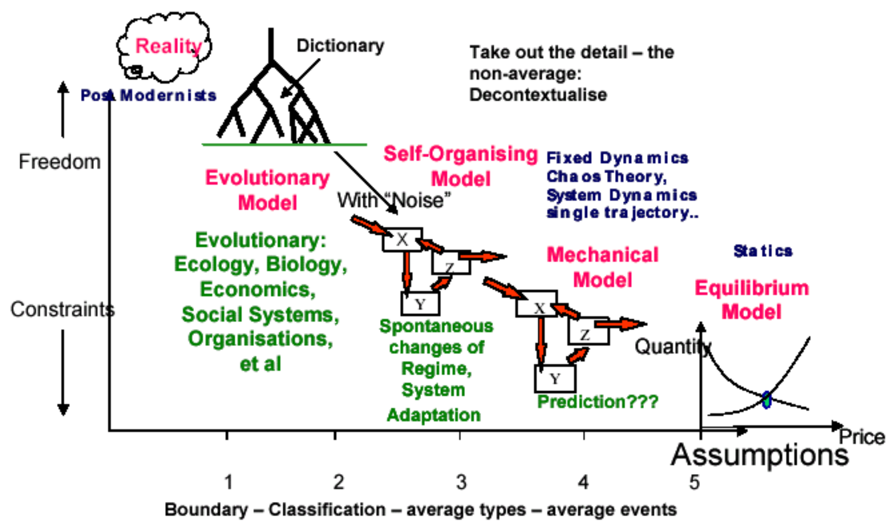


Figure 3.1: The overall conceptual scheme of increasingly simplified representation of a situation, as increasingly strong assumptions are made [Source: Allen (2000)]

- With no assumptions, reality is simply subjective experience, and survival would rely on intuitive, spontaneous responses.
- With the definition of a boundary, and with the ability to classify the elements and content of a situation, an evolutionary view can be arrived at, because over time almost all situations of interest are characterised by a qualitatively changing structure, with new entities and dimensions emerging and earlier ones disappearing. Evolutionary models can be developed for example of evolving markets, organisations or ecosystems.

- Considering the present however, the classification of the entities present, together with the probability of interactions between them yields a description in terms of a probabilistic differential or difference equations, expressing the coupled behaviour of the system. Because of the usual presence of feedbacks and non-linearities such systems would normally possess multiple possible dynamic attractors, and the probabilistic interactions would allow the system to move between different possible attractor basins under the effects of noise and fluctuations. For this reason, they are referred to as “ self-organising ” since the system could spontaneously jump from one configuration (attractor basin) to another. This kind of model could be used to test the spread of outcomes possible under various “ what if ” scenarios.
- Making a further assumption that only the most probable events actually occur, we arrive at a system dynamical description of the system. This corresponds to an apparently “ causal ” description of the behaviour of the system, one that supports rational decision-making, and with which participants feel comfortable. The behaviour of the system is apparently predictable, and can be used for “ what if ” scenario testing – and an exogenous “ sensitivity analysis ” can replace partially the effects of fluctuations and noise that the “ self-organising ” model would treat more correctly.
- One further assumption that is often made is that of equilibrium. In particular, such methods as cost / benefit analysis of a possible decision rely on comparing the initial (equilibrium) situation with the final one. This is appealingly simple, but does ignore the probable fact that the system and its environment are never at equilibrium, and hence the calculation is false.

This cascade of assumptions concerns the degree of understanding that we have of a situation. As we make successive simplifications, we are increasingly clear in our description of the situation, despite the fact that our assumptions may be false. We can only claim to really understand something if we can state exactly what it is made of, and how the different parts interact. But, in complex systems, and in organisations, “ what agents are ” may be changing as they learn new things and formulate new preferences, and the way that the different agents interact may also be changing if new connections are formed, or if communication produces new knowledge, or beliefs. In short, the right-hand side of Figure 3.1 is where we feel we understand what is going on and how the system works, while reality remains firmly on the left, and forces us to re-form our thinking when the dissonance between left and right becomes too great. Our understanding of reality is in terms of a set of interacting components that cannot evolve of themselves and the changes and innovations that occur in reality are merely taken account of by making a new, revised model of that reality. The mechanical, system dynamic, view of the " functioning " of the system at a given time is necessarily incomplete in that it does not include the micro-diversity within the agents that leads to new ideas and to learning, will in fact change and modify things. Figure 3.1 tells us therefore that the key assumption (3) in which we assume a description of the current situation in terms of the average types, or homogeneous elements, currently present, is the critical one in which the " evolutionary potential " is lost. In the real, complex system there is internal heterogeneity, multiple different perspectives and constructs, and differing aims and goals, and it is the interaction of these things over time that will lead to evolutionary, structural qualitative change.

3.1.3 Supply Chain Networks and Complex Systems

Choi et al. (2001) argue that supply chain networks should be recognised as complex systems. They referred to the key elements of internal mechanisms: agents and schema, self-organisation and emergence. One of the key points they made, a supply network emerges with no one firm deliberately organising and controlling it. Agents refer to entities that populate a complex system. In the context of supply networks, agents may be an organisation, a division, a team, or an individual, or even a function of an individual's job. The key important feature is that they have the ability to make decisions. As Whiting (2001, p118) confirms, *'along the supply chain, "There's an endless stream of decisions that are interdependent.'''* In the context of supply networks, schema are the rules that the organisations, or the decision makers within organisations use to make the decisions for and guide the actions of the organisation. Because the behaviour in complex systems comes from complex interactions between the environment and the agents and among the agents, the changes tend to be non-linear; similarly in supply chains a small fluctuation at the downstream can cause amplified and oscillating changes with phase lag in upstream.

Choi et al state (p. 357), *"The behavior of a complex system can not be written down in closed form; it is not amenable to prediction via the formulation of a parametric model, such as a statistical forecasting model."* Therefore, while it may not be possible to precisely predict what will happen to the system in the future, it may be possible to have some idea of what may occur as knowledge of the patterns increases and greater understanding of the systems develops. Analysis may even yield some knowledge of key patterns of behaviour that are likely to develop in the system over time.

Surana et al (2005) argue that supply chains should be treated as complex adaptive systems. Supply chain networks consist of individual entities that operate autonomously with different objectives and subject to different set of constraints. The supply chain networks are characterised by nonlinear interactions and strong interdependencies between the entities. The flow of materials, information and allocation of resources provides the binding force among the entities when it comes to improving customer service level or reducing costs. The welfare of any entity in the system depends on the performance of the others and their willingness and ability to coordinate. The entities in the supply chain often have conflicting objectives as stated before with regards to production and distribution functions. Control is generated through nonlinear though simple behavioural rules that operate based on localised cooperation. So in order to examine the resilience of supply chains, conceptualisation of supply chain networks as complex systems is extremely essential. Since supply chain resilience involves difficult judgments concerning trade-offs and interrelations between different mitigation and recovery capabilities ultimately resulting into sustainable competitive advantage over longer term, it is essential to understand the behaviours of the supply chain elements at both local and global scales. This will require complex systems representation of supply chain networks.

3.1.4 Agent Based Modelling (ABM)

Like any complex systems, the study of supply chains should involve a proper balance of simulation and theory. Obtaining a balance between various dimensions of performance and the resilience of a supply chain becomes intractable for most conventional mathematical modelling approaches as supply chains grow both in levels and linkages. Agent based systems could provide a solution to this problem, as they provide the opportunity to construct a large, complex system out of relative simple, autonomous parts (Jennings, 2001).

In the previous chapter, it is discussed that supply chain resilience is improved by designing decision making processes that constantly monitor changing conditions and dynamically evaluate viable trading and operational options in light of these conditions. Since resilience is a multidimensional phenomenon and involves collective dynamic judgment making, ABM is capable of improving resilience by providing methods of modelling the entire supply chain network under different decisions taken by different members and studying the entire network behaviour. ABM helps understanding the impact of adopting different strategies/ capabilities, which are beyond the individual capacities or knowledge of each agent, thus improves difficult judgement making through coordination, communication and negotiation across multiple agents. Agent based modelling provides a method of integrating the entire supply chain as a network system of independent echelons; different entities employ different decision making procedure in most cases (Gjerdrum et al, 2001). Hence agent based simulation modelling is regarded as the best candidate for addressing the research questions identified in previous chapter. The rapid developments in the field of agent-based systems offer new opportunities for the management of supply chains.

The model with 3 assumptions (Figure 3.2) constitute the basis for contingency planning, risk analysis and testing the resilience of an organisation (Allen et al, 2006a) and this is the type of multi-agent based model of a supply chain that I shall develop in this thesis. However, this assumes that the organisation and its environment do not evolve qualitatively, rendering the model incorrect. Many papers have been published (Allen, 1994, 2001a – b, 2004 ; Baldwin *et al* , 2003 ; Allen and Strathern, 2004 ; Allen *et al* , 2006b) concerning the mathematical modelling of structural, strategic evolution as being the most important aspect of complexity thinking. However, in this research I want to demonstrate the importance of the stochastic non-linear systems models that correspond to making assumptions (1), (2) and (3). In this situation, I assume that the " structure " of the system is known and is not going to change, so that the agents and their role in the organisation is already defined and will not change. However, what I explore is the different possible values of the parameters used by agents and the informational linkages between them, and the multiple possible performance of the organisation in dealing with its environment, and the unpredictable variations that occur there.

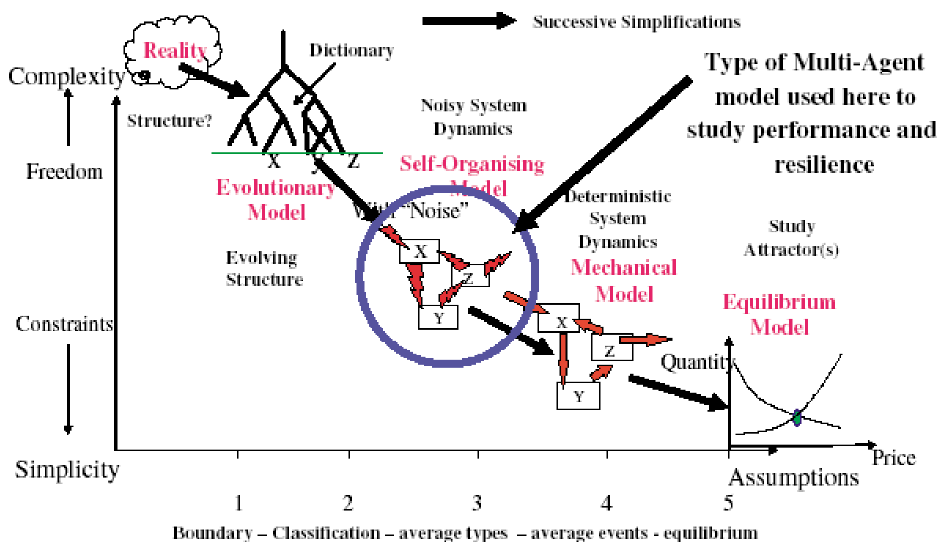


Figure 3.2: Successive assumptions are used to reduce reality to a simple, causal mechanical description, with models that can " run " but not evolve.

What are Agents?

Agents are a new paradigm of software system development. They are used in a broad and increasing variety of applications (Chaib-draa et al., 1992; Chaib-draa, 1995). For a long time, there was no single definition of an agent and a multi-agent system: several definitions have cohabited in the past. Nowadays, it seems that researchers agree on the following definition proposed by Wooldridge and Jennings (1995):

An **agent** is a system situated within and a part of an environment that senses that environment and acts on it without the direct intervention of humans or others but communicating with others, over time, in pursuit of its own agenda and so as to effect what it senses in the future. In brief, an agent is computer system situated in a certain kind of environment and is capable of autonomous action in order to meet its designated objectives (Jennings and Wooldridge, 1998).

According to this definition, humans as well as mobile robots are real world agents. Each is situated in, and is a part on some environment. Each interacts with coexisting agents. Each senses its environment and act autonomously upon it. No other entity is required to feed it input, or to interpret and use its output. Each acts in pursuit of it's own agenda, whether satisfying evolved drives as in humans and animals, or pursuing goals designed in by some other agent, as in software agents. Each acts so that its current actions may effect its later sensing, that is its actions effect its environment. Finally, each acts continually over some period of time. A software agent, once invoked, typically runs until it decides not to. An artificial life agent often runs until it's eaten or otherwise dies. Of course, some human can pull the plug, but not always. Mobile agents on the Internet may be beyond calling back by the user. Each agent has its own decision making stage to control its actions. The decisions are influenced by feedback from environment, communication and information sharing with other agents. In the context of supply networks, each member of the supply chain can be an agent representing the behaviour of the corresponding manager (for example, a distribution centre can be an agent, that represents the sales manager who has independent decision making power and guides the operation of the distribution centre after communicating with upstream and downstream members).

Agents vs Objects

The main difference between the two concepts of objects and agents is the *autonomy* of agents. In fact, while objects encapsulate some state on which their methods can perform actions, and in particular the action of invoking another object's method, an object has control over its behaviour. That is, if an object is asked to perform an action, it always does so, while an agent may refuse. Concerning this point, Wooldridge (2001, p26) recalls the slogan *"Objects do it for free; agents do it because they want to"*. Of course, some sophisticated objects may be very similar to agents. In fact, Wooldridge (1999) noted that there are clear similarities, but obvious differences also exist. Let us consider the case of objects in Java that can easily be transformed into threads exhibiting some behaviour. Such active objects have some autonomy like agents, but their behaviour is only procedural in reaction to message requests. On the other hand, autonomy of agents makes them perform activities without external intervention (Guessoum and Briot, 1999). In short, object-based concurrent programming has some relationships with distributed artificial intelligence (Gasser and Briot, 1992).

But objects and agents also present differences. In particular, object state is much simpler than agent state. In fact, an object state is only a data structure, i.e., an aggregation of variables of different types (integers, booleans, character strings. . .) in a common structure, while an agent state consists of components such as beliefs, decisions, capabilities, preferences and obligations.

Agent Architectures

There are different levels of complexity of implementing agent based models. Such complexity depends on the task that agents have to carry out and on the environment surrounding them. Russell and Norvig (2003) propose the following classification of agent architectures:

• *Simple reflex agents*: This type of agent is the simplest, because agents act on the basis of their current perceptions, ignoring what has occurred in the past, because they have no memory. Figure 3.3(a) describes how they select their actions according to condition-action rules, e.g., if sensors state that it-is-raining then actuators do take-umbrella.

• *Model-based reflex agents*: As agents cannot perceive their whole environment, model-based reflex agents, presented in Figure 3.3(b), keep track of the part of their environment they cannot currently observe. To achieve this, they have an internal representation of their environment, called a “model of the world”. Like simple reflex agents, they select their action according to condition-action rules, but now, the condition only depends on the model of the world, and not on the current perception from Sensors.

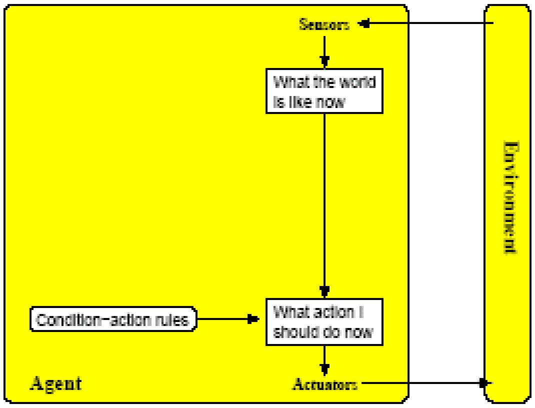
• *Goal-based agents*: As illustrated in Figure 3.3(c), this type of agent has goal information describing desirable situations, because the current state of the model of the world is not always enough to select an action efficiently. Conversely, to the two previous agent types, condition-action rules are no longer used, because the agent considers the possible futures of the world (cf. "What it will be like if I do action A” in Figure 3.3(c)) to decide which action it should do to achieve its goal.

• *Utility-based agents*: In order to improve the quality of agent behaviour, the agent is given in Figure 3.3(d) a utility function mapping its state (or a sequence of states) in the model of the world, onto a real number describing the associated degree of agent’s happiness. In comparison with goal-based agents, utility-based agents do not decide which action to do in order to achieve a goal, but which action to do to increase utility. This difference implies that both types of agents find which actions to do to achieve their goals, but utility-based agents find the best actions according to some given metrics. This agent architecture is hence the nearest to the definition of Economics agents, that only maximise their utility.

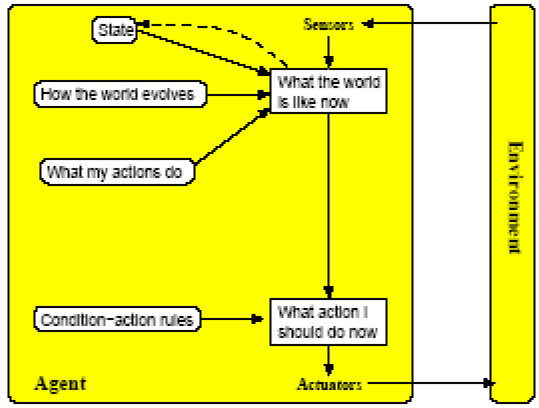
• *Learning agents*: Turing (1950) has noted the huge amount of work it takes to program an intelligent machine, and has concluded that it would be easier to build learning machines and then to teach them. Another advantage of learning agents is their adaptability to unknown environments, and the improvement of their behaviour with time. The learning agents presented in Figure 3.3(e) use a feedback, called critic, to learn which perceptions of the environment are desirable, and in consequence, how to behave.

Precisely, agents' learning consists in improving their future performance based on their past critic, by optimising their behaviour such as to maximise their utility when the world continues evolving as it has been. This kind of learning makes agents discover that some kind of (but not exactly) condition-action rules always do the same thing, based on their current knowledge. A problem arises here: after some learning time, agents are always going to do the same things because of these discovered rules, though the agents are not sure that these actions are optimal, while they might have a better performance if they had a wider knowledge of their environment. In fact, they should try to do very different actions than those prescribed by their learning process. This *exploration* of new actions is insured by the problem generator.

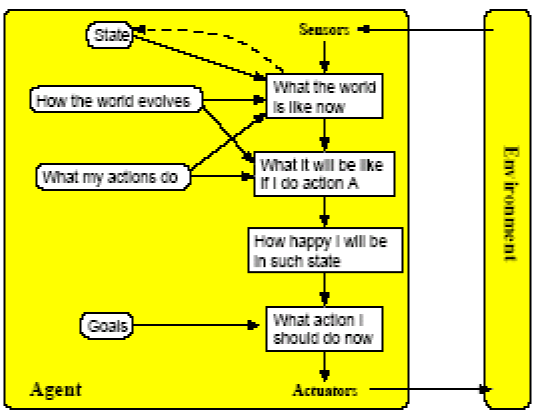
In this research I have used a combination of different types of agents. The agents used are mainly first type of simple agents, which can sense any changes in the environment through sensors and respond accordingly. However they also have some past memories for estimating a future world utilising the knowledge of sales-forecast mismatch, which are the predominant characteristics of the second type of agents. This world would be modelled in company-agents by some forecasting techniques predicting or giving an estimate of the future state of their environment, i.e., their future incoming demand. However, the third and fourth types of agents are not used in this research because in supply chain resilience there need to be a balance between both local and global goals. So if the agents all want to attain certain goals or utility objectives, then it might result in a vulnerable supply chain. Instead, in this research, a variation of the fifth type of agent is used. The limitation of the fifth type of learning agent is that, the learning is isolated. Each agent learns to optimise its performance after receiving feedbacks from the environment. Other agents in the environment are not modelled explicitly. The assumption that, the dynamics of the environment is unaffected by the behaviours of other agents is invalid in case of supply chain networks where there are multiple agents. Hence the learning techniques used by the agents may not be adequate under certain circumstances,



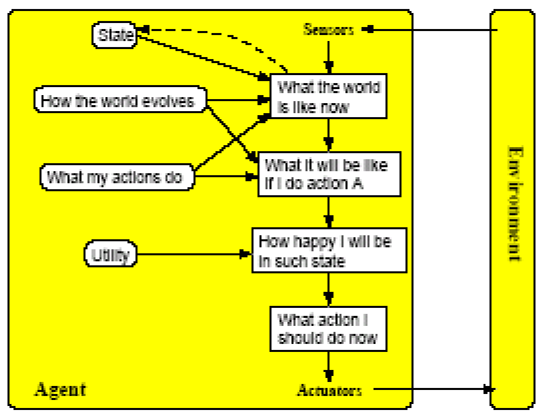
(a) *Schematic diagram of a simple reflex agent.*



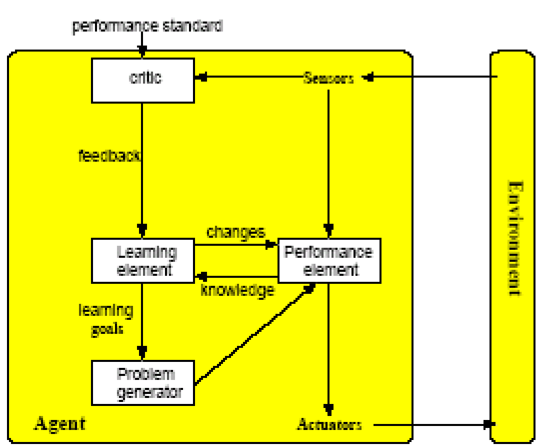
(b) *A model-based reflex agent.*



(c) *A model-based, goal-based agent.*



(d) *A model-based, utility-based agent.*



(e) *A general model of a learning agent.*

Figure 3.3: Architectures of intelligent agents (Russell and Norvig, 2003)

1) where actions of one agent strongly and frequently affect the plans of other agents (integrated supply networks/ tightly coupled systems); 2) where agents may not get feedback for their actions immediately (resource sharing over a time period by multiple agents) (Sen and Weiss, 1998). Under certain circumstances, it is very difficult to learn the best strategy because all actions are interlinked and the environment changes due to any single action by any single agent at any point of time. This problem with learning becomes really difficult, when situation changes every unit time interval due to tightly coupled systems as supply networks and decisions need to be made in real time at every unit time interval. So in the current research, real time learning is performed by each agent based on the perception of reality and reality itself. Decision variables are updated based on the deviation between reality and its perception or deviation of any performance measure from its desired value. The details of the agent architectures used for different elements of the supply chain network are described in the next chapter (Chapter 4).

Motivation for using Agent Based Models – Pros and Cons

Macy and Willer (2002) presented a historical development of agent based models as a tool for social simulation. They stated that ABMs defy classification as either micro (bottom-up modelling approach to simulate the evolution through time of each decision maker) or macro (holistic approach in dynamical systems models) levels of simulation but instead provide a bridge between levels. Agent based approaches offer increased robustness against unpredictability of supply chain operations. In general, the ability to orchestrate good global performance via local interaction protocols and strategies remains a significant and ill-understood challenge as discussed before.

One reason for adopting this approach is that, in order to address the research questions identified in this thesis, I am interested in the intentions of firms and the consequences of their collaborative behaviour over a longer time span. Attempts to empirically explore these issues are hindered by difficulties in collecting longitudinal data on entire network over a longer period (Kenis and Knoke, 2002). Empirically investigating people's intentions and motivations is notoriously difficult. People may not know why they do or have done things, or they may be reluctant to reveal their real motivations (Flick, 1998 and Vennix, 1999).

Another reason for adopting this approach is the complicated nature of the phenomenon studied and the necessity to understand the actual decisions taken by each member of the supply network. In a complicated production-distribution network involving multiple tiers of suppliers and customers, it may be impossible to derive attitude from behaviour because the interactions involved are simply too complicated (Elias, 1998). Agent based simulation addresses these two issues effectively. An agent-based model can represent many actors, in particular their intentions, internal decision rules and their interactions (Holland, 1995 and 1998; Axelrod, 1997; Prietula, 2001). This is most important for addressing the research questions in this thesis.

ABM begins, not with equations that relate observables to one another, but with behaviours through which individuals interact with one another (Parunak et al, 1998). These behaviours may involve multiple individuals directly or indirectly through a shared environment. The modeller begins by representing the behaviours of individuals, and then turns them loose to interact. The natural tendency in ABM is to define agent behaviours in terms of observables accessible to the individual agent, which leads away from reliance on system-level information. In other words, the evolution of system-level observables does emerge from an agent-based model. ABMs explore the micro-foundations of global patterns. Unlike the socially isolated actors in micro-simulation of social systems, in ABM, agents interact interdependently.

Researchers have already applied agent technology in industry to concurrent engineering, collaborative engineering design, manufacturing enterprise integration, supply chain management, manufacturing planning, scheduling and control, material handling, and holonic manufacturing systems (Shen et al., 2001). Concerning supply chains, Dodd and Kumara (2001) think that Fox et al (1993) was probably the first to organise the supply chain as a network of intelligent agents. Indeed, supply chains are made up of heterogeneous production subsystems gathered in vast dynamic and virtual coalitions. Intelligent distributed systems, e.g., multi-agent systems, enable increased autonomy of each member in the supply chain. Each partner (or production subsystem) pursues individual goals, while satisfying both local and external constraints (Maturana et al., 1999). Therefore, one or several agents can be used to represent each partner in the supply chain (plant, workshop, etc.). Moreover, the agent paradigm is a natural metaphor for network organisations, since companies prefer maximising their own profit than the profit of the supply chain (Viswanathan and Piplani, 2001). In fact, the distributed manufacturing units have the same characteristics as agents (Cloutier et al., 2001) (based on Wooldridge and Jennings (1995)'s definition of agents, quoted previously):

• *autonomy*: a company carries out tasks by itself without external intervention and has some kind of control over its action and internal state;

• *social ability*: a company in the supply chain interacts with other companies, e.g., by placing orders for products or services;

• *reactivity*: a company perceives its environment, i.e., the market and the other companies, and responds in a timely fashion to changes that occur in it. In particular, each firm modifies its behaviour to adapt to market and competition evolutions; if modelling the supply network of a single company, each unit of the company may respond to any action taken by other units of the same company to adapt to changing conditions

• *pro-activeness*: a company not only simply acts in response to its environment, it can also initiate new activities, e.g., launching new products on the market; introducing promotion drives to boost sales of a product which is already in mature stage of its life cycle.

Agent based models have many desirable features as described above (autonomy, intelligence and collaboration) for understanding supply chain behavioural dynamics essential for understanding and improving supply chain resilience and hence addressing the research questions (Barbuceanu and Fox, 1997, Nissen, 2001, Swaminathan et al, 1998, Yuan et al, 2001). This is because, first, there are multiple units as producers, distributors, and retailers. Secondly, these units are independently managed with independent decision making authority (autonomous); they are interdependent through exchange of information on customer demand, inventory levels, and exceptional events but there is no single authority to govern the whole chain collaboration. And thirdly, intelligent coordination is required for planning and scheduling of production and logistics in a dynamic market situation.

Moreover, multi-agent systems offer a way to elaborate production systems that are decentralised rather than centralised, emergent rather than planned, and concurrent rather than sequential. Therefore, they allow relaxing the constraints of centralised, planned, sequential control (Parunak, 1996). Unfortunately, an agent-based approach is not the panacea for industrial softwares. Like other technologies, this approach has advantages and disadvantages: it must be used for problems whose characteristics require its capacities. According to Parunak (1998), five characteristics are particularly salient. In fact, agents are best suited for applications that are:

• modular;
• decentralised;
• changeable;
• ill-structured;
• complex.

To judge relevance for supply chains of autonomous agents, Parunak (1996) compares this approch with conventional technologies (discussed before in section 3.1.1) in Table 3.1, thus highlighting differences between these two philosophies. Table 3.1 summarises the main disadvantages of multi-agent systems:

1. theoretical optima cannot be guaranteed, because there is no global view of the system;
2. predictions for autonomous agents can usually be made only at the aggregate level;
3. in principle, systems of autonomous agents can become computationally unstable.

	Issue	Autonomous agents	Conventional systems
	Model	Economics, biology	Military
	Issues favouring conventional system		
1	Theoretical optima?	No	Yes
2	Level of prediction	Aggregate	Individual
3	Computational stability	Low	High
	Issues favouring autonomous agents		
4	Match to reality	High	Low
5	Requires central data?	No	Yes
6	Response to change	Robust	Fragile
7	System reconfigurability	Easy	Hard
8	Nature of software	Short, simple	Lengthy, complex
9	Time required to schedule	Real time	Slow

Table 3.1 Agent-based vs conventional systems (Parunak, 1996)

But on the other hand, the autonomous, agent-based approach has some advantages too:

4. because each agent is close to the point of contact with the real world, the systems' computational state tracks the state of the world very closely. . .

5. . . . and without need for a centralised database;

6. because overall system behaviour emerges from local decisions, the system readjusts itself automatically to environmental noise . . .

7. . . . or to the removal or addition of agents;

8. the software for each agent is much shorter and simpler than would be required for a centralised approach, and as a result is easier to write, debug and maintain.

9. because the system schedules itself as it runs, there is no separate scheduling phase of operation, and thus no need to wait for the scheduler to complete. Moreover, the optima computed by conventional systems may not be realisable in practice, and the more detailed predictions permitted by conventional approaches are often invalidated by the real world. All these reasons show the relevance to use agents in supply chain management. In other words, thanks to their adaptability, their autonomy and their social ability, agent-based systems are a viable technology for the implementation of communication and decision-making in real-time. Each agent would represent a part of the decision-making process, hence creating a tight network of decision makers, who

react in real-time to customer requirements, in opposition to the flood of current processes, which is decided before customers place an order (Dodd and Kumara, 2001).

Benefits of agent based systems in modelling supply chain networks can be summarised as follows:

1) ***Ability to model more complex systems realistically:*** since agent based models use inter-connected intelligent as well as autonomous entities to model the environment, the resulting model is a more realistic approximation of the system.
2) ***Achieve increased flexibility and adaptability without losing efficiency or productivity:*** because of the ability to negotiate and interact with different interconnected agents, agent based models can be used to study the behaviour of the system under a variety of scenarios while giving near-optimal results.
3) ***Attain lean and agile enterprise operations:*** more real time handling of information and coordination, multi agent systems can lead to more flexible organisations that can efficiently handle change on various levels as well as cut slack in operations.
4) ***Achieve better integration of enterprise functions:*** With increased interaction between agents representing various functionalities of an organisation, operational response time can be drastically reduced and operational coordination improved. This leads to better informed and integrated enterprise functions.
5) ***Results in improved quality of decision making:*** because of the holistic approach of agent based models, the overall quality of decision making improves in agent based models.

Thus agent based technique has many distinctive features, making it attractive for addressing the research questions addressed in this research. It constitutes a very effective technique for designing distributed supply chain systems. Agents can mimic the supply chain structure, i.e., systems for individual chain components can be developed and maintained independently and the overall system behaviour and decision making is through interactions of the subsystems. A table (Table 3.2) showing the comparison of traditional methods with ABM is presented. Each method used for modeling supply chains is discussed. A critique of each method is also given. The suitability of each method in satisfactorily addressing the research questions is also stated.

Table 3.2 Comparison of supply chain modelling methods with ABM

Method	Description/ Critique	Assessment of suitability in addressing the research questions
System Dynamics	Aggregate dynamic representation of systems Use of averaged parameters results in long term equilibrium Time and space invariant rules No representation of individual decision making Use of continuous material and order flows, while in reality flows are often discrete	Aggregate deterministic descriptions are limited in their ability to reproduce the behaviour of each individual member of the supply chain network and hence is not suitable for addressing the research questions
Optimisation Methods	Central assumption that there exists an optimal set of solutions which either minimises costs or maximises profit This optimal set of solutions is time invariant Methods calculate the static equilibrium, which is not observed in reality Optimises technical parameters and does not explore each individual member's decision making process The abstractions and assumptions limit the extent to which the models reflect reality of complex inter-organisational relationships Is more suited for isolated system analysis and becomes mathematically intractable when integrated system needs to be considered	Traditional optimisation models have a different aim, which is to search for an optimal solution for a problem as opposed to exploration of behavioural dynamics essential for addressing the research questions in this research
ABM	Disaggregate method of using local rules for individual computational entities representing each member of the supply chain Potential for introduction of diversity and adaptation into a computer model Explicitly models the decision making process for each agent	Extremely useful bottom-up methodology for addressing the research questions More closer representation of real world supply network possible as ABM allows more detailed in-depth representation of each member

3.2 Previous work on agent based modelling in supply chain research

This new software architecture for managing the supply chain views the supply chain as consisting of a set of intelligent agents, each responsible for one or more activities in the supply chain and each interacting with other agents in the planning and executing of their responsibilities (Gunasekaran et al, 2000). The notion of agents is naturally associated with the modelling of control structures, that is, the managers or systems deciding on the use of supply chain resources, their activities and the mutual attuning of these activities.

Caridi and Cavalieri (2004, p114) on reviewing the applicability of multi-agent systems (MAS) in industrial environments commented, *'despite the density of efforts and projects carried out, there is still no clear understanding where and how multi-agent systems can provide better results than 'traditional' models. Authors often dwell on the theoretical description of design hypotheses and structural characteristics, but do not provide satisfactory indications on their level of applicability.'* They summarised, MAS are suitable for applications, which are modular, decentralised, complex, time varying and ill-structured. According to them, this approach is effective in fields as supply chain management, collaborative planning forecasting and replenishment (CPFR) where much of the efforts and time are spent in carrying out collaboration tasks among a definite and limited number of actors and where decision making activities are spread among more partners. However the issues pointed out by the authors are, agent based problem solving does not always succeed in optimally solving a problem and the results may not converge for the extensive number of agents required; MAS approach fails in modelling physical systems that cannot be decomposed into sub-problems and sub-objectives.

Swaminathan, et al (1998) use the notion of agents to propose a flexible modelling framework to enable rapid development and customised decision support tools for supply chain management. According to their approach, supply chain models are composed of a reusable set of software components that represent types of supply chain entities (e.g., retailers, manufacturers and distributors), their control policies (e.g., inventory policies and routing policies) and their interaction protocols, i.e., message types that regulate the flow of information, goods and cash. A major shortcoming of their approach is that little attention is paid to modelling control structures and their adjustment with respect to changes. Except for the notion of control policies, entities responsible for control, their mutual relationships (e.g., concepts of hierarchy and coordination) and the timing of their activities are either not covered or left implicit (Fu and Piplani, 2000). Essentially, Swaminathan et al (1998) model a supply chain as a flat network, in which physical transformations form the starting point for modelling (Sauer, et al. 2000).

Fox et al (2000) investigate and present solutions for the construction of an agent-oriented software architecture. The approach relies on the use of an agent building shell (ABS) providing generic, reusable and guaranteed components and services for communicative-act-based communication, conversational coordination, role-based organisation modelling and others. Their work incorporates the three levels of decision making, strategic, tactical and operational. In a parallel study, Chen et al (1999) studied the negotiation methods using agents in supply chain management. They showed how virtual supply chains could be formed by solving distributed constraint satisfaction problems. In a similar way, Lin and Pai (2000) show how Swarm, a multi-agent simulation platform, may be used for studying supply chain networks. However, neither Fox et al, nor Lin and Pai present a more generic approach like that of Swaminathan et al. Instead they restrict themselves to some specific applications within the supply chain context.

Parunak et al (1998) explore the capability of equation and agent based models in the problem domain of manufacturing supply networks. They discuss the relation between these two approaches at a high level and then compare their practical performance in three specific areas. The agent based model included three types of agents: *Company agents* represent the different firms that trade with one another in a supply network. They consume inputs from their suppliers and transform them into outputs that they send to their customers. *PPIC agents* model the Production Planning and Inventory Control algorithms used by company agents to determine what inputs to order from their suppliers, based on the orders they have received from their customers. *Shipping agents* model the delay and uncertainty involved in the movement of both material and information between trading partners.

Schieritz and Größler's (2003) is a very interesting piece of work. They make a case for using simulation to theoretical investigations of supply chains. Followed by a discussion of the differences and similarities between systems dynamics modelling and agent-based modelling they seek to integrate the two. Their model is interesting in that they explicitly identify some features of the model as being more macro level features and others as being micro level. Their model has ten identical agents in four levels in a supply network. They examined the network formation and stability under different order fulfillment strategies in terms of order preference and different "memories" of an organisation's performance. They used system dynamics modelling to represent the decision making behaviour of each agent at the micro level.

Same principle of integrating ABM and system dynamics was also used by Akkermans (2001) for examining a supply network with 100 agents and three echelons. He examines the emergence of a supply network given the preferences of the individual agents for conducting business with others in the network. He finds that the network gains stability rapidly and that agents that take short-term viewpoints perform as well in the long run as agents with a longer view of others performance.

Chang and Harrington (2000) modelled a retail chain as a multi-agent adaptive system. Their goal was to use simulation to study the effects of centralisation versus decentralisation on innovations. The conceptual framework employed in this research has two major components, innovation is viewed as an act of information creation that improves the organisation's ability to satisfy the demands of its external market environment. And the organisation is viewed as a collection of agents each of whom is capable of generating new ideas.

Cavalieri, et al. (2003) described a multiagent model for coordinated distribution chain planning. The model is applied to a real two-level distribution system, constituted by a supplier and a geographically distributed network of wholesalers. The modelling activity is focused on the distribution part of a logistics chain. The model comprehends a production agent charged with the fabrication of the product and the management of a centralised warehouse, wholesaler agents, distributing items of different brands and covering the whole market and final consumers, which are representative of the final demand. The models require the presence of a monitor agent who carries out at the same time a triggering action for the negotiation process and a control function for the transaction of information and materials. The vertical coordination model is based on a market like negotiation system able to model both cooperative and competitive relationships. The negotiation dynamics intrinsically finds an adequate equilibrium between specific goals of two supply chain partners, respecting their needs and constraints. The process is based on a pricing mechanism with an offer, a first selection, a counteroffer and a selection of best offers. An antagonistic lateral coordination policy is implemented in the model, which is activated only when the stock-out risk for a wholesaler agent rises up. The model described below is of theoretical value with virtual pricing model, but it is a fragmented representation of reality. Introduction of mental state negotiation models and real cost transactions is necessary to make the model a closer representation of reality.

Ahn et al (2003) proposed a flexible agent system, which is adaptable to the dynamic changes of transactions in the supply chains. They suggested a flexible conversation model (FCM) for multi-agent systems because conversations of agent systems are determined by transaction methods. This consists of an interpretable and exchangeable conversation policy model (CPM), a procedure for exchanging conversation policies and a mechanism about how actual transactions can be performed using new conversation policies. With the suggested model, agent systems are enabled to acquire new conversation patterns from counterpart agents when changes occur. The illustration of the suggested approach is discussed in context of a PC supply chain. The changes focused on in this paper are mainly supply chain structural changes (new trading partners, new product introduction, new information systems incorporation). The changes in demand or partial failure in production functions are not taken into account in this paper as those can be handled by re-planning productions and re-scheduling logistics, not necessarily changing the information systems. However, this is also a major limitation of this model, as it does not take into account of different sorts of changes.

Lin et al (1999) focus on a multiagent approach for enterprise modelling. This approach models the enterprise as networks of agents that possess capabilities and perform certain functions according to their roles in an organisation. They particularly focused on the order fulfillment process (OFP), one of the core tasks of supply chain network (SCN). Multiagent Information System (MAIS) is developed to simulate the OFP. The MAIS is implemented on the Swarm simulation platform based on the artificial life model in which biologic beings (i.e., agents) come and go (just as companies in an economy). Inspite of its promises, Bonabeau and Meyer (2001) however mentioned (p114), *'Many people have great difficulty understanding how swarm intelligence can work, mainly because they are unfamiliar with self-organising systems… critics often object that insects and people cannot – and should not – be described with the same mathematical frameworks.'* Frayret et al (2001) presented and illustrated a strategic framework for designing and operating agile networked manufacturing systems. It provides a framework to design responsibility based networked manufacturing systems, which operates in a dynamic environment. In this approach a manufacturing business dynamically organises its operations through the configuration and activation of a distributed network of inter-dependent business entities, called NetMan centers, responsible for fulfilling their own mission and maintaining business-oriented partnerships between themselves. According to its capacity and privileges, these centres may fulfil mission using approaches allowing partner business centers to self-organise and to dynamically reconfigure their partnerships according to environmental changes. MASCOT (Multi-Agent Supply Chain cOordination Tool) is a reconfigurable, multilevel, agent-based architecture for planning and scheduling aimed at improving supply chain agility. It coordinates production among multiple (internal or external) facilities, and evaluates new product/subcomponent designs and strategic business decisions (e.g., make-or-buy or supplier selection decisions) with regard to capacity and material requirements across the supply chain (Sadeh et al., 1999).

3.3 Summary

So from the above review of the publications on agent based supply chain systems, it can be inferred that they have either focused on cooperative decision support or distributed simulation but none has simultaneously addressed both. And most of these research works concentrated on a top-down, decentralised, communicative, coordination mechanism, which needs a lot of prior knowledge. Thus these models are usually limited by actual problems and lack of flexibility and adaptability and design complexity grows significantly as the scale of the problem increases. The adoption of these systems in practical case studies involving supply chain risk or resilience has been very limited so far. Most studies generally focus on optimising one aspect resulting in a mismatch between existing reality and theoretical mechanism design. Although ABM may offer a powerful means of simulating supply chain dynamic behaviour, so far it has made a modest entrance in supply chain literature. Recently researchers (Parunak and Vanderbok, 1998; Lin et al, 1998; Barbuceanu and Fox, 1995; Kohn, et al. 2000) have used multiagent technology in supply chain modelling for optimising the physical flow in a supply chain. Also these current models do not capture the rich dynamics in supply chain execution (Li et al, 2002), which is essential in studying the resilience of supply chain networks. In this thesis, a generic agent based computational framework is developed implementing the detailed decision making framework for management of uncertainty and improving resilience. This is then applied to a real world case study. The framework allows one to implement and test different decision rules in order to compare performance under different strategies (pushing or pulling materials) or design features (flexibility, redundancy, visibility, centralised planning) thus understanding the effective strategies for improving resilience. Agent-based modelling provides a sound methodology for analysis of supply chain behaviour, which will eventually lead to important insights into the issue of improving supply chain resilience.

Chapter 4

Model Formulation

4.1 Description of the generic agent framework

The agent-based decision making framework developed here is targeted at any supply chain consisting of a production factory, a central warehouse and distribution centres. The factory produces multiple products with differing demand patterns which are at different stages of their life cycles, are demanded in different markets and are sourced from different elements of the same supply network. The central warehouse stores all finished products after they are produced and supplies to multiple distribution centres (*Figure 4.1*). The distribution centres serve different markets with differing requirements for the same product categories. The markets may be supplied directly from the central warehouse or the different distribution centres situated close to the market. The current agent based framework is not only applicable to this structure of supply networks, but it can be extended to other structures to understand the behaviour under conditions of uncertainty.

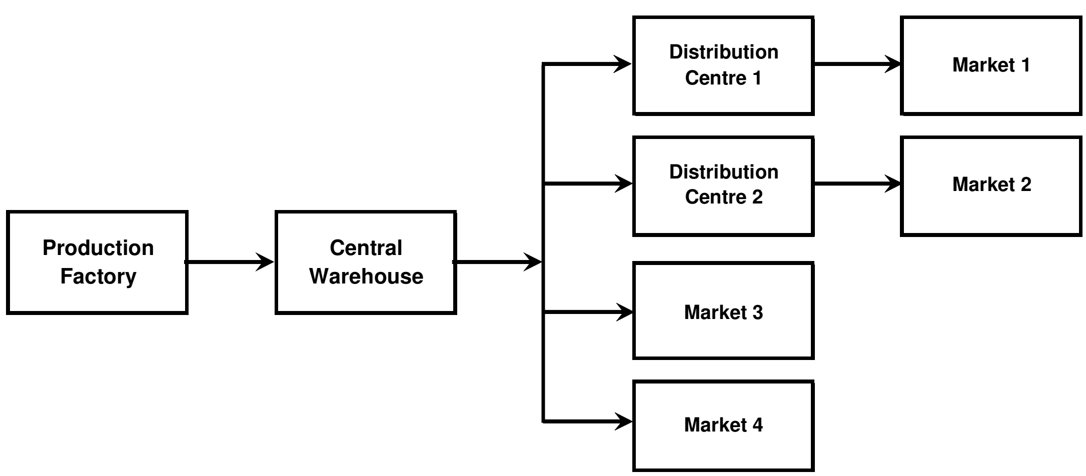


Figure 4.1: The supply chain structure addressed in the generic agent based framework

The arrows in the figure 4.1 depict the flow of materials from one member to another. The number of distribution centres and markets served by the central warehouse or the distribution centres can vary. Transport lead times from the central warehouse to each of the distribution centres or markets and from the distribution centres to the markets vary widely. The raw materials supplier in this network is not considered. Two types of informational structures are considered in this thesis to understand their impacts on supply chain resilience. The information flow diagram shown in figure 4.2(a) considers centralised planning of all activities, with very limited autonomy provided to individual members. The dotted arrows signify flow of information; double-pointed arrows imply flow of information in both directions.

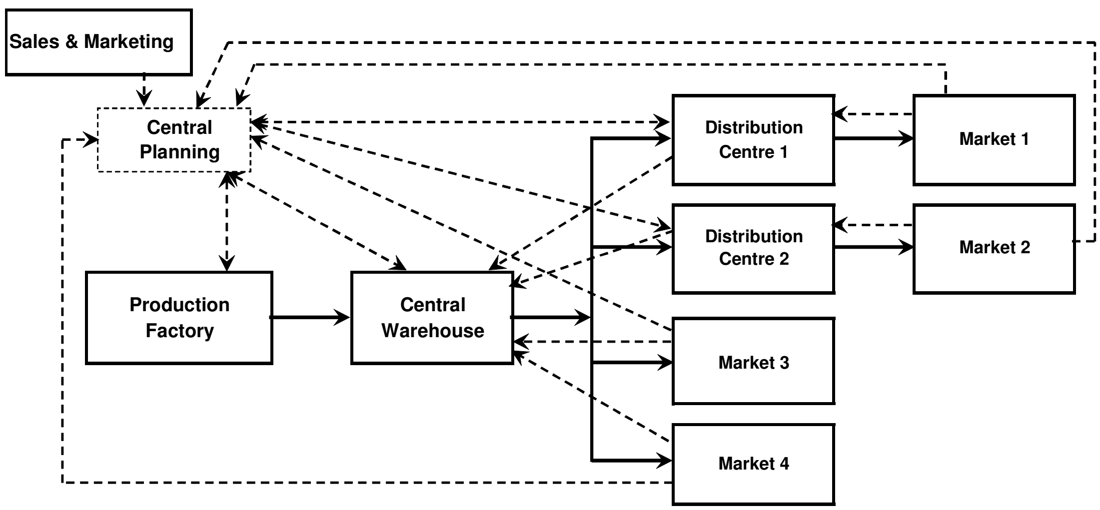


Figure 4.2(a): Centralised informational structure for the supply network

Central planning receives information from all elements of the network. First it receives information on past sales at various markets. Based on this information and the information on new product launch, planned promotional campaigns of existing products from sales and marketing, the central planning generates forecasts of different products for a long time horizon and communicates that to the different distribution centres and the central warehouse. The central planning generates production plans for the production factory based on the total forecasts of different products. These guide the factory on how much to produce in every product for a certain time horizon. These are revised after that time interval based on the real demands in the market, the stocks held at various locations across the supply chain and the forecasted demands of the different products for the coming period. The regional distribution centres take in the orders from the markets, get information from central planning on the forecasted demand next period and after reviewing own inventory position order materials from the central warehouse. The central warehouse gets replenished automatically by the factory. The factory only decides on the sequence of production of different products after getting the intimation of the production amounts from central planning. The distribution centres' autonomy is restricted to ordering materials based on replenishment strategies adopted. The central warehouse dispatches materials as per order to the requesting distribution centres, rationing the orders in case of scarcity of materials. The central planning agent generally has the full visibility of the supply chain network and possesses the decision making power to control all the activities of each member.

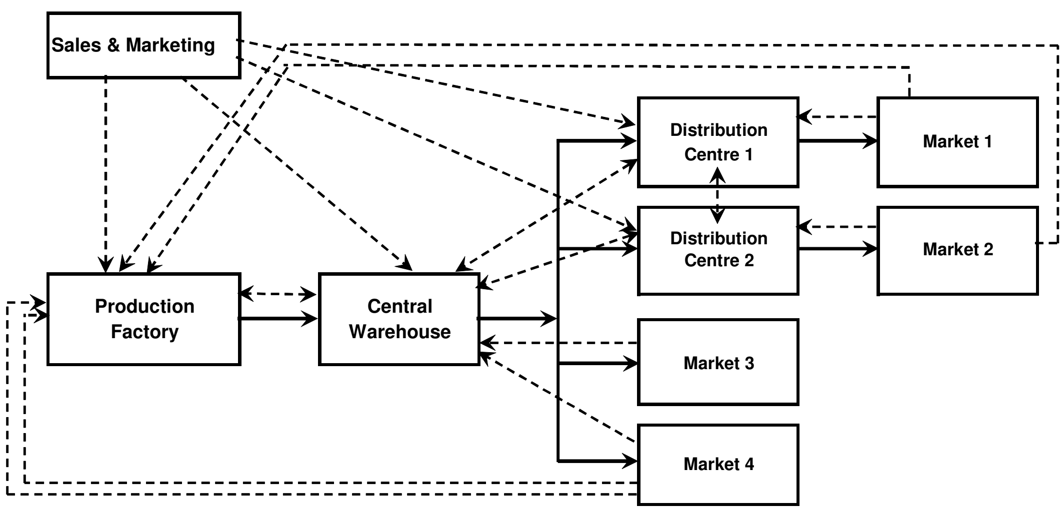


Figure 4.2(b): Decentralised informational structure for the supply network

A decentralised informational structure is depicted in figure 4.2(b), where the factory has access to network-wide information on sales, forecasts, stock levels, strategies. It has the full autonomy to decide when to produce which product and for how long based on the above information. The central warehouse and the distribution centres will have more autonomy in deciding which products to order more and which products to order less based on the information shared between different distribution centres (information of the demanded products and their respective demand patterns). The central warehouse and the production factory have more information sharing between them and provide more effective demand-responsive production planning. Each distribution centre receives orders from the markets. At the same time, projected forecast of each product is communicated to all the members from sales and marketing department. The factory receives information on stock levels from all distribution centres including the central warehouse. The central warehouse gets the information on the products being produced at the factory for running its own operations. The distribution centres place replenishment orders on the factory based on their own stock levels, the stock levels of the central warehouse and the ordering action of other distribution centres.

Each member is modelled as an independent agent with autonomous decision-making ability. Appendix A describes the programming language and platform used for modelling the different agents. The production facility is represented by a factory agent, which replicates the decisions made by factory managers based on the physical flow of materials and the information of strategic decisions taken by the organisation (for example, introduction of new products, new market entry etc.). The distribution centres replicate the regional sales manager's decisions based on country sales, forecast and organisation's strategic intent. The agent architecture is defined below. In order to make the agents a true representation of real business units, the agent structure is divided into two stages: the functional and the decision making stage. Figure 4.3 shows the internal structure of each agent. Each time interval, the decision making stage of the agent first takes in inputs from the environment and feedback from its own actions. Next the agent performs monitoring of key variables and performance measures. From the differences in targeted and actual performance levels, the agent learns to decide on the appropriate response action for the functional stage of the agent. The functional stage of the agent then implements the regular activities decided by the decision making stage. The impact of these activities on the performance measures is then fed into the decision making stage for making decisions on the appropriate actions at the next time interval.

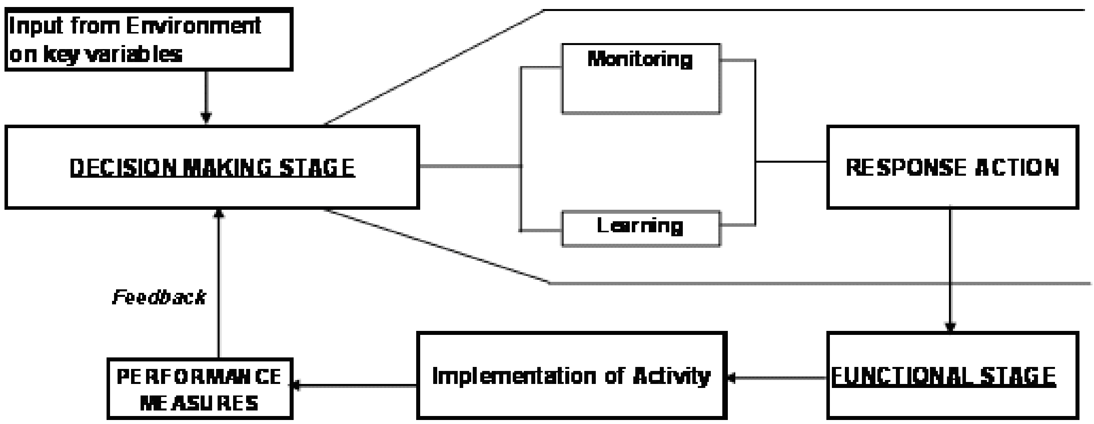


Figure 4.3: Internal Structure of the Agent

The details of the functioning and decision making stages are –

1. Functioning stage: This describes the regular order fulfilment process, in which orders are received and goods dispatched and goods are produced. This level operates at a regular periodic interval according to a set of fixed difference equations which depend on certain parameters and variables.
2. Decision-making stage: This part of the agent monitors the key performance indicators (KPI) identifying the states of different agents and the global supply chain network over time. This assesses the performance of competing downstream elements, ranks the products for production and determines safety stock levels, dispatching and replenishment policies. This stage may include a learning phase, where the agent will learn to modify the different parameters in response to the difference between desired and actual values of performance measures.

These form the internal structure of the agents in the decentralised informational structure shown in figure 4.2(b). In the case of a centralised informational structure of the supply network, the decision making stage is controlled by the central planning agent while the factory and distribution centre agents consist mostly of the functional stages for carrying out the regular activities. I will first discuss the generic structure of the agents used in the decentralised informational structure of the supply network discussed above. In the next chapter, I would discuss the formulation of the central planning agent and the variation in the formulation of other agents in that more centralised informational structure.

Such a structure of an agent for modelling a supply chain network dynamics was first constructed by Allwood and Lee (2005) but was limited to simplistic supply chain structures. The agent described in their work did not consider global and local KPIs for basing their decisions. Also Allwood and Lee's agents were incapable of performing the complex task of multi-product production allocation and sequencing through incorporation of intelligent rules.

4.1.1 Distribution Centre Agent Description

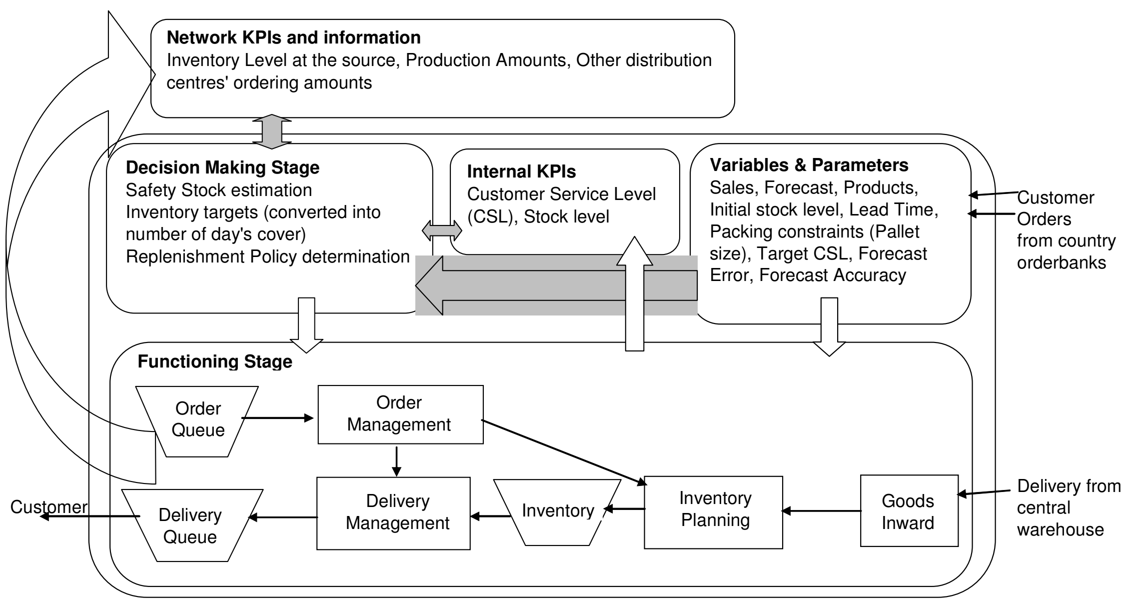


Figure 4.4: The agent structure for the distribution centre agent used in the model

The structure of the distribution centre agent is illustrated in figure 4.4. The figure shows the functioning stage and the decision making stage that includes real time learning and monitoring of a set of variables and KPIs. These combine to define the behaviour of the agent in response to a stream of orders from a set of customers. The grey arrows signify the monitoring and learning phases of the decision making stage of the agent, as shown in figure 4.3. First, the decision making stage of the distribution centre agent takes in the information on network KPIs, local KPIs and various variables and parameters, as shown in the figure and decides on the appropriate replenishment strategy. As per the instruction from the decision making stage, the functioning stage of the agent then carries out the following functions. This in turn affects the KPIs at all levels, which the decision making stage monitors and learns to adjust the decision variables at the next time interval. At this stage it decides on the target inventory covers and subsequently provides instructions to the functioning stage of the agent. There are certain variables, such as sales, forecast, forecast errors and accuracies, types and numbers of products, which depend on the different markets the distribution centres serve.

Functioning Stage

The functioning stage of the agent must implement three major functions:

- Receipt of orders from customers and the aggregation of these orders. Comparing them with forecast demand. Calculation of mean and standard deviation of the demand and storing the pattern of each product's demand variation in the form of statistical data in memory for using at decision making level.
- Delivery of goods to customers, with determination of priority when insufficient finished goods are available to meet all current orders.
- Review of inventory position at regular intervals, receipt of materials from suppliers and generate an order to its preceding stock point to raise the inventory position to its order-up-to level. In generating the order the amount of safety stock acting as a buffer needs to be monitored.

The mathematical and algorithmic model of each of these functions is now shown. The model assumes one day as one time pulse. The internal mechanism inside each agent actually prepares a sequence of the above functions at each pulse. For carrying out each of the above functions, the agent breaks each pulse into fractions and executes the functions one after another in the order stated above. This implies, the agent performs the above functions at different time of the day.

Order Management

Total demand at time t for product i is calculated from the daily incoming orders as,

$$D_{t,i} = \sum_{c=1}^{C} d_{c,t,i} \tag{1}$$

This agent does not have the knowledge of micro-level end-demand but takes in the aggregate orders from each market as their customers' demands to be met. It is assumed that orders are to be satisfied at the same time instance t as they are placed.

The total forecast ($F_{t,i}$) of a particular product i at time period t is calculated as,

$$F_{t,i} = \sum_{c=1}^{C} f_{c,t,i} \tag{2}$$

The delivery lead time of materials from the upstream stock point to the distribution centres is variable depending on the order placement date (this is to generalise the real-life condition where most of the distribution centres are closed during weekends and receive and place orders during weekdays). So the agent at the order management stage also calculates a measure of uncertainty of the forecast. This is the standard deviation of actual realised demand over the maximum lead time (T_{max}). The standard deviation is calculated in a dynamic fashion to take care of the changing demand and is given by the following formula,

$$\hat{D}_{t,i} = \sqrt{\frac{\sum_{m=0}^{T_{\max}-1} D_{t-m,i}^{2} - T_{\max} \sum_{m=0}^{T_{\max}-1} \left[\frac{D_{t-m,i}}{T_{\max}} \right]^{2}}{T_{\max} - 1}} \tag{3}$$

This measure is important for the decision making level of the agent as a measure of the uncertainty of orders, which can be used to determine an appropriate order-up-to level for finished goods inventory.

Goods Delivery Management

After receiving all the orders at time t, the distribution centre agent dispatches the materials in response to orders at time $t+\partial t$, which is before the time pulse of receipt of the next set of orders. All orders are for immediate dispatch, so if insufficient inventory $I_{t,i}$ is available, a record of backlogged orders in each product is kept in order to ensure they are delivered in future. This record is kept both for individual customers, $b_{c,t,i}$ and the aggregate over all customers, $B_{t,i}$. The dispatch function is based on availability based partial fulfilment of orders (Banerjee et al, 2001). The delivery is denoted by $y_{c,t,i}$. The rationing and priority for allocation is determined based on increasing order size (Lagodimos, 1992), i.e., downstream member ordering more will receive more if insufficient inventory is available at the next upstream stock-point. The logic of dispatching is described below and the following flowchart 1 summarises the logic:

if $D_{t,i} + B_{t,i} \leq I_{t,i}$,

$$y_{c,t,i} = d_{c,t,i} + b_{c,t,i} \qquad \forall c \ \forall i$$

$$b_{c,t+1,i} = 0 \qquad \forall c \ \forall i$$

$$I_{t+1,i} = I_{t,i} - \sum_{c=1}^{C} y_{c,t,i} \quad , \forall i \tag{4}$$

else,

$$b_{c,t+1,i} = b_{c,t,i} + d_{c,t,,i} \qquad \forall c \ \forall i$$

$$y_{c,t,i} = 0 \qquad \forall c \ \forall i$$

while $I_{t+1,i} > 0, \qquad \forall i$

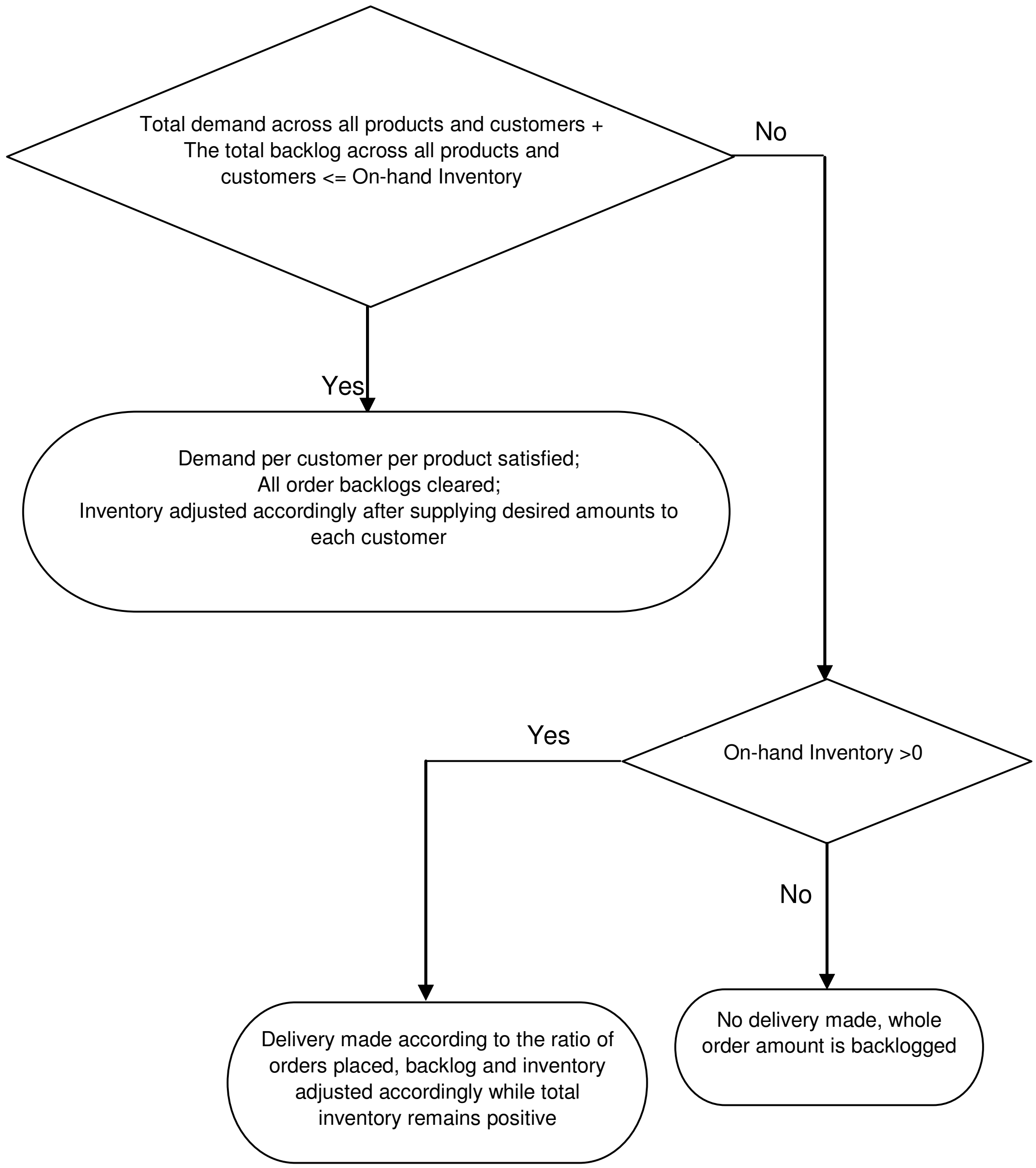
$$y_{c,t,i} = I_{t+1,i} \times \alpha_c / \sum \alpha \qquad \forall c \ \forall i$$

$$b_{c,t+1,i} = b_{c,t,i} + d_{c,t,i} - y_{c,t,,i} \qquad \forall c \ \forall i$$

$$I_{t+1,i} = I_{t,i} - \sum_{c=1}^{C} y_{c,t,i} \quad , \quad \forall i \tag{5}$$

end

end



Flowchart 1: Dispatch Management Decision Scheme

If the 'if' statement is satisfied, sufficient finished goods inventory exists to deliver all orders. If not, the orders are allocated according to the importance of the customer and described by $\alpha_c / \sum\alpha$. The value of this coefficient is based on the amount of order placed and amount of order backlogged. The higher the value of α, the higher is the amount supplied to that customer. It is assumed that, order backlogs have the highest priority and would be cleared before newly placed orders when inventory is available. So, the expression $\alpha_c / \sum\alpha$ is computed by the agent as,

$$(b_{c,t,i} + d_{c,t,i}) / (\sum_{c=1}^{C} d_{c,t,i} + \sum_{c=1}^{C} b_{c,t,i}) \qquad \forall c \ \forall i$$

After the allocation of products to customers is determined according to the above algorithm, the products enter a delivery queue – a delay of time T_d – representing logistic delays prior to reaching the customers.

Finished Goods Inventory Management

Each distribution centre agent will monitor its inventory position in each product, $IP_{t,i}$ every time pulse t and check with the reorder point at that time, $r_{t,i}$. If the stock falls below the reorder point, an order, $q_{t,i}$ is raised to replenish the stock to a target level. The determination of target stock level, $I^*_{t,i}$ is done at the decision making level of the agent. The decision making stage also determines the appropriate safety stock level, $SS_{t,i}$ to be used. The inventory of product i at the distribution centre, $I_{t,i}$ is reduced according to daily customer supply $Y_{t,i}$ (given by $\sum_{c=1}^{C} y_{c,t,i}$), and increased by all incoming orders, $IO_{s,t,i}$, from supplier s at period t. Supplier in this case is the central warehouse for all the distribution centres. Any unfilled demand is backlogged as noted before, by $B_{t,i}$, the aggregate of all the backlogs of product i at time t. The inventory position at period, t $(IP_{t,i})$ is the sum of existing inventory $(I_{t,i})$, ordered quantities in all outstanding orders, commonly termed as in-transit stock $(IT_{s,t,i})$ from all suppliers s at period t. Mathematically, they can be summarised as below,

$$I_{t,i} = I_{t-1,i} - \sum_{c=1}^{C} y_{c,t,i} + \sum_{s=1}^{S} IO_{s,t,i} \quad , \forall i \tag{6}$$

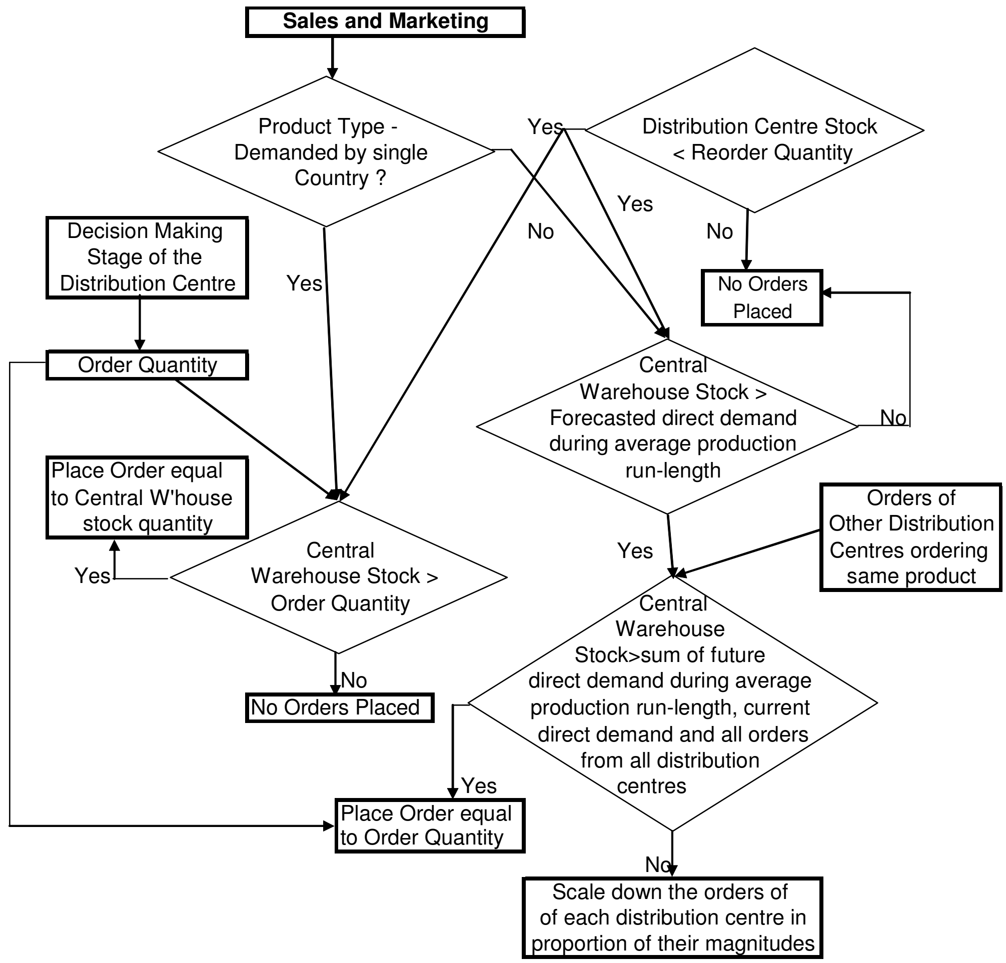
$$IP_{t,i} = I_{t,i} + \sum_{s=1}^{S} IT_{s,t,i} \ , \ \forall i \tag{7}$$

$$r_{t,i} = B_{t,i} + T_{max} \times F_{t,i} + SS_{t,i} \quad , \forall i \tag{8}$$

$$q_{t,i} = I^*_{t,i} - IP_{t,i} \qquad , \forall i \tag{9}$$

Considering local and global perspectives

On deciding the reordering point, the distribution centres in the model consider the maximum lead time for delivery instead of the actual lead time for delivery. This is a more safe procedure for ordering materials as this gives more cushion towards uncertain events that might adversely affect the performance of the supply chain networks. These orders are then placed on the next upstream stock-point. However this inventory management principle generates orders in response to possibility of the distribution centre's stock falling below the reorder point in that particular distribution centre. This is more a local perspective, as the distribution centre looks at its own inventory position, backlogs and the products it is dealing in only. A more global perspective is taken by the distribution centres when they also take care of the information on the inventory levels of products at the central warehouse, which acts as the source of materials for all distribution centres. Also the distribution centres need to know which products are demanded only by them over the entire time horizon and which products are demanded by them and several other distribution centres. At the same time, the distribution centres need to have knowledge of the ordering amounts of other distribution centres on the central warehouse and also the orders received by the central warehouse from the markets it directly serves. This is depicted by the Flowchart 2. The distribution centres get the information about the products which are demanded by only one distribution centre over the entire time period the model is run. This information is obtained from the sales and marketing department at regular intervals, based on the changing demand patterns of products. Based on this information, the ordering pattern of the distribution centres also changes.



Flowchart 2: The decision making framework (with local and global knowledge) for inventory management of each product

For products which are just demanded by a single distribution centre or a single market (designated as single country in Flowchart 2), the distribution centre demands materials from the central warehouse based on the order quantity specified by the decision making stage of the agent. As soon as materials are available at the central warehouse, the entire stock is ordered by the distribution centre, since no other distribution centres need those products. On the other hand, products which are demanded in multiple markets, require knowledge of stock levels at the central warehouse, the order quantities of each distribution centre demanding the same product, current demand of the product in markets directly served by the central warehouse, the average run length of production at the factory and the forecast of demand of the product in markets directly served by the central warehouse. If the central warehouse stock level exceeds the sum of the forecasted direct demand at the central warehouse during the average production run-length (includes average set-up time), the orders from all distribution centres and the current period direct demand, orders are placed as per the quantity specified by the decision making stage of the agent. However, in case of short-fall, the amount by which the stock falls short at the central warehouse is deducted from all the distribution centre orders in the proportion of their respective order volumes.

First each distribution centre estimates the orders to be placed on the factory after receiving the incoming orders from their respective customers and the forecast figures. Then they communicate with other distribution centres and the central warehouse to know the order quantities of other distribution centres and the direct sales figures at the central warehouse. If for any product the total stock amount after dispatching the direct sales quantities ($DFS_{t,i}$) at the central warehouse falls below the replenishment orders from the distribution centres, the distribution centres scale down their respective orders according to their order magnitude ratios. This is done after keeping aside the average production run-time worth of stock in that product. The entire algorithm is expressed below and figure 4.2b depicts the communication process between the distribution centre agents.

$\forall i, \forall dc$

Get information of all $\tilde{q}_{dc,t,i}$ *, the orders to be placed by each distribution centre (dc)*

$$\tilde{Q}_{t,i} = \sum_{dc=1}^{DC} \tilde{q}_{dc,t,i}$$

if $FI_{t,i} \leq \tilde{Q}_{t,i} + DFS_{t,i} + \bar{t} \times DFF_{t,i}$

if $FI_{t,i}=0, \quad q_{dc,t,i}=0$

if $FI_{t,i} - DFS_{t,i} \leq \bar{t} \times DFF_{t,i}, \; q_{dc,t,i}=0,$

else $q_{dc,t,i} = [FI_{t,i} - DFS_{t,i} - \bar{t} \times DFF_{t,i}] \times \tilde{q}_{dc,t,i} / \tilde{Q}_{t,i}$

end

else $q_{dc,t,i} = \tilde{q}_{dc,t,i}$
end

Such combined knowledge of vital global and local key state variables, inventory levels, forecasts, and sales helps in improving supply chain's ability to adapt to unforeseen circumstances.

Decision making stage

At this stage, the agent makes crucial decision on how much to order from the upstream stock-point in order to avoid any stock-outs but at the same time keep a low inventory to reduce holding and handling costs. So each stock holding location manager has to decide a safety stock amount, which is a "time-independent lower bound on the inventory level such as to absorb some level of demand uncertainty" (Jung et al, 2004, p.2087). There exists a large body of literature on estimating safety stock levels based on traditional inventory theory (Silver et al, 1998). This is based on forecast demand and its variability for each product and is calculated as, $k\hat{D}_{t,i}\sqrt{T_{\max}}$, where k is the constant service level factor. Although this solution is elegant in its simplicity, it fails to address the key features of realistic supply chain problems, namely non-normal probability distributions of demand, the dependence of the overall customer satisfaction level on meeting the demands for several different products produced in the same production facility.

The traditional model for safety stock (TMSS) assumes forecast errors and demand (forecast minus actual) are independent and randomly distributed according to a Normal distribution. At any instant in time there is an equal probability of actual demand being above or below the forecast. Although this model is simple to understand and many organisations use this for deciding the replenishment amounts, it may cause an overstocked or under-stocked situation when there is a significant forecast bias. In the model being developed here forecast errors do not form a Normal distribution.

A different safety stock estimation technique is introduced in the model to take care of forecast bias and lumpy demand scenarios. Krupp (1982) invented a method to adjust safety stock levels to compensate for the non-Normal distribution of forecast errors associated with forecast bias (KMSS). KMSS incorporates the demand forecasts in safety stock calculations so that safety stock levels change with time. This is particularly useful in the case of a declining trend of demand. In a traditional safety stock model, the safety stock remains stationary even though the demand forecast falls to zero. The following formulation summarises KMSS in mathematical terms:

$$SS_{t,i} = (1-FETS_{t,i}) \times k \times TICF_{t,i} \times F_{t,i} \times T_{max} \qquad \forall i \qquad (10)$$

TICF is the time increment contingency factor and converts the statistical variance of demand in units of time rather than quantity. It is expressed as,

$$\frac{1}{T_{\max}} \sum_{t=1}^{T_{\max}} \left| \frac{F_{t,i} - D_{t,i}}{F_{t,i}} \right|, \qquad \forall i \qquad (11a)$$

The bias of forecast from the actual mean is often expressed mathematically through the use of Forecast Error Tracking Signal (*FETS*). This is the sum of the average actual deviations over the maximum lead time period divided by *TICF* and is expressed as,

$$\frac{1}{T_{\max} \times TICF} \sum_{t=1}^{T_{\max}} \left({(F_{t,i} - D_{t,i})}/{F_{t,i}} \right), \qquad \forall i \qquad (11b)$$

An *FETS* equal to zero is considered optimum in that it indicates a condition where, regardless of the magnitude of the individual deviations, the total population of deviations is centred around the forecast and all plus and minus deviations compensate for each other. An *FETS* less than zero indicates a skew where actual demands are chronically greater than the forecast; the greater the negative value the greater the skew, with -1.0 indicating that in all cases where a deviation existed actual demand was greater than forecast. Conversely, an *FETS* greater than zero indicates a skew where actual demands are less than forecast, with 1.0 indicating that all deviations, forecast was greater than actual demands.

However, this procedure of safety stock estimation may give rise to anomalous order generation pattern in case of zero forecasts. So, the agent uses a self correction procedure as below, (the agent uses the average demand of the product over the lead time period, given by $\overline{D}_{t,i}$)

if $F_{t,i}=0$ *and* $\overline{D}_{t,i} > 0$ *then* $F_{t,i} = \overline{D}_{t,i}$ $\forall i$

if $F_{t,i}=0$ *and* $\overline{D}_{t,i} = 0$ *then* $F_{t,i} = \partial$, *where* ∂ *is a small positive integer, in the model it is taken as 1,* $\forall i$

The above decision making is necessary to avoid any division by zero while evaluation of *FETS* and *TICF* in adjustable safety stock estimation used by the agents.

After determining the method of estimating safety stock and adjusting it to demand variability, the agent determines the target stock level for the distribution which will ensure good customer service. The mathematical formulation is given by,

$$I^*_{t,i} = B_{t,i} + (T_{max} + T_{review}) \times F_{t,i} + SS_{t,i} \qquad \forall i \qquad (12)$$

Since the inventory is reviewed at each time pulse, so the review period, T_{review} is 1.

Although the standard method of continuous review of inventory and generation of an order as soon as the inventory position falls below the reorder point, is perfect in responding to demand variation in some cases, it is reactive in its application and is dependent solely on the stock level. So even though the actual demand might be well above forecast, if the stock level does not reach the reorder point, the policy will not react. In order to make the replenishment policy more sensitive to the order-forecast variability, the replenishment decision needs to be based on some other variables, which tracks the order-forecast variability. Apart from the theoretical replenishment policy, the agent is also capable of incorporating this more flexible replenishment policy to avoid any customer service issues.

This is achieved in the following way,

$MD_{t,i} = \overline{D}_{t,i} - F_{t,i} \quad ,\forall i$

$$G_{t,i} = (MD_{t,i} - MD_{t-1,i})/ MD_{t-1,i} \quad ,\forall i \tag{13}$$

To avoid division by zero for the case when $F_{t,i} = \overline{D}_{t,i}$ and $D_{t,i}>0$, $G_{t,i} = F_{t,i} - D_{t,i}$ *and* $MD_{t,i} = G_{t,i}$. The replenishment is made when $G_{t,i}<0$. But this condition will not replenish when the forecast is not zero but demand is zero. So an additional condition is required to take care of the cases when the inventory position is less than the forecast or less than the demand or when demand at any instant exceeds the forecast at that instant. The algorithmic expression is given below,

$\forall i$,

if $IP_{t,i} \le F_{t,i}$ *or* $IP_{t,i} \le D_{t,i}$ *or* $D_{t,i} \ge F_{t,i}$ Generate order quantity $q_{t,i}$ according to (9)

else

if $G_{t,i}<0$ Generate order quantity $q_{t,i}$ according to (9)

end

The different safety stock estimation procedures and different replenishment policies would be used as different experiments to understand their effects on system behaviour. In the next section I will show the use of learning mechanism at the decision making stage of the agent to decide on the appropriate ordering quantity for the distribution centres. The above decision making process to determine the target inventory levels based on adaptive safety stock methods is also reactive. This is mainly due to the updating of the forecast values after the difference between sales and forecast values actually occurs. So the problem is, this stage generates large replenishment orders after large customer orders are placed and result in big deficits in the inventory of the distribution centre. So it might result in accumulating large inventory at the distribution centre just after a large customer order is placed and there might not be any such orders coming along in the future. Also applying this adaptive safety stock policy without any information sharing or use of global information actually implies the selfish, inconsiderate behaviour of these agents and more focus on building redundancy to ward off demand uncertainties.

Learning Stage

Along with the ability to decide on the target stock levels, the decision making stage of the distribution centre agents need to learn in real time how much to order and when. The target inventory of each product in each distribution centre is expressed in number of days cover. To avoid excessive inventory build-up, the agent follows a simple heuristic using the knowledge of the total forecast on each product type over the total time horizon (say, one year) and assumes a relationship between the day's cover of inventory and total annual forecast of each product. It is assumed that products with low annual forecast will have more days' cover of inventory, while products with higher annual forecast will have lower days' cover. This relationship is assumed as a non-linear one as products with very low or high annual forecasts might require very large or small inventory covers respectively within a difference of few units of forecast. Every time interval, the total annual forecast changes based on the real demand and the forecasts for the coming periods. The target inventory cover at time t for product i, $I^*_{t,i}$, is expressed by the following mathematical expression.

$$I^*_{t,i} = \phi(TAF_i) \times F_{t,i} \tag{14}$$

Here $\phi(\ )$ is a nonlinear function. After running the model several times for the same number of days (say, one year) with different sets of days' cover but with same set of demand data, the best number of days' cover is obtained for the maximum customer service level. The best fit function $\phi(\ )$ is then obtained between the total annual forecast of each product and the numbers of days' cover that result in the best customer service level. The target days' cover can be fixed throughout the entire run-length of the simulation or it can be adjusted with variation in certain key performance measure such as the customer service level (CSL) or the variables as forecast error (FE), given by the difference between actual demand and real demand, TAF updated by the actual sales volumes. The distribution centre can use the fixed TAF values for each product provided by the sales and marketing department or it can adjust them based on the actual sales. This can be expressed as below,

$$ATAF_{t,i} = \sum_{t=1}^{T_o} D_{t,i} + (TWD - T_0 + THol_t) \times F_{t,i} \tag{15}$$

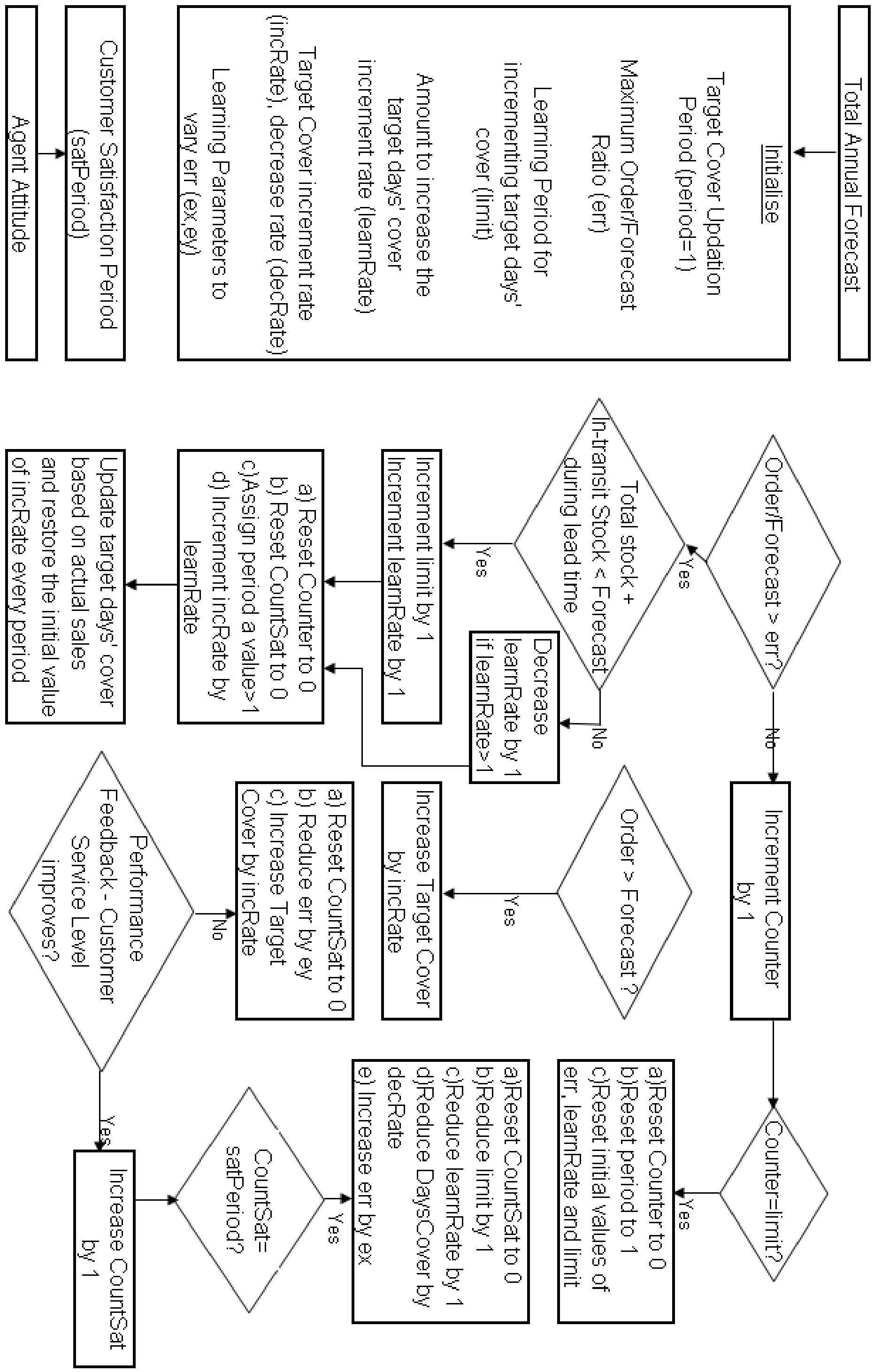
Here the total annual forecast is replaced by adjustable total annual forecast, which is the sum of the total actual demand falling on the distribution centre from the start of the model to current time T_0 and the total forecasted demand during the rest of the model run-time (the inactive period is not taken into consideration, as shown in (15), where the weekends are subtracted from the time spent so far, T_0, and only total working days are considered for the time left).

The distribution centres (DCs) can choose to balance the efficient and safe ordering policy. Assuming an inverse relationship between target days' cover and annual forecast actually portrays the efficiency oriented focus of DCs while the adjustable safety stock shows more redundancy focus of the DCs. The DCs can balance the two by adding another element to the estimation of target days' cover. This is given by $\lambda \ln(\hat{D})$ and is based on the standard deviation of demand during the transit lead time. λ is a fraction which decides the importance of the entire factor (taken as 1 in this case, which is reduced or raised by a constant fraction 0.2 to a minimum value of 0, every time stock position in the distribution centre exceeds or lags the target days' cover worth of stock respectively). Also the DCs place orders based on adjustable safety stock if they find the CSL deteriorating.

Apart from this adjustment to the total annual forecast at every time interval, the distribution centre agents also scale down or up the number of days' cover by a particular amount based on changes in performance measures, variables and the attitudes of the agents. If the customer service level in each product falls below a target level or the actual demand exceeds the forecast, the agent increases the target days' cover for that product. However, if the customer service level remains the same at the target level for a sufficiently long time (decided based on agent's attitude – more risk averse agents would choose a longer time period whereas agents trying to reduce inventory risking the chance of stock-outs would settle for a shorter time period), the agent reduces the target days' cover by a certain amount. The amount by which the agent increases or decreases the days' cover also depends on the agents' attitudes. If the agent is more concerned with the reduction of inventory or the efficiency of the system, it will tend to reduce the target days' cover by larger amounts and increase them by smaller amounts. However, if the agent is more concerned with the resilience of the system to unforeseen demand, the agent will tend to reduce the target days' cover by smaller amounts and increase them by larger amounts. Both these actions are concerned with satisfying local objectives of efficiency. But, in a tightly coupled system, as shown in figures 4.2 (a) or (b), which is to be modelled in this research with aim to improve resilience of the entire network, increasing the order amounts for the distribution centres can result in reduced production efficiency with reduced production run-length. This is because the more the replenishment orders, the more the inventory gets reduced at the central warehouse. Since the factory replenishes the central warehouse, frequent reduction in inventory in any product will result in need to produce that product more often. As any product gets produced more often, it requires more set-up time and thus less run-length for not only itself but also other products. On the other hand, low order volumes will definitely improve the production performance but will give less protection against unforeseen demand rises at the distribution centres. So an effective learning mechanism needs to be designed for properly balancing these local and global requirements while procuring materials from the central warehouse. The agent may choose to learn the target days' cover in real time (discussed before) or use a specific period (to be explored in next chapter).

The distribution centre agent first categorises all products based on their total annual forecast figures. This categorisation is done to differentially assign learning rates for adjusting days' cover in response to the variation in real demand. Products below certain total annual forecast sales are categorised as low, medium or high demand products. At any point of time however, the agent changes this categorisation based on the real sales of the different products. This means, if any product initially categorised as a low demand product because of the set total annual forecast figures, is found to be selling a larger amount than forecasted its category is moved and along with that the learning parameters also change. So in this whole process of learning the target day's cover, the agent updates the target day's cover based on the assumed relationship given by eq.14. But the agents do not solely base their decisions on this equation and they use their internal judgement and learning parameters to update the target days' cover. The full details of this learning process are described below. As can be seen from Flowchart 3, initially the distribution centre agents use the knowledge of categories of products based on their total annual forecasted demand to decide on the values of the maximum order to forecast ratio (*err*) signifying the error in forecasting, periods for target inventory cover update (eqs. 14 and 15) and increase. At this stage, the agents also define the learning parameters for varying the increment amounts for the target days' cover.

Normally the updating period of the target days' cover based on real sales is taken as 1 day by the agents. But if the agent finds the actual order to forecast ratio above the maximum (*err)*, it increases the updating period (*period*). In addition to that, the agent also takes care of the excessive forecasting error by increasing the amount (*learnRate*) by which the target inventory cover increment rate (*incRate)* is increased until a certain period (*limit*). Since the agent increases the period of updating, the days' cover thus increases at an increased rate until the end of *limit* and at the initial rate until the end of the new updating period (*period*) set by the agent because of the excessive forecast error. This learning step provides extra care against stock-outs when orders exceed the forecast values excessively. But also at the same time to avoid building up excess inventory when not needed, the learning period is adjusted accordingly, so that the target inventory cover does not get incremented continuously. In order to be safer and to avoid any chance of stock-out, the agent increases *learnRate* and *limit* when the inventory position (on-hand inventory and the in-transit stock) falls below the lead time demand. At the same time to reduce chance of excess stock-build-up and hamper productivity, the distribution centres reduce the *learnRate* when the inventory position exceeds the lead-time demand.



FlowChart 3: Learning Stage of the Distribution Centre Agent to decide target inventory for each product

A counter is incremented every time the order to forecast ratio does not exceed *err*. If the counter equals *limit*, "*err, learnRate* and *limit"* are all reset to their initial values, *period* is reset to 1 again to update the target days' cover based on actual sales on a daily basis and counter is reset to 0. This mechanism is introduced to avoid increasing the target days' cover by large amounts. When the order exceeds the forecast by *err,* this counter is reset to 0. There is also another counter (*CountSat)* for counting time instances when the customer service level in any product either remains same at some target level or improves. *CountSat* is also reset to 0 when the order to forecast ratio exceeds *err.* This is the tendency of the agent to be circumspect about any large incoming orders, when the order-forecast mismatch is massive. So although the service level might have been better but the distribution centre might have been just at the brink of a stock-out by just managing to supply the excessive order. This is again an attitudinal behaviour of the agent to not getting satisfied by the target customer service level achieved. Instead it is aware of wear-out of its stock level due to the unforeseen excess demand. This serves as a step towards building resilience in the operation of the distribution centre.

As described before, the distribution centres, based on their attitude towards risk of stock-out, select a period (*satPeriod*) until which they will continue to increase target inventory whenever the order exceeds the forecast. If *CountSat* equals *satPeriod*, *CountSat* is reset to zero; *limit*, *learnRate*, target days' cover are reduced but *err* is increased. This step is the efficiency increasing step to reduce target cover when not needed. Increasing the maximum order to forecast ratio implies that, the distribution centre gains confidence through implementing this rule. Since the distribution centre has been able to hit the target of no stock-outs with the previous *err,* so it is confident that it will achieve the same for a higher *err.* However, if the service level drops in comparison to earlier period, *err* is reduced, target cover is increased by *incRate* and *CountSat* is reset to 0. This is done to improve the response time of the distribution centre to lower error levels. Since the increment rates for target inventory cover vary based on the above learning process, each time real demand exceeds the forecasted demand, the target inventory cover is also increased by different *incRate.*

Appendix B.1 lists the programmes built to represent the Distribution Centre Agent with combination of adjusted safety stock and target days' cover.

4.1.2 Central Warehouse Agent Description

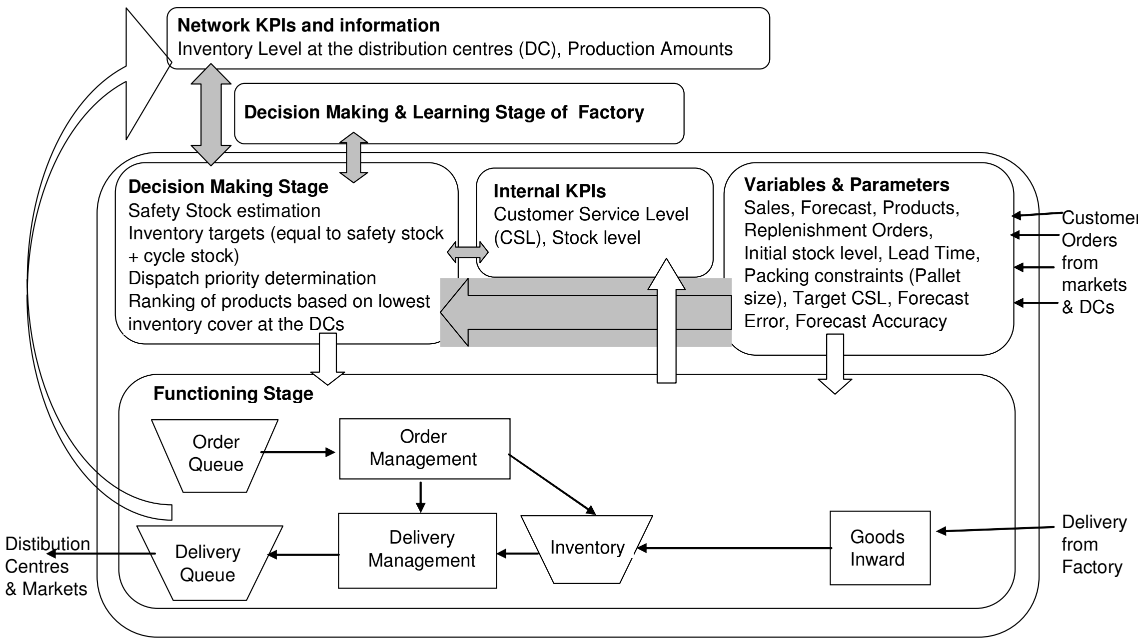


Figure 4.5: The agent structure for the central warehouse agent used in the model

The agent representing the central warehouse is similar to the distribution centre agents in some respects of the functioning stage. However, this agent does not have any ordering and inventory management activity. This agent's main function is to manage delivery based on the direct sales orders received from the markets and the replenishment orders received from the different distribution centres downstream. The decision making stage is concerned with setting the target inventory levels to be maintained in each product the warehouse deals in and setting the priority for making delivery in case of insufficient stock availability. Apart from this, the decision making stage of the central warehouse agent being coupled to the factory's decision making stage gets the knowledge of the inventory covers on each product at different distribution centres and produces a ranking of products. The product with the least inventory cover is placed on the top. This ranking list is fed to the decision making stage of the factory for setting up priority for production of different products. The structure of the central warehouse agent is shown in Figure 4.5.

The grey arrows signify only monitoring as this agent does not perform any learning action and the learning is actually done by the factory and the stock levels are augmented continuously through production function at the factory. So the factory actually performs the learning function to decide when to produce which product and by how much amount so that there is no dearth of stock at the central warehouse. Also the decision making stages of the factory and the central warehouse are inter-linked (to be discussed in next section).

Functioning & Decision Making Stage

The functioning stage of the central warehouse agent must implement the following major functions:

- Receipt of orders from customers and distribution centres and the aggregation of these orders.
- Delivery of goods to customers first and distribution centres next; Determination of priority when insufficient finished goods are available to meet all orders.

The functioning stage of the central warehouse is different from the distribution centres' functioning stages in the aspect that, it does not place orders on the upstream stock-points since it is directly fed from the factory through continuous production. The decision making stage of the factory is actually coupled to the decision making stage of the central warehouse, which performs the function of deciding the priority for dispatching. So the decision making stage and functioning stage are more interlinked in the case of central warehouse than the distribution centres. The decision making stage is similar to that of the distribution centres in method of estimation of the safety stock, inventory target as the sum of cycle and safety stock. It also makes decisions on the appropriate priority determination for dispatching materials to different distribution centres. Ordinarily, this is done at the functioning stage of the distribution centres, where they have to supply materials directly to the customers, whose stock data they do not know. However, in the case of the central warehouse, the priority for sending materials to customers is determined on the basis of order size proportions at the functioning stage but the determination of priority for sending materials to the distribution centres is done at the decision making stage.

The mathematical and algorithmic models of each of these functions are now shown and are very similar to those for distribution centre agents. Only in this case, in addition to the customer demands, the central warehouse also faces replenishment orders from the different distribution centres.

Order Management

Total demand at time *t* is therefore calculated from the daily incoming orders as,

$$D_{t,i} = \sum_{c=1}^{C} d_{c,t,i} \tag{1}$$

Total order at time *t* is calculated by summing the replenishment orders received from all distribution centres and is given by,

$$O_{t,i} = \sum_{dc=1}^{DC} o_{dc,t,i} \tag{16}$$

It is assumed that all orders are to be satisfied at the same time instance *t* as they are placed.

Delivery Management

After receiving all the customer orders at time *t*, and the replenishment orders at time $t+\gamma$the central warehouse agent dispatches the materials at time, $t+\partial\,(\partial>\gamma)$, which is before the time pulse of receipt of next set of orders $(t+1)$. All orders are for immediate dispatch, so if insufficient inventory $I_{t,i}$ is available, a record of backlogged orders in each product is kept in order to ensure they are delivered in future. The agents try to meet the customer demands first and then meet the replenishment orders with the remaining inventory, if available. The record of backlogs is kept both for customers and the distribution centres, a) $b_{c,t,i}$ for each customer c and the aggregate over all customers, $B_{t,i}$ and b) $pb_{dc,t,i}$ for each distribution centre dc and the aggregate over all distribution centres, $PB_{t,i}$. The logic of dispatching is described below:

if $D_{t,i} + O_{t,i} + B_{t,i} + PB_{t,i} \leq I_{t,i}$,

$$y_{c,t,i} = d_{c,t,i} + b_{c,t,i}\ ,\ y_{dc,t,i} = o_{dc,t,i} + pb_{dc,t,i} \qquad \forall dc\ \forall c\ \forall i$$

$$b_{c,t+1,i} = 0\ ,\ pb_{dc,t+1,i} = 0 \qquad \forall dc\ \forall c\ \forall i$$

$$I_{t+1,i} = I_{t,i} - \sum_{c=1}^{C} y_{c,t,i} - \sum_{dc=1}^{DC} y_{dc,t,i} \qquad ,\ \forall i$$

else,

$$f1_{dc,t,i} = (o_{dc,t,i} + pb_{dc,t,i})/(O_{t,i} + PB_{t,i}) \qquad \forall dc\ \forall i$$

$$f2_{c,t,i} = (d_{c,t,i} + b_{c,t,i})/(D_{t,i} + B_{t,i}) \qquad \forall c\ \forall i$$

if $D_{t,i} + B_{t,i} \leq I_{t,i}$,

$$b_{c,t+1,i} = b_{c,t,i} + d_{c,t,,i} \qquad \forall c\ \forall i$$

$$y_{c,t,i} = d_{c,t,i} + b_{c,t,i}\ ,\ b_{c,t+1,i} = 0,\ I_{t+1,i} = I_{t,i} - (D_{t,i} + B_{t,i}) \qquad \forall c\ \forall i$$

if $I_{t,i} - \sum_{c=1}^{C} y_{c,t,i} > PB_{t,i}$

$$y_{dc,t,,i} = pb_{dc,t,i}\ ,\ pb_{dc,t+1,i} = 0 \qquad \forall dc\ \forall i$$

while $I_{t,i} - \sum_{c=1}^{C} y_{c,t,i} - \sum_{dc=1}^{N} y_{dc,t,i} > 0\ \ \&[N = DC] \qquad \forall i$

$$y_{dc,t,i} = y_{dc,t,i} + (I_{t,i} - PB_{t,i}) \times \alpha_{dc} / \sum \alpha \qquad \forall dc\ \forall i$$

$$pb_{dc,t+1,i} = o_{dc,t,i} - y_{dc,t,,i} \qquad \forall dc\ \forall i$$

increment N by 1

end

$$I_{t+1,i} = I_{t,i} - \sum_{c=1}^{C} y_{c,t,i} - \sum_{dc=1}^{DC} y_{dc,t,i}\ , \qquad \forall i$$

else

$$y_{dc,t,i} = (I_{t,i} - \sum_{c=1}^{C} y_{c,t,i}) \times f1_{dc,t,i} \qquad \forall dc\ \forall i$$

$$pb_{dc,t+1,i} = pb_{dc,t,i} + o_{dc,t,i} - y_{dc,t,,i} \qquad \forall dc\ \forall i$$

$$I_{t+1,i} = I_{t,i} - \sum_{c=1}^{C} y_{c,t,i} - \sum_{dc=1}^{DC} y_{dc,t,i} \quad , \qquad \forall i$$

end

else

if $I_{t,i} > B_{t,i}$

$$y_{c,t,,i} = b_{c,t,i}\ ,\ b_{c,t+1,i} = 0 \qquad \forall c\ \forall i$$

while $I_{t,i} - \sum_{c=1}^{N} y_{c,t,i} - B_{t,i} > 0,\ \&\ N = C \qquad \forall i$

$$y_{c,t,i} = y_{c,t,,i} + (I_{t,i} - B_{t,i}) \times \alpha_c / \sum \alpha \qquad \forall c\ \forall i$$

$$b_{c,t+1,i} = d_{c,t,i} - y_{c,t,,i} \qquad \forall c\ \forall i$$

increment N by 1

end

$$I_{t+1,i} = I_{t,i} - \sum_{c=1}^{C} y_{c,t,i} \quad , \ \forall i$$

else

$$y_{c,t,i} = I_{t,i} \times f2_{c,t,i} \qquad \forall c\ \forall i$$

$$b_{c,t+1,i} = d_{c,t,i} + b_{c,t,i} - y_{c,t,i} \qquad \forall c\ \forall i$$

$$I_{t+1,i} = I_{t,i} - \sum_{c=1}^{C} y_{c,t,i} \quad , \ \forall i$$

end

end

end

The above algorithm is similar to the dispatching function of the distribution centres, the only difference being the distinction between replenishment orders (*O)* and the customer orders (*D)*. First, the backlogged customer orders are cleared in case of unavailability of stock, next if stock is not available to meet the current customer demand, demand is met in the ratio of their relative size. Next, if after meeting backlogged and current demand from the markets the central warehouse serves, there is still stock available, the warehouse tries to fulfil the backlogged replenishment orders from the distribution centres. So in the functioning stage, the rationing occurs for customer orders according to the relative order volumes. However the α's for distribution centres are determined in the decision making stage described below.

The ***decision making stage*** of this agent decides the priority rules (α's) for dispatching materials to various distribution centres, in case the inventory falls short of the customer orders and the replenishment requests. The customer orders in any product are distributed first and if still stock is left in that product, the decision making stage prepares a ranking of distribution centres based on their forward inventory covers (inventory sufficient to cover the forecasted demand updated by using forecast error and bias, during the transportation lead time period). The above method of rationing orders based on relative order sizes might be very risky, when there is very little stock available at the central warehouse. In that case, smaller distribution centres may be deprived of their share because of their comparatively lower order volumes. So a complementary ranking scheme may be used to facilitate sending the full requested volumes to the smaller distribution centres, while larger order volumes are scaled down based on their relative order sizes as described before. However, the agents have to use this ranking scheme carefully, so that when any distribution centre placing large orders inspite of coming to the top of the list does not get supplied the full requested amount in case of non-availability of stock. So in this procedure for allocating stock to different distribution centres, smaller orders are supplied first in full if stock is available and rest is distributed to the larger distribution centres with large orders in proportion of relative order sizes. Again this might deprive the distribution centres placing larger orders of their ordered amounts, even if they might have a genuine need for placing larger order quantities.

Another strategy would be to rank the distribution centres according to their forward covers and satisfy their requests based on the ranks, until stock is available. Other orders are not considered. In the next period a fresh ranking list is prepared and orders are supplied based on that. However, this strategy is also going to back-fire depending on the inventory position of the different distribution centres. Say, at any time period, one distribution centre does not get preferred for delivery of a particular product type. In the current strategy, the distribution centre will be pushed up the ranking list and get preferred in the next period. But sudden huge customer orders at other distribution centres in that product might worsen their inventory positions and thus push them up the ranking list. So the distribution centre which was supposed to be supplied last period did not get preferred in the next period as well due to uncertain demand pattern in some other distribution centres. This might continue for some period if enough stock is not available at the central warehouse thus resulting in stock-out at the said distribution centre.

A more resilient and safe mode of deciding on the distribution priority is allocating the materials based on the combined score of inventory cover on the one hand and the cumulative sales to average stock ratio on the other. Each distribution centre is given a score based on these two factors that take care of forecast errors and avoids rewarding distribution centres which consistently over-forecast or punishing those which under-forecast. This score can be expressed in mathematical form below:

$$saleScore_{dc,t,i} = TD_{dc,t,i}/\bar{I}_{dc,t,i},\ where\ \bar{I}_{dc,t,i} = \frac{1}{T_0}\sum_{t=1}^{T_0} I_{dc,t,i},\ TD_{dc,t,i} = \sum_{t=1}^{T_0} D_{dc,t,i} \qquad \forall dc\ \forall i$$

$$if\ \bar{I}_{dc,t,i} = 0,\ saleScore_{dc,t,i} = 1 \qquad \forall dc\ \forall i$$

$$forwardCoverScore_{dc,t,i} = e^{\frac{-IP_{dc,t,i} + T_{\max} \times F_{dc,t,i} + B_{dc,t,i}}{1000}},\ 1000\ is\ a\ scaling\ factor \qquad \forall dc\ \forall i$$

$$CombScore_{dc,t,i} = \beta \times ln(\ saleScore_{dc,t,i}) +\ \eta \times forwardCoverScore_{dc,t,i} \qquad \forall dc\ \forall i$$

$$If\ ln(\ saleScore_{dc,t,i}) < 0\ ln(\ saleScore_{dc,t,i}) = 0 \qquad \forall dc\ \forall i$$

$$\alpha_{dc,t,i} / \Sigma\alpha = CombScore_{dc,t,i} / \sum_{dc=1}^{DC} CombScore_{dc,t,i} \qquad \forall dc\ \forall i \qquad (17)$$

So each individual distribution centre will have its own preference ratio (eq.17) in each product for dispatch by the central warehouse when enough stock is not there. And materials will be sent in the proportion of these ratios. In this way, all distribution centres will be rewarded based on their actual stock position, future forecasted demand and actual sales. The combined score for each distribution centre depends on the importance assigned to each factor by the central warehouse, given by β and η (taken as 1 in the model).

The above delivery strategy adopted by the central warehouse is based on replenishment requests from the DCs, i.e., based on pull strategy solely. However, in this research effect of pushing materials when stock is available at the central warehouse will also be investigated. In this case, the central warehouse retains bare minimum stock only to just meet the direct demand. Excess material is pushed to the different distribution centres, based on their excess stock absorption power (defined by variable *ratio* below). So it is not full push system, but controlled push system as the excess material pushing occurs only when the average demand over the lead time of a product in a distribution centre exceeds its average forecast during the same time by a certain multiple (*err).* This can be formulated in mathematical way below,

$$\forall i\,,\forall dc\,,\ ratio_{dc,t,,i} = D_{dc,t,i}/\bar{I}_{dc,t,i}\,,\ where\ \bar{I}_{dc,t,i} = \frac{1}{T_0}\sum_{t=1}^{T_0} I_{dc,t,i}$$

$$\forall dc\,,\ \overline{D}_{dc,t,i} = \frac{1}{T_{\max}}\sum_{t=1}^{T_{\max}} D_{dc,t,i}$$

$$\forall dc\,,\ \overline{F}_{dc,t,i} = \frac{1}{T_{\max}}\sum_{t=1}^{T_{\max}} F_{dc,t,i}$$

$$if\ FI_{,t,i} > \tilde{Q}_{t,i} + DFS_{t,i}$$

$$xp_{t,i} = FI_{t,i} - DFS_{t,i} - \tilde{Q}_{t,i} - FSS_{t,i}$$

$$ff_{dc,t,,i} = e^{ratio_{dc,t,i}} / \sum_{dc} e^{ratio_{dc,t,i}} \quad , \ \forall dc$$

$$if\ xp_{t,i}>0\ and\ \overline{D}_{dc,t,i}/\overline{F}_{dc,t,i} > err_{dc,t,i}\ ,\ \forall dc$$

$$if\ xp_{t,i}\times ff_{dc,t,i} < FETS_{t,i}\times F_{dc,t,i}\times(T_{max}+T_i) - IP_{dc,t,i} \qquad \forall dc$$

$$delivery_{dc,t,i} = \tilde{q}_{dc,t,i} + xp_{t,i}\times ff_{dc,t,i} \qquad \forall dc$$

else

$delivery_{dc,t,i} = \tilde{q}_{dc,t,i} \quad \forall dc$

end

end

else $delivery_{dc,t,p} = \tilde{q}_{dc,t,p} \quad \forall dc$

end

end

In this case, the central warehouse apart from satisfying ordered quantities also sends products when it has surplus stock after maintaining a desired safety stock for its direct sales products. However the amount of material pushed is controlled by two conditions, one is the timing of the push, discussed above and the second is the maximum amount to be pushed is capped by the maximum stock a distribution centre can hold. This maximum stock holding by a distribution centre is estimated by the amount it must hold to satisfy demand during the production cycle time and the delivery lead time of that product. This amount is corrected for the forecast bias to reduce pushing stock to over-forecasted areas.

Another important function performed by the decision making stage of the central warehouse is the categorisation of the different products based on their total annual forecast values. The products are assigned a rough production cycle time (time between two consecutive production runs of the product or the time after which the product is expected to be produced again). The central warehouse assumes that products which are demanded more are produced more often and so have less cycle time in comparison to low demand materials. So at the start-up phase of the model, the agent initialises the approximate production cycle times and uses them as the lead times for deciding on the target stock levels to be maintained at the central warehouse. These figures are then used by the factory agent to set up the priority for production. The agent determines the target finished goods stock level in a similar way as the distribution centre agent does. Only the lead time used for calculation is changed to production lead time (same as the production cycle time defined above). The mathematical formulation is given by,

$$FI^*_{t,i} = FB_{t,i} + T_i \times FF_{t,i} + FSS_{t,i} \qquad \forall i \tag{18}$$

Since the production is assumed to be a continuous process and no formal review of inventory is done at discrete time intervals, so the review period is omitted from (18). A similar formula as in (10) is used to calculate the finished goods safety stock.

The ranking of different products based on global or local information is performed at this stage.

(a) Ranking based on local information – The first method of ranking the products is based on the forward cover *($FC_{t,i}$)*, determined as the difference of total stock of that product in the central warehouse and the total forecasted demand of that product during the production cycle time (eq.19). The product with the lowest forward cover is ranked 1. The mathematical formulation for the forward cover based on stock and forecast information of central warehouse only is given below,

$\forall i$,

$$FC_{t,i} = FI_{t,i} - T_i \times FF_{t,i} \tag{19}$$

(b) Ranking based on global information – This ranking of products is based on the minimum stock cover in the products at each of the distribution centres demanding that product (eqs 20 and 21 below). This can be expressed as following:

$$FC_{dc,t,i} = IP_{dc,t,i} - B_{dc,t,i} - T_{max} \times F_{dc,t,,i}, \qquad \forall dc \tag{20}$$

$$FC_{t,i} = \min_{dc} [\, FC_{dc,t,i}] \tag{21}$$

$$Rank_i = \underset{i}{sort} [\, FC_{t,i}]$$

The minimum inventory cover in each product is found by sorting all the inventory covers in all the distribution centres dealing in that product. Then these covers are used to carry out the ranking with the product with the lowest forward cover ranked 1. The next sub-section describes the functioning and decision making stages of the factory agent, which will show the inter-linkages between the decision making stages of the factory and the central warehouse in order to effectively deal with uncertainty. Appendix B.2 lists the programme used to model the central warehouse agent.

4.1.3 Production Factory Agent Description

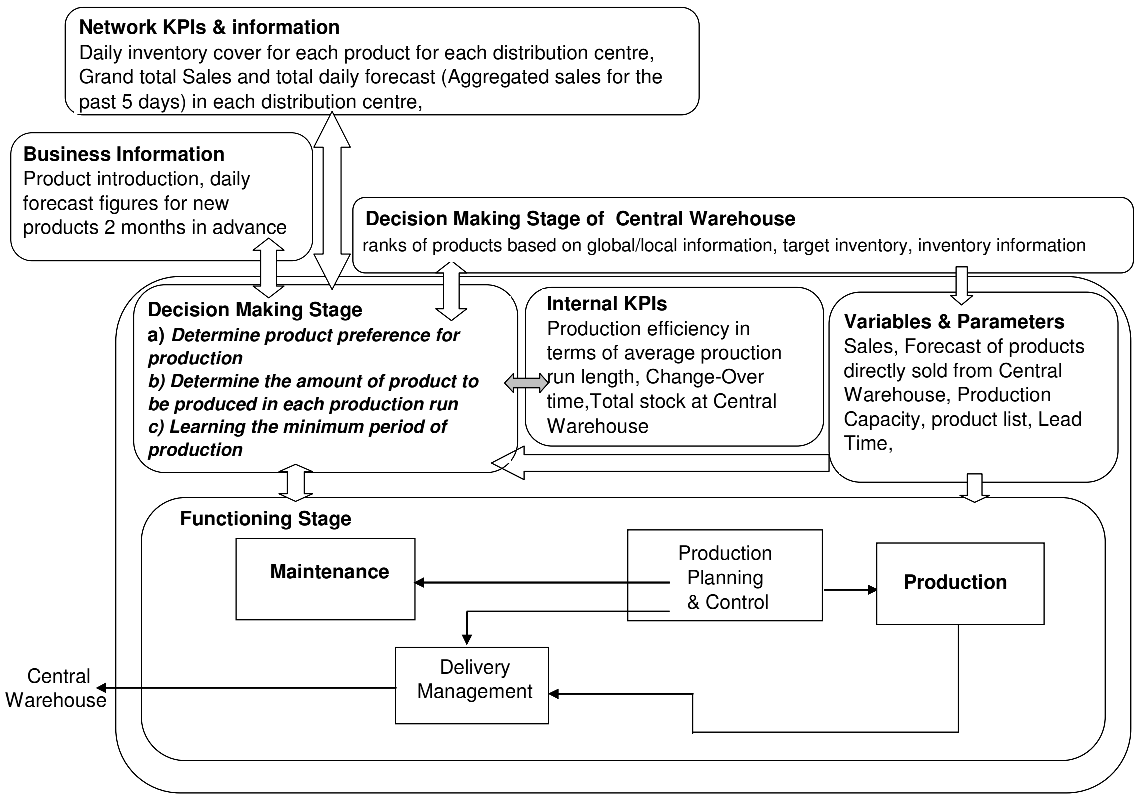


Figure 4.6: The agent structure for the production factory agent used in the model

It is assumed that the factory will not store any materials. Also it is assumed that the factory has infinite stock of raw materials and so does not base its decisions on raw material stock levels. This agent will also have the same two stages as the distribution centre agent. Figure 4.6 represents the structure of the factory agent. The factory is assumed to have full access to all information from the entire organisation. It is assumed to know about the new product introduction, their daily forecasts two months in advance from the business planning division of the organisation. The factory also monitors the local KPIs as total idle time in changing from one product to another and setting up the machine, the production efficiency in terms of average run length and the central warehouse stock-level. The factory agent also receives the information on the ranks of different products based on their inventory cover across the entire network, target inventory covers from the central warehouse decision making stage.

The *functional stage* of the factory agent carries on the regular production activities in regular intervals of time as guided by the decision making stage. The main functions are:

- Production, planning and control of one product at a time. Production is a continuous activity and occurs at fixed production rate. The amounts produced are added to the finished goods stock without any consideration for wastage or damage.
- Once a product is chosen for production by the decision making level of the agent, it continues the production until the stop condition is imposed by the decision making level of the factory agent. So this function is mainly concerned with the start and stop of production of a particular product.
- Another function integrated in the production function is the preventive maintenance. No production occurs at this stage. This is also planned at the decision making stage.
- Naturally the production function also includes a change-over phase. This is the idle stage when no production is made and the machine is set up for the next product.

The *decision making stage* of the factory agent sets the priority to produce the products and decides how much to produce on each product while dealing with multiple products with varied demand patterns. Thus the decision making stage intelligently decides on the sequence of production based on own goal of improving production efficiency along with improving customer service level at the central warehouse and the regional distribution centres across the entire supply network. There are two stages in arriving at the decision of which product to produce before and for how long. The first stage consists of deciding which product to choose for production. This depends on getting information on stock positions (local information on central warehouse inventory position alone and global information on inventory positions at each of the distribution centres) of the supply network to which the factory acts as the source of supply, and sorting them to find out the product with the worst inventory position across the network. The second stage involves decision of stopping the production of a product at the right time to avoid over or underproduction of any of the several products the factory is trying to schedule. This is done by getting information from the central warehouse on the target inventory cover of the selected product in the first stage and then calculating the time required to produce the product up to the target level. However, the factory agent also maintains a knowledge base of the stock position of all other products in the central warehouse and finds the time each product's stock-level can sustain its estimated demand (given by forecast). If any of the other products' stock level is found to be reduced to zero before the production-time of the selected product up to the target level, the factory produces the selected product only for the minimum time during which no product's stock falls to zero. This will avoid any customer service issues. A lower time limit is also learnt with time by the factory agent to take care of very low production run-lengths.

The *learning stage* of the factory agent monitors the average run length of the products produced and tries to increase its value. If the production run-length is found to be very low, the factory produces the products for a minimum time length to prevent the average production run-length from dropping. Each time a product is produced (signifying its frequency of production), the minimum production-time of that product is increased by certain duration, while for others the minimum time is reduced. This stage of the agent actually looks at the achievement of goals of production efficiency, while at the same time maintaining the customer service level. This stage also ensures that valuable production time (especially when a lot of elements in the supply network are sharing the common production resource) is shared intelligently between different products based on their real demand signified by their frequency of production.

Functioning Stage

Production, Planning and Control

The production amounts per time unit (a day in the current model) are fixed and are denoted as PR_i. First, the decision making stage of the agent decides intelligently on which product to manufacture first. The functioning stage of the factory agent starts production with the selected product h. The time to produce h is given by t_h and is expressed mathematically below.

$$t_h = (FI_{t,h}{}^{*} - FI_{t,h})/(PR_h - FF_{t,h}) \quad (22)$$

$FI_{t,h}$ is the finished goods inventory at the central warehouse and $FF_{t,h}$ is the total daily forecast of product h at all successive downstream stock-points to which the factory is a supplier and is determined the same way as in (2). Through this formulation, the factory agent assumes that the entire forecasted sales for the future period falls entirely on the factory, although the total forecast involves the individual distribution centre forecasts and may not directly fall on the factory. So this formulation of production time estimation is a safe one and considers global inventory positions.

Eq.22 does not take into account the inventory positions of all other products sharing the production facility. So the above planning model will start production with one product and continue producing it until it reaches its target stock level. But during that time, other products might be deprived of their share of production time and result in gross customer service issues in all subsequent downstream distribution centres to which the factory supplies materials.

A more responsible and robust dynamic production plan would be to take into account the finished goods inventory position of all other products at the central warehouse. It will estimate the inventory cover of all other products and would produce the product *h,* for the time that equals the lowest inventory cover value

$while\ i \neq P,$

$if\ \ t_h > FI_{t,i}/\, FF_{t,i}\,,\ \ t_h = FI_{t,i}/\, FF_{t,i}$ (23)

end

P is the last product of the list of products manufactured in a machine. But equation (23) will give rise to large number of changeovers as sometimes t_h would result in unusually low values or even zero. This will result in continuous execution of the changeover and large changeover time might result, thus deteriorating the production efficiency. So a lower bound is determined for the product's manufacturing time. This is generally done by talking with experienced production planning managers. Some products might not be worth producing more than 1 time unit, which is a day in a year in the current model. And some products might be required to be produced more often for longer spells. All these are dependent on the product demand patterns and practical experience. This model implements this field experience and individual product demand pattern based choice in the decision making function of the agent to fix these bounds. So the decision making function, provides a lower limit for production run-length t_{iL} based on the practical experience of practising managers. This is expressed as,

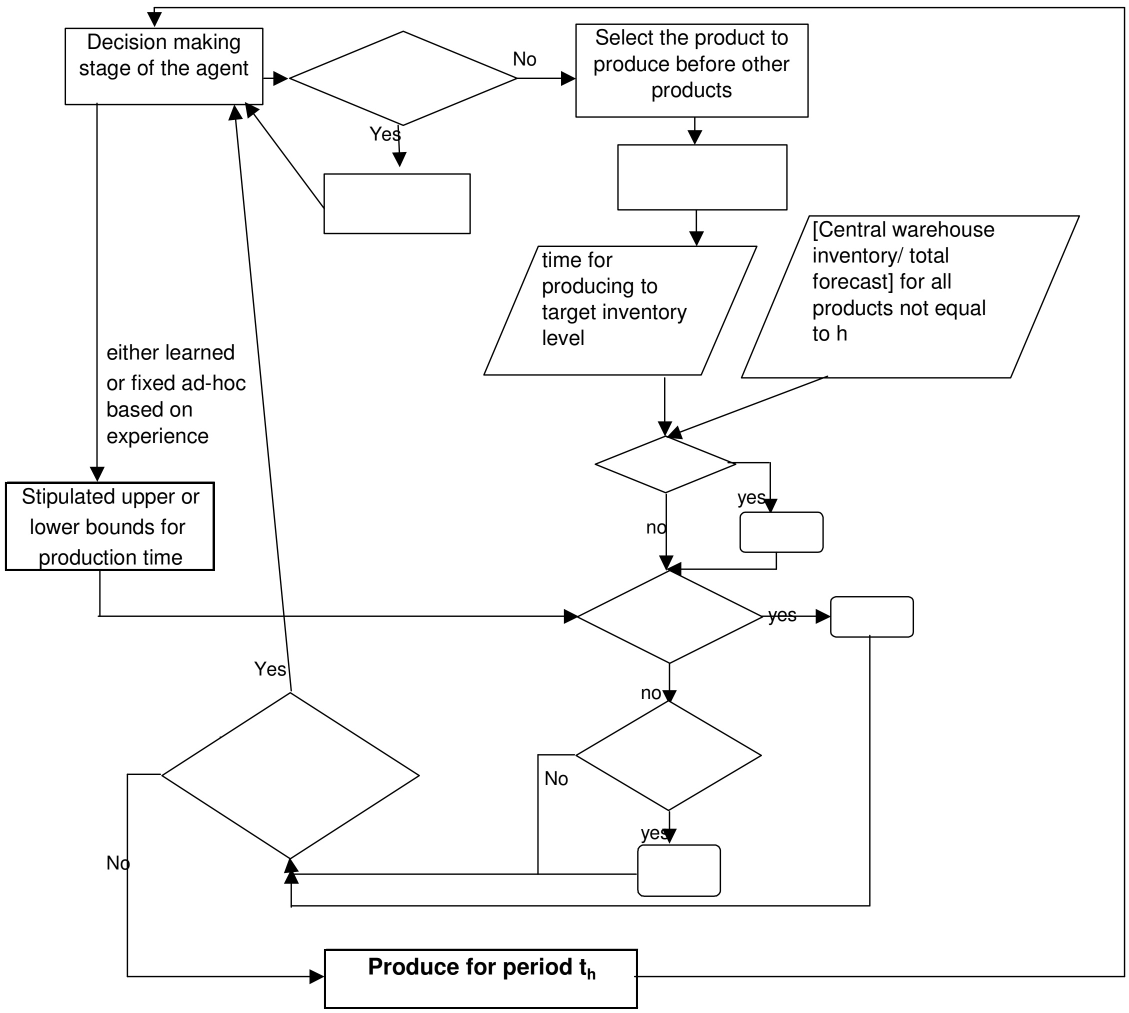
$if\ t_h \leq t_{hL},\ t_h = t_{hL}$

This lower bound of production can be made variable by making the factory agent learn the lower limit of production based on the frequency of production.

Sometimes, the upper limit of production (t_{iU}) run-length can also be constrained by experienced production managers in case, when the production time-length appears to be very large. This can be expressed as,

$if\ t_h > t_{hU},\ t_h = t_{hU}$

In this research, no upper bound on production run-length is assumed. Instead, there will be continuous checks at small intervals on the inventory levels across the network during production of any product for a long time. As soon as there is detection of fall in inventory levels beyond certain level in any of the stock-points across the network in any of the products, it is communicated to the decision making stage of the factory, which then intelligently decides which product to produce next or continue with the existing product for some more time. This mechanism is shown in Flowchart 4.



Flowchart 4: Production, Planning and Control

The production is assumed to be continuous with time and production planning occurs at every unit time interval (daily basis) and the amount produced (AP_i) is expressed as,

$$AP_h = \int_{t=1}^{t_h} PR_h dt \tag{24}$$

After producing the selected product for the time determined above, the next product is set up for production. This operation would incur some fixed changeover time $co_{t,i,,h}$, ($i,h \in \{1,..., P\}$) depending on the product produced before, i and product to be produced h. An account is kept for all the changeover times over the entire period of simulation T and over all the product types changed. This is given by, $CO = \sum_{t=1}^{T} co_{t,i,h}$

Maintenance is organised by the decision making stage of the factory agent on the basis of inventory cover in all the products across the entire network. No production takes place for the fixed maintenance period. First, the decision making stage decides whether to do maintenance or produce the selected product. Next, the product change-over takes place and the production planning and control stage determines the production run-length based on the rules described above. If the production run-length is less than the average run-length so far, the production takes place for the decided run-length period. However, if the run-length exceeds the average run-length, the decision making stage uses an intelligent rule to decide whether to carry on producing the product for the calculated run-length with strict vigilance on the stock levels at the various stock-points across the network or produce for a shorter duration. This will be discussed in the decision making stage of the factory agent. The important point to note in this production planning and control stage of the factory agent is that, it takes place at every unit time interval when sales occur and the inventory gets updated at each and every stock-point in the network.

Decision Making Stage

This stage actually decides on which product gets priority over others for production. This stage also monitors the different KPIs across the entire supply network (in case of full visibility) at regular small time-intervals to decide when to stop producing one product and make a decision to produce the next product.

As mentioned before in the description of the functioning stage, this monitoring occurs multiple times before deciding on the next product to produce. Several aspects are tested here based on the attitudes of the factory agent – (1) the factory may wish to satisfy local objective of reducing central warehouse service level issues by considering information on stock-covers at the central warehouse alone and disregarding ranks based on whole network inventory cover information; (2) the factory may consider the entire network inventory information on each product before deciding on the next product to produce. The factory needs to know regularly from the strategic planning department, which products are launched, which products are most-selling and which products are not demanded much in each of the markets the organisation serves and the factory acts as the source of supply. In summary, the factory agent in this decentralised informational structure monitors at which stage of life cycle the products are by monitoring the actual sales volume and forecasts. This is essential to avoid producing dying products in large quantities and resulting in huge residual inventories. Also, the factory needs to know the sales profile of each product, the approximate time of introduction in each market, the approximate time to withdraw in each market, the forecast of new products some period in advance. The details of the formulation are given below. First, the decision-process to produce a particular product ahead of others is analysed (Parts I and Ia, Flowcharts 5 and 6). As can be seen from the flowcharts, the factory agent's decision making scheme takes a global and local perspective while making decision on the product to produce ahead of others.

The factory uses global information in the form of network level inventory information of all products at all the stock-points across the network. Coupling the decision making stages of the central warehouse and the factory agent facilitates the interchange of global and local information. Local information of central warehouse stock-levels, direct sales and forecast information are shared between the factory and central warehouse agents. The global information is used by the central warehouse to categorise the different products based on their total annual forecast volumes. An approximate production cycle time is assigned to each product if their total annual forecasts fall within a specific range.

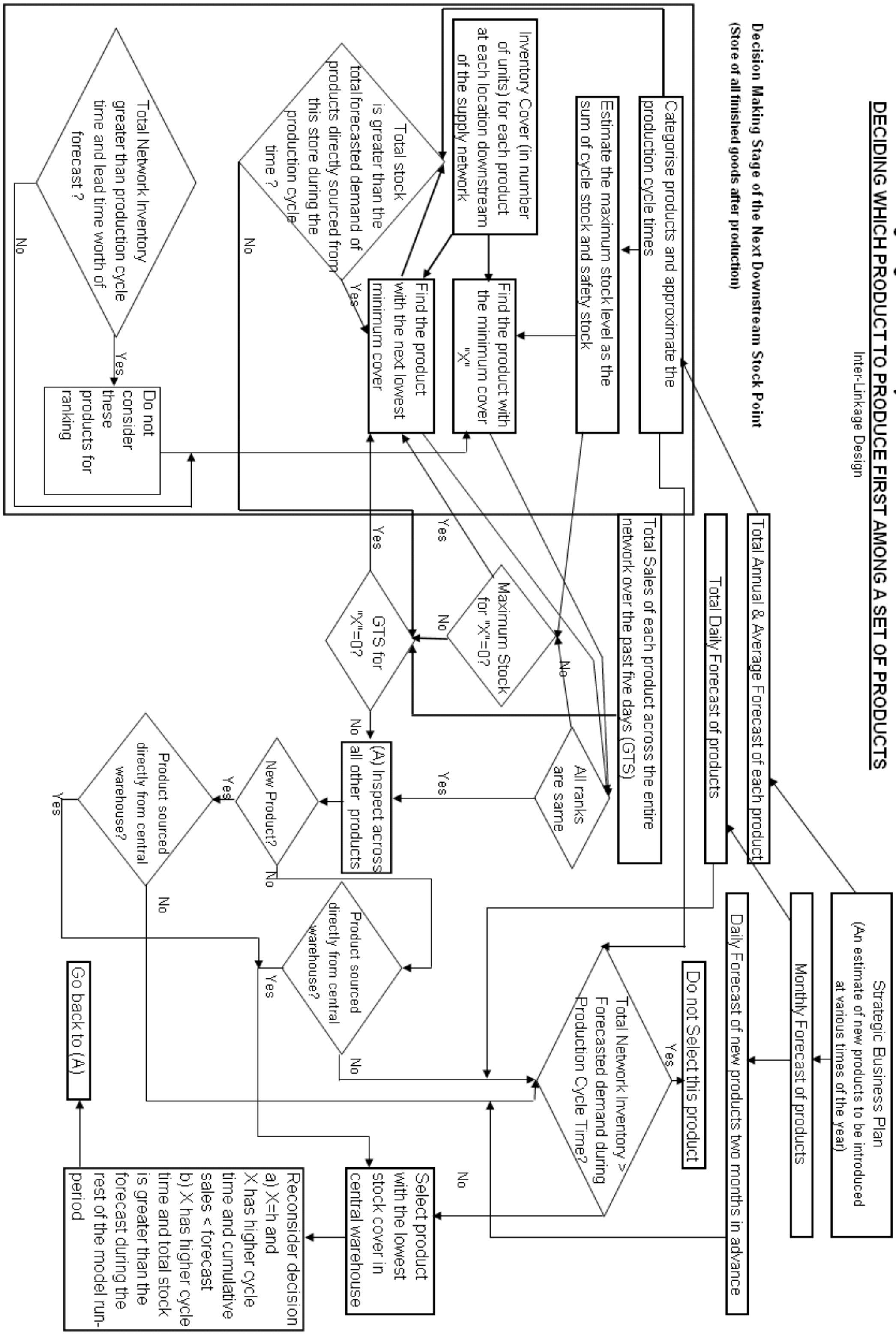
Basing the decision on global information – First the factory agent takes in the ranks of all products from the central warehouse decision making stage. It can either use this information or use local information for making decision. If it wishes to use this information, flowchart 5 shows it first checks whether all the ranks are different or same. There can be situation when no product gets priority over others for production. This can be explained if the decision making stage of the central warehouse (which is the next downstream stock-point to the factory) is analysed.

The central warehouse ranks the products based on the global inventory cover information of each product in each distribution centre in the network. But the central warehouse reserves the right to exclude some products from the ranking procedure based on a simple heuristic. As in this case, the central warehouse does not consider products for ranking if the network inventories of those products exceed the cycle time and transportation lead time worth of forecast. So one stage will arise, when there will be no products available to consider for ranking due to continuous accumulation of stock and low actual demand in comparison to forecast. In that case, the factory uses local information, which will be discussed later.

If the ranking process generates one product, which is ranked first among all other products, the factory first tries to find out whether the selected product's target inventory level is not equal to zero. If it is zero, the factory agent asks the central warehouse agent to provide the next ranked product and does the same check until a product is found with a non-zero target inventory level. Next the factory agent checks for the total sales across the network for the past five days of the selected product. Five is selected to simulate past one week's sales (assuming 5 day week). Again an iterative process is executed to find a product with non-zero total sales for the past one week and total stock at the central warehouse is less than the forecasted demand during the production cycle time. In this way, using the ranking procedure based on global information along with the reasoning system, the factory agent decides on the product to produce first.

Basing the decision on local information –

After selecting the product based on global information, the factory agent would use local knowledge of central warehouse inventory (starts from (A) in flowchart 5). However, the agent can straightaway use the local information without any information on the ranks generated using the global information.



Flowchart 5: Decision making Stage of the Factory Agent, part I

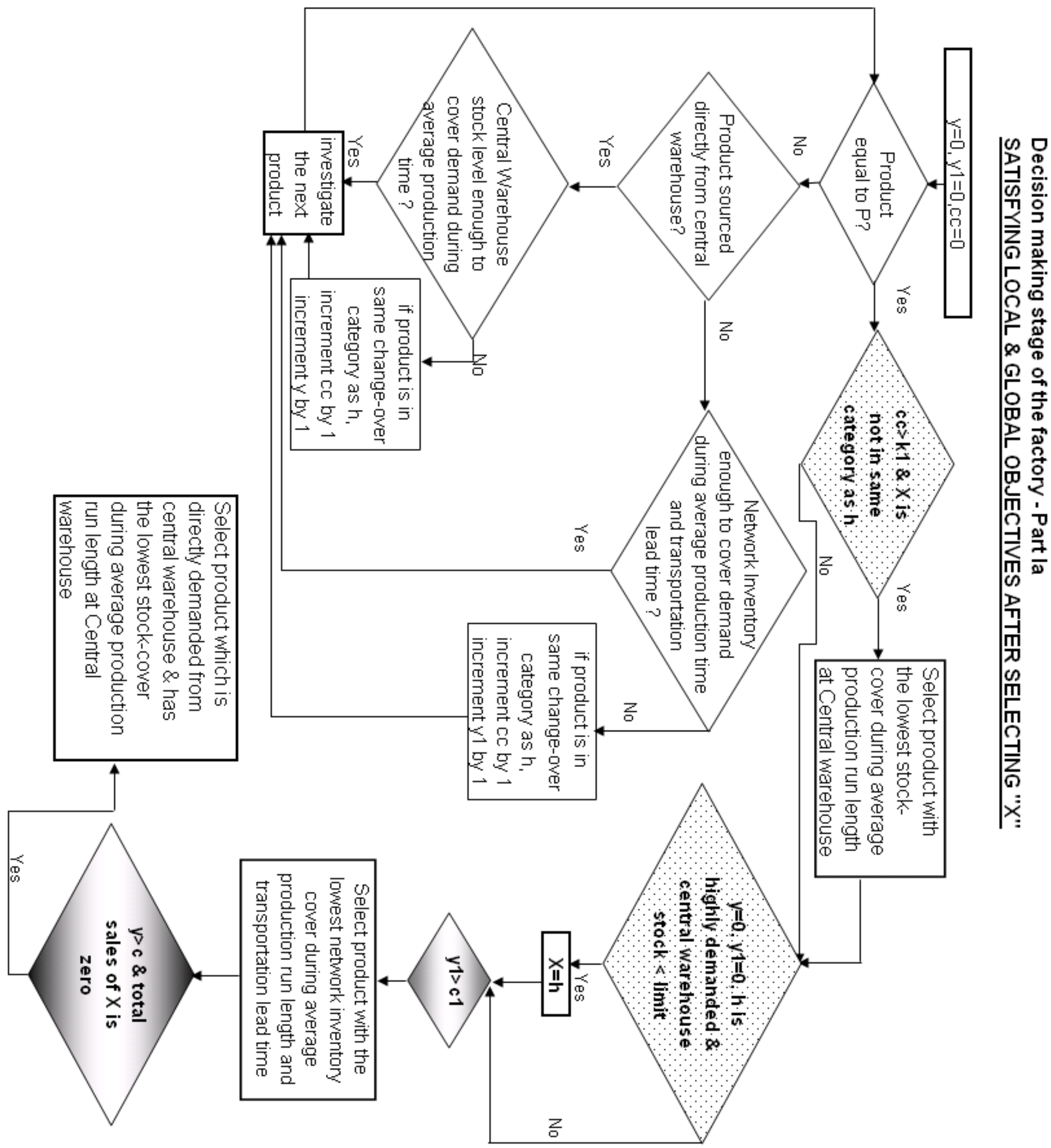
Even when the agent cannot decide based on the global information; it can use the local information to decide which product to produce first. Although this is based on local information on central warehouse stock, sales and forecast only, but the agent also uses the knowledge of which products are newly introduced throughout the network and which product is sourced from where. So, if the product is new and the sales volumes are highly unpredictable, the factory agent uses two months advance forecast data to build up stock beforehand. Otherwise, the agent uses the forecast of sales direct from the central warehouse. In this way, the agent finds the product with the least inventory cover in the central warehouse only. However, the agent reconsiders the entire decision making process to avoid producing products, which are not demanded in large quantities over the year, for a long time. The agent has knowledge of the categories of products decided by the central warehouse and uses that to reconsider the product selection decision. If the selected product at the end of the decision making process turns out to be the same as the product being produced just before (*h*), has high production cycle time above a threshold signifying low demand products and the total sales until the time of decision making is less than the estimated demand, the factory agent carries out the entire process of decision making by reverting to the stage (A) of decision making to select another product. Another important condition for reconsidering the decision is when the selected product has high approximate production cycle time decided by the central warehouse while categorisation and total stock exceeds the total forecasted demand during the rest of the model runtime or the time when the product is known to be withdrawn. This ensures avoiding producing products which are already being produced for enough time and do not require any further production unless need arises. This also helps in reducing any residual inventory in case this product is withdrawn or the product is at the end of its life cycle.

Basing the decision on both global and local information to satisfy local and global objectives –

To avoid the chance of not producing products, which are not directly demanded from the central warehouse by the markets it serves, at the right time, the factory agent uses the information on the inventory covers of these products. This is described in Flowchart 6, where balancing the decision making procedure on both global and local information is shown in details. Also, through this total information, the factory agent devises intelligent rules to balance the local objective of improving production efficiency by increasing production run-length and reducing change-over time and the global objective of improving service level issues across the entire network in all products.

First, the local objective of reducing changeover time for the factory is satisfied by selecting the product with the minimum change-over or setup time. This is done by selecting a product in the same category as the current product being produced, *h*. However, if products are only given priority in this way selfishly by the factory without any knowledge of global inventory information, it will result in huge customer service deterioration in other products across the network. So the factory intelligently selects products with low changeover times according to the rules charted out in flowchart 6. Three counters are initiated at each time a decision is to be made to select a product. Investigation is made across all products. If product is supplied from the central warehouse to the market, counter *y* is incremented by 1, if insufficient stock is there at central warehouse to cover demand during production run-length. However, if product is supplied to markets by distribution centres only, a counter *y1* is increased by 1 in case of insufficient stock at central warehouse to cover demand during production time and the transportation lead-time. Another counter, *cc* is incremented by 1 in each case of stock insufficiency of the product falling in the same category as the currently produced product, *h*.

The dotted decision making points in flowchart 6 highlight attending to local objective satisfaction and the shaded points indicate global objective satisfaction. So the factory decides on a threshold value *k1* denoting the number of products in the same category as *h* having insufficient stock level to satisfy forecasted demand. If $cc>k1$ and the selected product using the part I of the decision making stage is not in the same category as *h,* the product with the lowest stock cover at the central warehouse and in same category as *h* is selected for production.



Flowchart 6: Decision making stage of the factory, Part Ia

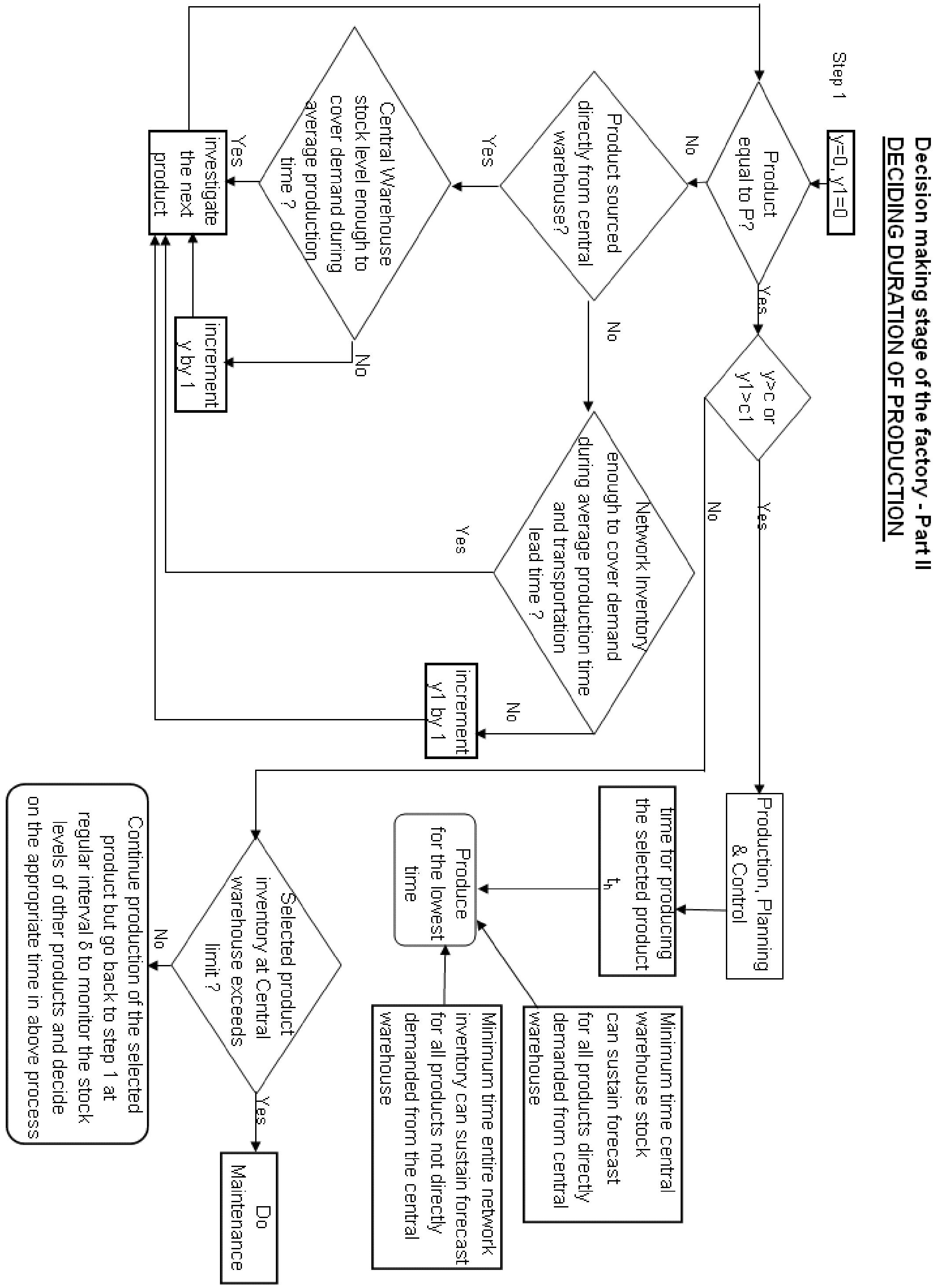
This will ensure both reduction in changeover time and improve customer service level. To avoid the number of costly changeovers between products, the factory agent monitors the inventory level of all products and if both *y, y1* are zero and the currently produced product is a highly demanded product, it continues producing the product without making any changeover.

In order to satisfy local objectives of increasing production efficiency and service level at central warehouse, the factory might overlook products, which are not sourced from central warehouse and instead are only supplied from distribution centres to the respective markets. So it uses the counter $y1$ and if it is greater than a threshold value, $c1$, decided by the factory, the factory selects the product with the minimum inventory cover irrespective of the changeover time required. If the factory wants to be considerate to satisfy the global objectives, it sets $c1$ at zero.

In order to avoid producing products, which are not directly sold from the factory and have zero sales in spite of having forecasted demands, when products directly sold from the factory are in risky inventory position, the factory checks whether the counter $y>c$, where c is a threshold value decided by the factory, based on its perception of risk. If the factory is very risk averse, it will set c to zero. If $y>c$, the factory selects the product which has non-zero cumulative sales and the worst inventory position.

Next, the decision to stop the production of a selected product is made by the decision making stage of the factory agent. This is described in details in flowchart 7 and is termed as Part II of the decision making stage. The counters y and $y1$ are the same as the counters defined before in Flowchart 6. These counters provide the factory agent with the inventory cover information in each product in central warehouse and the different distribution centres.

After selection of a product for production, this stage determines how long it should be produced with detailed information on the inventory covers of all products. If *y or y1* is found to be more than their respective thresholds, the selected product cannot be produced for a long time as there might be chance of more than one product facing a stock-out during that period.



Flowchart 7: Decision making stage of the factory: Part II, deciding on duration

So the factory agent gets a production time estimate from the production planning function, estimates the minimum time the central warehouse stock level would sustain the demand in any of the products directly sold from central warehouse and also estimates the minimum time the entire network inventory can sustain the forecasted demand in any of the products not directly sold from the central warehouse. The factory agent then decides to produce the selected product for the least of the above three time estimates. If the factory finds the inventory covers are in better position, it decides to carry on production of the selected product but at small regular intervals it iterates the entire process to check the inventory positions. At this point, if the factory finds the inventory positions are better and the selected product's inventory has exceeded a fixed limit, it decides to stop production for certain time period (1day) and decides to carry out preventive maintenance.

Learning Stage

The learning stage of the factory agent is an integral part of the decision making stage and takes place in real time. This stage actually attempts to improve the production efficiency of the factory by adjusting the minimum production run-length based on production frequency. So the agent uses the knowledge of the categories of products designed by the central warehouse based on their total annual demand volumes and initialises a value of minimum time for production at the start of production. So each time a high demand category product is selected for production, the minimum time for production of that category is increased by a certain fixed amount, while the minimum time for production of other demand categories are reduced by a certain fixed amount. In this way, the minimum time for production is increased for product categories, which are more frequently produced. This avoids frequent changeovers in products, which are frequently produced thus reducing the number of changeovers and increasing the effective production run length.

Appendix B.3 describes in details the programme used to model the different stages of the factory agent.

4.2 Summary

This chapter provides a detailed description of the formulation of the agent based simulation model to be used in the current research for improving resilience. The conceptual model described in Figure 2.4 informs the formulation of the model.

Distribution Centre Agent – The functioning stage considers both global information of product demand patterns, central warehouse stock level, other distribution centre stock levels along with local information of own stock levels. In this case looking at own inventory pattern to place replenishment orders without global awareness may have a strong mitigation focus (with intention to increase redundancy) but at the same time the judgment focus should balance both mitigation and recovery capabilities (end-to-end visibility of all stocks, all product patterns). Similarly, the replenishment strategies (TMSS, KMSS and learned target days' cover – real time and experiential) are also directed by the conceptual framework developed in Chapter 2. First of all, TMSS is not used to improve resilience and is discussed to represent the existing industry practice (will be discussed later in Chapters 5 and 6). TMSS is more efficiency focused while KMSS is more redundancy focused. A more balanced approach is taken in the learned target days' cover method of safety stock estimation. The target days' cover is varied continuously after receiving performance feedback. The variation is controlled by balancing the thoroughness and efficiency focus of the conceptual model. On the one hand, the supply chain cannot accumulate large stock that might affect efficiency (leanness) and on the other hand the supply chain cannot afford to lose valuable customers by failing to supply orders on time (agility). The replenishment methods are also used to test the effects of routinisation (TMSS/KMSS) and improvisation (combining learning with KMSS or learning only) on the resilience of the supply chains.

The Central Warehouse – Basing the decision to send materials to different distribution centres on days' cover of stocks (based on forecasts) and cumulative sales to average inventory ratio (based on actual inventory position and sales) actually shows the importance of different mitigation and recovery capabilities like foresight (ability to know which distribution centres are constantly over-forecasting), awareness / end-to-end visibility (full information based decision making to send materials in case of shortfalls). This also shows the ability of the central warehouse to evaluate the relative importance of information before making decisions on actions to take for improving resilience.

The Production Factory – The use of flexible or fixed minimum production run-length for producing each product by the production factory can be related to the flexibility, routinisation debate in the conceptual model (Figure 2.4). The different flowcharts (4-7) show the continuous monitoring of global and local information by the factory for producing different products. This highlights the judgement focus of the factory agent (according to the conceptual model) to make effective evaluation and use of available information.

The agent based model actually provides a framework to test different alternative strategies / policies designed to improve resilience (as informed by the conceptual framework). This chapter actually describes all the possible rules and procedures corresponding to different capabilities described in the conceptual framework. A study of supply chain performance under uncertain situations will be carried out in next few chapters by either incorporating all or some of the rules, strategy or control procedures discussed here. The different parameters signifying the attitudes of the different agents can be changed to visualise their effects on supply chain resilience. Use of local or global information, basing decisions solely on local objectives or considering global objectives will be examined as well. In this way, several alternative rules, procedures can be designed into the agent based framework and tested for their effectiveness in understanding and improving the resilience in terms of managing disturbances with no adverse effects on the performance. In order to address the research question of how to improve supply chain resilience without involving rules or control procedures that could be potential sources of disturbance, this framework is well suited to be applied to a real world supply network. The possible application of this generic framework to different production/distribution systems is discussed in Appendix F.

Chapter 5

Application of the framework to a real world supply chain network

5.1 Description of the supply chain network

The diagram (figure 5.1) shows the material flow structure of the real-world supply network of a paper tissue manufacturer to be used as a case study for understanding the impact of different rules, control procedures used by different agents (based on their behavioural attributes, inter-linkages, access to information) on the resilience of the supply network. The operational data obtained from the company for a certain time period are used to determine the theoretical distributions for demand for each product in each market. These are then varied to generate several scenarios to understand the behaviour of the supply chain under different demand conditions (Chapter 6).

Material Flow

The end products of the supply network are industrial wipers. The organization produces different grades of industrial wipers and sells them to multiple countries. For producing, the factory requires raw materials in the form of base-sheet rolls of paper of different grades and colours. In the present case, the organization sources base-sheets from owned mills. It procures packing materials, labels etc. from outside suppliers. All raw materials are stocked before being consumed for production. The basesheets are sent to Koblenz, Germany for converting into small rolls of specific size. The factory has several converting machines to convert the large basesheets into smaller rolls depending on the size, grade and shapes of the end products. Each converting machine produces multiple product categories requiring different set-up times. So each time a new product is to be produced the converting machine needs to be set up for that particular product. This changeover can take several hours depending on the product categories. Based on the product categories used (depending on the quality of paper used), the products produced on the same machine can have different changeover periods. In the current case, the supply network integrated to only one converting machine is used. From the converting machine, the rolls are automatically stacked into different sized pallets and sent to the central warehouse at Koblenz via a conveyor on the same day of production. The products are next distributed to different regional distribution centres (RDCs) across Europe from the central warehouse in containers. Most of Europe order E5 type europallets. Germany and Benelux countries demand E3 type of pallets, which are double the height of E5 types of pallets. Only the UK demands a special type of pallet size S2. Each of the country RDCs (depicted by the names Flint for UK, Logis for Czech Republic, Arceniega for Spain and Portugal, Niederbipp for Switzerland, Russia, VSE for France, Marene for Italy and Ede for Switzerland as well) deals in different product types with different demand patterns. They also face different lead times for delivery. The delivery lead times for different countries from the central warehouse are shown in Table1. Koblenz central warehouse stores products both in E3 or E5 pallets. As can be seen from figure 5.1 for the particular supply network, both central warehouse and the individual country RDCs supply to French and Swiss markets. The RDC at Arceniega caters to both Spanish and Portuguese markets. A separate RDC at Ede caters to different demand in different pallets in the Swiss market. The converting machine produces thirteen products (X1 to X13). Of these thirteen products, all are not sold in all countries. Products X1, X5, X7, X11 are sold in all the country markets. The product codes “X8” and “X9” are only sold in Swiss markets and supplied by the regional distribution centre (RDC) at Ede. The products “X3” and “X4” are only sold in Swiss market and supplied by Niederbipp RDC. Product “X13” is sold only in Germany and supplied by the central warehouse at Koblenz. Table 2 shows in details the countries that deal in the different product types in different pallet sizes and their supplying RDCs. The current supply network structure used in the research is for the finished products.

Informational Flow

Electronic Data Interchange (EDI) is in place and the stock points receive orders issued instantaneously.

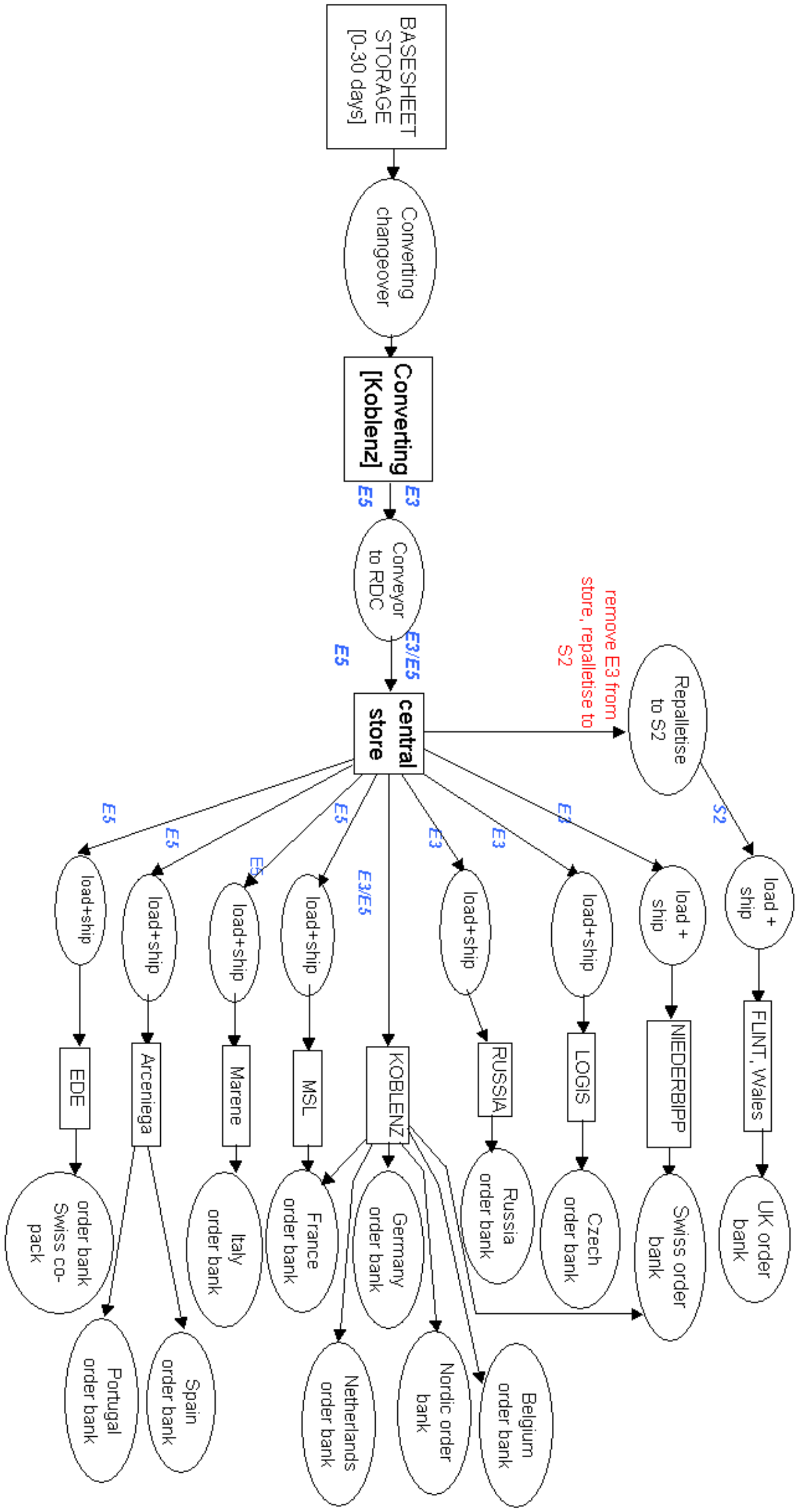


Figure 5.1: Paper Tissue Company Product Process Flow

Customer demand arrives at each country order-bank on a daily basis except the weekends. The RDCs try to fulfil the customer demand from its inventory and generate orders everyday through enterprise resource planning (ERP) software to raise their inventory position to target inventory level. The countries place orders on the central warehouse. Except for the production facility, the warehouses and RDCs in each country do not operate during weekends. Since there can be no deliveries or order placement during weekends, the delivery lead-time varies for each country. The actual material and information flow from the raw materials to the production factory are shown in fig.5.2. Each month, based on the monthly sales forecast, the central planning makes a yearly stock plan for the central warehouse. This and the yearly production budget (the labour hours available) are used to make rough monthly production plans for the factory by central planning group situated at company headquarters in the UK. Actually, from the rough planning of production at the factory the central planning department draws up requirements of base-sheets and generates rough basesheet production plans. These rough plans are essential for ordering raw materials and also serve as a guide to the production units on the amounts to produce in each product. The factory or the basesheet mill produces exactly the amounts planned, only changing the order of production of each code based on their stock cover at the central warehouse. This is done at the fine planning stage of the process. Rough planning is to control the capacity of the production machines, while fine planning helps in manufacturing as efficiently as possible. Any review of production plan occurs once in a month and factory cannot change the plan without the consent of the central planning department. The finished product production planning includes the orders received from customers and internal orders generated from the network supply chain members to replenish the stock levels. The entire information flow process actually starts with the customer or the different RDCs placing orders on the factory. All inbound orders are checked for product specifications, capacity to supply and due date. Once everything is fine, the orders are accepted commercially for supply and moved into an order bank. If enough capacity is not available, the orders are placed in a backlog queue and receive priority over incoming orders in the next time interval.

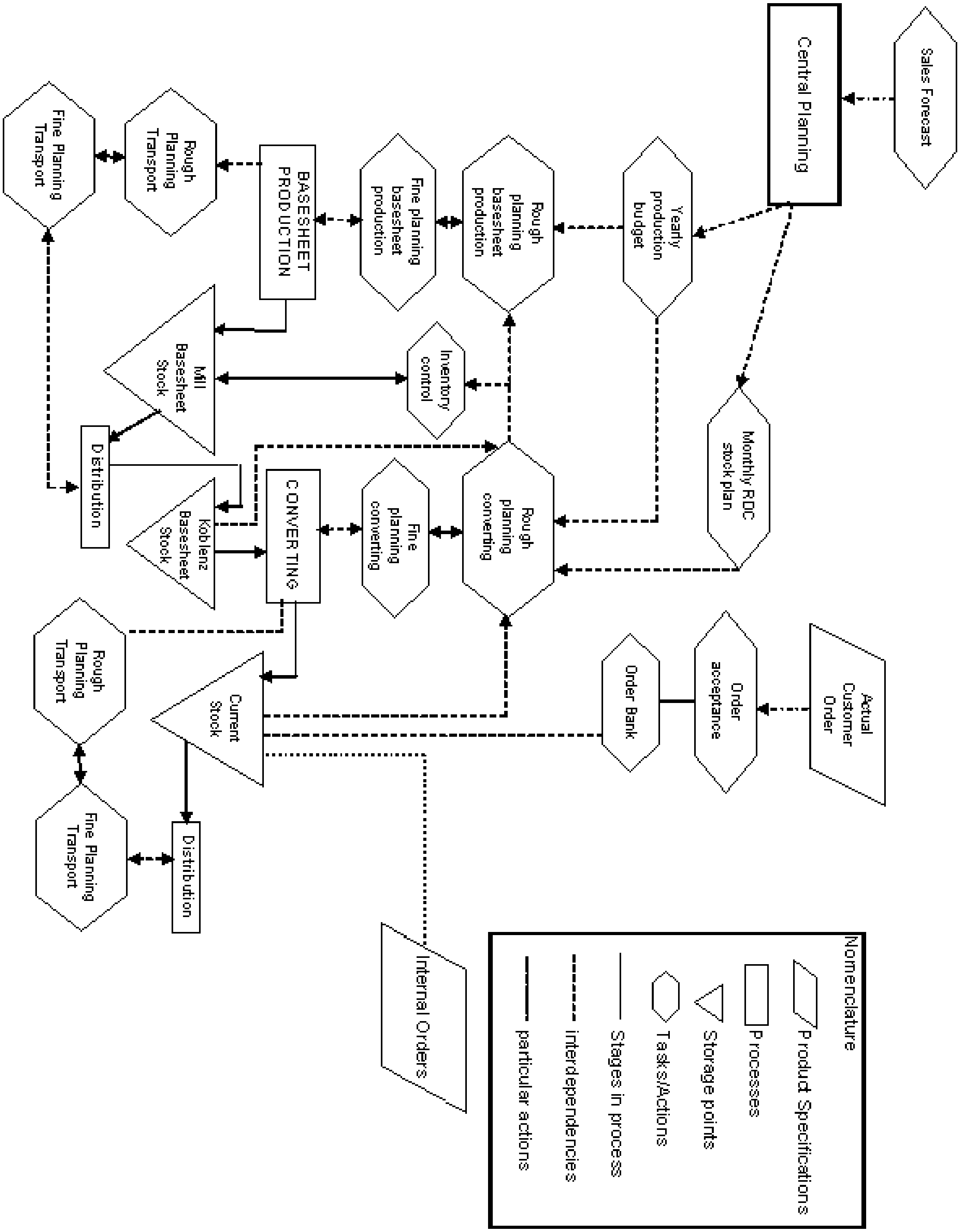


Figure 5.2: Combined material and informational flow diagram for production

After production, stocks are maintained at the central warehouse to cater to the variability of orders, both internal and external. Based on the amounts produced for each product and the distribution decisions, rough and fine transport planning is carried out. Rough transport planning is done to reserve transport options for the future based on approximate transport requirements. Fine transport planning involves efficiently allocating resources or products to the different members of the supply network or the customers based on internal orders or external customer orders respectively. This would involve optimally sending materials to the distribution centres in case of internal demands by building 100% full trucks. Rarely does the company use less than full-load trucks for inter-company material transfers. The priority for sending materials to different distribution centres is set at this stage of the transport planning process. This would involve human judgements from the planners. The planners monitor the stock levels at each individual distribution centre for each product and review the target inventory level, the lead-time demand (termed as critical stock) and the truck-fill rate across all other products sent from the central warehouse to that distribution centre to decide on the amount to be sent to the distribution centre when an internal order is received. From the above material and informational flow structure, it can be summarized that, the entire process operates on the basis of a make-to-stock system. Since there are long lead-times associated with the transport of finished products from the central warehouse to different RDCs and the markets served by the central warehouse, stocks are held at each RDC to satisfy customer needs during the transit time. It is also true for the raw material part of the supply chain. Because of the separate locations of basesheet production and converting (Germany and UK), the factory in Germany needs to maintain base-sheet stock to decouple basesheet production and converting operations. This is to isolate any disturbance in the raw material supply chain (wood/pulp). So the basesheet production occurs to stock held at the factory and the final products are also manufactured to stock held at the central warehouse. However, there are several sources of potential disturbances in the current operation of the system – some due to the inherent unique characteristics of the paper industry and some due to the centralized, inflexible rules, procedures and mechanisms designed to operate the system.

5.2 Sources of disturbances

The paper industry has some characteristics that make it unique. The volume and quality of the supply materials are stochastic and hard to predict with high accuracy. The planning horizons range from very short (seconds in case of planning production runs for products) to very long (decades in case of making strategic plans for investing in new equipment/machines assumed to be lasting for 30/40 years). The industry has a divergent flow, i.e., there are many more end products (several hundreds) as compared to the raw materials (a few species of trees). The industry has a tradition of using manual planning in a push-based system. The industry is very capital-intensive with small margins and the paper tissue manufacturing industry is no exception. Due to the specific characteristics in the industry it is difficult to use standard planning systems (Carlsson et al, 2006). Hence there is need for an intelligent planning system. The different problems of planning will now be discussed below in the current supply chain network.

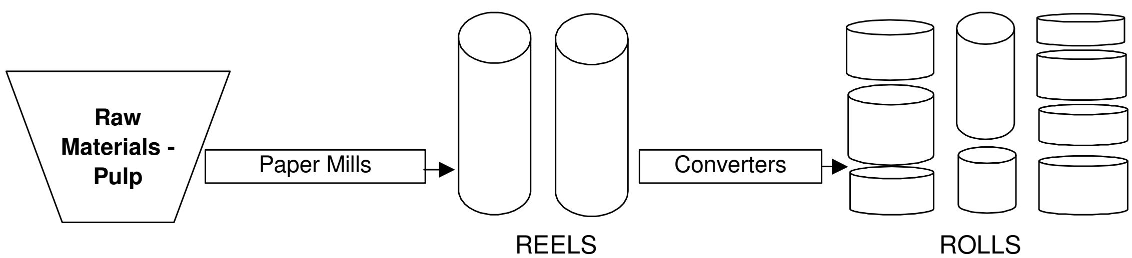


Figure 5.3: An over-view of the paper manufacturing process

Production – One general property of process industries is production occurring by batch (van Wezel & van Donk, 1996). This also holds for paper tissue manufacturer. Figure 5.3 presents an overview of the paper tissue manufacturing process used in the company studied in the research. Pulp, the main ingredient of paper, is fed into paper mills alongwith the other ingredients that define the “recipe” for producing a particular paper product (defined by the physical and optical characteristics of paper, such as grade and basis weight). A paper mill produces large rolls of paper called reels. Next, another machine, called a converter, cuts the reel into rolls of smaller diameter and width. Finally the rolls are shipped to customers through merchants and/or retailers. Paper production is a continuous process in which a machine can produce only one product at a time. When the product on a machine is changed, the machine continues to operate, but the paper it produces is of poor quality for some time after the change is initiated. The length of this "transition time" depends on the machine and on the products being produced before and after the transition. This is the reason for variable changeover times between products produced in the current case. There are long set-up times between different product types. A production run is the period of time over which the paper machine produces the same product. Manufacturing policies often bound the minimum length of a run; very short runs are likely to cause quality problems. While long production runs can improve trim efficiency, reduce setups, and meet the minimum run-size requirements, shorter runs can provide more flexibility. As noticed, the production machines are rigid and inflexible, making it difficult to completely revise previously formulated production planning. Production by batches combined with rigid, inflexible production machines make it difficult to completely revise previously formulated production planning. So adaptive production planning is required to set up a balance between short and long production runs.

Another problem with current production process in the converting factory is the lack of visibility of the factory. The entire visibility and decision making control is limited to the central planning department and they guide the factory on how much to produce each month in the converting machine in factory. The production planning is done centrally based on the central warehouse stock and aggregate forecast information. The fine planning in the form of making decisions on when to stop and start particular products takes place at the factory based solely on the raw materials and finished goods stock at the factory. Thus whenever there is an actual rise or fall of demand the factory reacts only after the event, when it affects the total stock level. So this reactive production planning procedure reduces the ability to sense and respond to any changes.

Raw material variability – The paper manufacturing process from reels to rolls has not been considered here for the research, since paper mills and the converting operation are decoupled by inventory held at the factory. Whilst the raw material aspect is not considered in this research, the availability of raw materials varies considerably over the year depending on the availability of wood. So disturbances in the supply of raw materials may influence the planning of production in the converting factory in Germany and subsequently affect the entire network. This particularly creates problems in customer service level issues, when seasonality occurs. In any time of a particular year the basesheet stock increases due to continuous production by the paper mills in anticipation of low wood availability in the next few months. This forces the converting machines to run continuously and consume the excess basesheets to produce and accumulate huge stocks of finished products. Throughout this period of excess production, the demand remains same or sometimes reduces. Since changeovers and start-ups after any stoppage are costly, the converting machine needs to be operated 24 hours a day. But in this case of surplus stock, the production planner is faced with gaps in his planning. So if the condition deteriorates, the planner has to stop machines for a long time in order to eliminate gaps in planning. So in case of excess capacity or excess raw materials, it is not profitable to stop the converting machines for few hours. In this case, the planners generally produce several weeks' demand in advance and then stop the machine for a long time, if conditions do not improve and demand does not continue to rise. However, here again the planner runs into the risk of deciding to stop the machine at the wrong time. Since, in this particular case study the central warehouse serves several markets and regional distribution centres, any change in any of the markets in any of the product demands can force the machine to start after a short time. So the planner has to be absolutely careful about the safety stock levels for all the products produced in any of the converting machine before deciding to stop it for a long time.

If however, the opposite situation arises and the raw material stock is low for some or all of the finished products, it might be impossible to convert the reels into rolls in the most efficient way. Say, within a certain week, several finished rolls need to be produced and sent to customers (externals first and internal customers next). The production planner needs to make smaller plans on both machines, which cause more set-ups and a capacity loss. Within that week, the raw material stock levels might dip further with very little supply due to lack of availability. So without any action, the vicious circle continues to worsen the utilization of capacity. Since, both these situations can happen unexpectedly, the standard planning or scheduling of the paper machines would need to be changed totally. So this calls for flexible and intelligent planning rules.

Customer Orders & Long Transition Lead Times – The entire system cannot see the real end-demand. Half of the company's customers are distributors and not real customers. So the company has to depend on history based forecasts. This results in obvious sales-forecast mismatch. Also current industrial trends indicate that customers demand reduced time windows for due dates, increased product variety, smaller order quantities and higher quality and reliability standards. The general industrial trends in customer demand in different markets require more flexibility from the production process of the factory, thus disturbing the production-distribution plan. Planning is done often based on aggregate forecasts, but in reality the forecasts at country level are often wrong. Consequently the network is plagued with huge stocks in locations where it might not be required or less stock where there might be a surge in demand. This is specially aggravated by the long transactional/processing lead times for each step in the process. The long time in inter-country movement of materials results in back-orders when there is surprise demand in a particular country and there is insufficient stock in the regional distribution centre and no stock in transit. The situation is far more worsened by the inability to cross-transfer materials between different country RDCs. The only source of finished goods is the Koblenz factory. So the factory production and distribution needs to be resilient to any changes in each country demand to minimize stock-outs and maximize customer service levels with least network inventory. Another potential source of disturbance is the existence of rush orders (orders which are due on the same day). However, considering the industrial trend, the increasing number of rush orders requires the entire supply network to build a capability to respond to them successfully.

Human Errors in Deployment/Distribution Planning – Another potential source of disturbance in the current supply chain network of the company studied is the judgement of the central planners to send materials to different distribution centres from the central warehouse. So even though sometimes the stock in any product in any one RDC falls below the target level, the planner may decide not to send materials to the RDC on the same day and instead wait for the trucks to be filled 100%. However, theoretically they should send materials as soon as the RDC stock level falls below the lead-time demand, but even then also sometimes the transport planners do not send materials until a truck is filled for dispatch to that RDC. This is particularly a problem for smaller RDCs such as Niederbipp, Czech Republic. Sometimes, exactly the opposite thing happens, when a RDC might need only one pallet of cases (pallet sizes are shown below in the next section) but actually receives much more than that although its stock level may be well above the safety level (lead-time demand). Even when an RDC might have enough stock in any product greater than the target stock level, it might receive some products. This happens when the planner tries to fill a truck with certain filler products and uses products, which are not demanded at all or demanded in smaller quantities. This results in anomalous assignment of products to different RDCs and might result in more stock at one place where it is not needed, while resulting in less stock at another place where it is needed urgently. This causes network-wide disturbance in customer service levels.

Figure D: Map of different disturbances faced by the paper tissue manufacturer

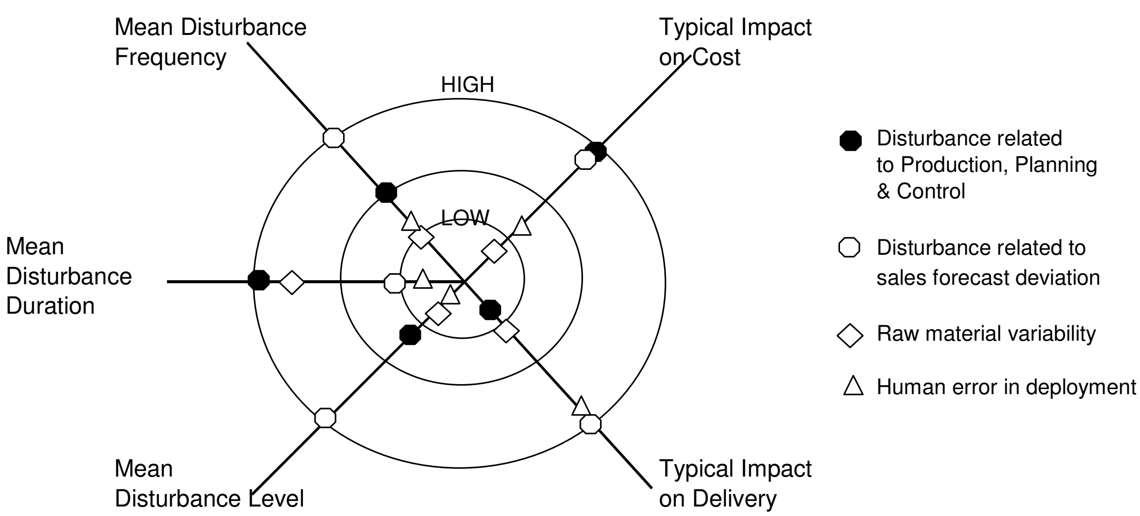


Figure D above shows the map of different disturbances faced by the organisation. The disturbance characteristics and their impact on performance of the entire supply network are plotted in Figure D. The chart axes rated the characteristics from high to low. From the left hand side of the figure, it can be seen that disturbances due to sales-forecast deviations (demand surges) are most frequent but short-lived. The level of disturbance is also the highest for demand forecast deviation. This is because, although the company forecasts uniform demand for most of its products but orders arrive in huge chunks. Even for some products sales occur during some periods although there might not be any forecasts. Such disturbances are associated with high impact on the performance of the actual supply network in terms of cost and delivery. Among the other forms of disturbances, production planning related disturbance are found to be infrequent but occurs for longer duration. The level of disturbance is moderate and impacts on the cost target of the supply chain due to different set-up requirements. Raw material variability also has similar characteristics as the disturbance caused by production planning but it has very low impact on over-all performance goals of the supply network. Finally, human error is deployment is a low level of disturbance, quite infrequent and short-lived. However, when it occurs it causes delivery issues which might result in loss of customer trust. Over-all, it can be said that, the most severe form of disturbance is the demand-forecast deviation and hence is considered the most worthy of attention in this thesis.

5.3 Data

The daily sales history of the thirteen products in each of the RDCs and the central warehouse at Germany are collected from this supply chain during the period from 1st January 2004 to 31st December 2004. The historical forecast data for each product at each country is available per month. These are converted to daily figures by dividing the monthly figures by 21.5. Initial stock levels at the beginning of the year for all RDCs and the central warehouse at Koblenz are provided by the company. Data on orders to each RDC for each product each day of the year is also obtained. Production amounts per day per product code are also obtained from the organisation.

Apart from this, the operational data is also obtained. The lead times for transport from the central warehouse to the different distribution centres are given in Table1.

Table 1: Delivery lead times for different RDCs supplied by the central warehouse		
	Minimum (excluding weekends)	Maximum (including weekends)
Uk RDC	5	7
Niederbipp RDC	2	4
France RDC	3	5
Czech RDC	5	7
Russia Rdc	16	18
Italy RDC	4	6
Arceniega RDC	4	6
Ede RDC	3	5

Table 2 shows the details of all the product codes converted in one machine in Germany after receiving raw materials from UK. In this table, Koblenz RDC implies the central warehouse located at Koblenz in Germany. As described earlier, product codes X1, X5, X7 and X11 are supplied to all the countries in different pallet sizes. As can be seen, all northern and eastern European countries (Germany, Netherlands, Switzerland, Nordic countries, Belgium, Russia and Czech Republic) demand products in E3 type pallets. Southern European countries (Spain, Portugal, Italy and France) demand products in E5 type pallets. Only UK demands all products in S2 type pallets. Table 3 shows the cases per pallet type for each of the products. Switzerland demands two products X8 and X9 in E5 pallet types. Although it is clear from fig.5.1 about the countries served by the different RDCs, but it is not clear which products are supplied from which RDCs. Table 2 clearly states that all countries have each product supplied by a single RDC except Switzerland and France. Switzerland is supplied by three RDCs. Ede RDC supplies products X8 and X9; products X1, X3, X4, X5 and X12 are supplied solely by Niederbipp RDC. Products X7, X10 and X11 are supplied by both central warehouse at

Koblenz and Niederbipp RDC. All products for France are supplied from either the central warehouse at Koblenz or the French RDC.

Table 2: Details of the Product Codes, markets sold, supplier RDCs and pallet types

Country	UK	Russia	France	Italy	Czech	Germany	Netherlands	Switzerland	Nordic	Belgium	Spain	Portugal
Pallet Size	S2	E3	E5	E5	E3	E3	E3	E5/E3	E3	E3	E5	E5
Supplier / Product	UK RDC	Russia RDC	France RDC, Koblenz RDC	Italy RDC	Czech RDC	Koblenz RDC	Koblenz RDC	Koblenz RDC, Ede RDC, Niederbipp (NBP)	Koblenz RDC	Koblenz RDC	Arceniega RDC	Arceniega RDC
X1	✓	✓	✓	✓	✓	✓	✓	✓ [NBP]	✓	✓	✓	✓
X2			✓			✓	✓					
X3								✓ [NBP]				
X4								✓ [NBP]				
X5	✓	✓	✓	✓	✓	✓	✓	✓ [NBP]	✓	✓	✓	✓
X6	✓	✓	✓			✓	✓				✓	✓
X7	✓	✓	✓	✓	✓	✓	✓	✓ [Koblenz/NBP]	✓	✓	✓	✓
X8								✓ [Ede]				
X9								✓ [Ede]				
X10	✓	✓	✓		✓	✓	✓	✓ [Koblenz/NBP]	✓	✓	✓	✓
X11	✓	✓	✓	✓	✓	✓	✓	✓ [Koblenz/NBP]	✓	✓	✓	✓
X12	✓	✓	✓		✓	✓	✓	✓ [NBP]	✓	✓	✓	✓
X13						✓						

Table 3: Cases per pallet for each product type

Pallet Type / Product Types	E3	E5	S2
X1	36	24	30
X2	32	24	30
X3	32		
X4	32		
X5	48	36	36
X6	32	24	30
X7	32	24	30
X8	96	72	
X9	72	54	
X10	32	24	30
X11	32	24	30
X12	32	24	30
X13	32		

To assist in the planning process, the proportions of forecasted demand to be supplied to France or Swiss markets from Koblenz or respective country RDCs are shown in Table 5. Product codes X10 and X12 are demanded in all markets except Italy. X3, X4, X8, X9 (Switzerland) and X13 (Germany) are all demanded by only one country. X2 is introduced in France, Germany and Netherlands during 2004 and X6 is introduced in all markets except Italy, Czech Republic, Switzerland, Belgium and Nordic countries.

Table 4a: Product Categories and Change-over times

Category 1	X1
Category 2	X4, X5, X9
Category 3	X3, X8
Category 4	X2, X6, X7, X10, X11 X12,X13
Change-Over time between categories	4 hours
Change-Over time between products in the same category	1 hour

Table 4b: Production Rates per Hour for different products

Product Code	Production rate (cases/Hour)
X1	90
X2	106
X3	63
X4	97
X5	85
X6	104
X7	96
X8	102
X9	113
X10	108
X11	118
X12	106
X13	70

All the products are put into four categories based on their changeover times. This is shown in Table 4a. The time for changing over products from one category to another is more than the time required to change products within the same category. This is the characteristic of the paper industry as described before. Normally to keep the time of changeover low, the factory tends to select products within the same category as the product last produced unless any other product in another category is in a precarious inventory condition to trigger customer service issues. The production capacities for each product in the converting machine are fixed and are given in Table 4b. A sample of the sales, forecast, production and distribution data collected from the supply network is listed in Appendix C.

Table 5: Sales split data for Switzerland and France RDCs

(A) Swiss Sales Split in %

	Koblenz	Neiderbipp	Ede
X1	0	100	0
X2	0	0	0
X3	0	100	0
X4	0	100	0
X5	0	100	0
X6	0	0	0
X7	49	51	0
X8	0	0	100
X9	0	0	100
X10	34	66	0
X11	37	63	0
X12	0	100	0

(B) France Sales Split in %

	France RDC	Koblenz
X1	70	30
X2	61	39
X3		
X4		
X5	69	31
X6	91	9
X7	65	35
X8		
X9		
X10	43	57
X11	74	26
X12	20	80

Description of the products –

Actual monthly sales data for year 2003 is obtained to understand the characteristics of the products and the stage of lifecycle they are in. Products *X1, X11* and *X12* are sold in 2003 for all twelve months and expected to be sold for entire 2004 (as shown in figure 5.4). The monthly demands for all the three products *X1, X11, X12* are expected to rise in

2004 compared to 2003. So these are the most popular and widely selling products of the company. And as can be seen from the forecast figures, all these products have still not entered maturity; in fact all the product markets are growing in various countries excluding the large markets (as will be shown later). All the other products are introduced in the years 2003 or 2004. So the supply chain network faces another problem in the form of the relatively uncertain sales of most of its products as most of them are newly introduced across the supply network and the company does not know how they will perform in all the country markets the company serves. *X5* is introduced in the first month of 2003. However, in the 11th month the total sales rise due to introduction of the product in more markets. Products *X7* and *X10* are introduced in the 10th month of year 2003. However, *X7* is estimated to grow at a rapid rate from the first month of 2004 in comparison to product *X10*. Since every year the company reviews the marketing and sales plan, in 2004, the company forecasts *X7* to be the highest selling product compared to all other products including the already established products. All other products are introduced at different points of the year 2004: *X2, X4* in the 7th month, *X6, X8* in the 1st month, *X3* in the 5th month, and *X9* in the 4th month. Since the company operates in an uncertain environment, some products might have very small life cycle and can be withdrawn within a short time of launch due to vanishing of actual demand. This is very difficult to predict for the company and so they continuously strive to capture market-share in face of fierce competition by inventing new products. Such innovation churn could give rise to production and inventory planning problems. This problem is a common problem across different industries. This requires flexible and adaptive planning of the integrated supply chain network.

Another notable feature of this supply chain is the seasonality of demand in the products. It can be observed from figure 5.4, most of the products suffer a dip in estimated demand during the 2nd and 8th month of every year.

Figures 5.5, 5.6, 5.7 and 5.8 show the estimated market growths for the different popular products *X1, X11 & X12* along with product *X5* (introduced in the year 2003). From Fig.

5.5 it is understood that product *X1's* estimated sales is going to decrease in 2004 compared to that in 2003 in the two large markets France and UK. While all small markets are estimated to register larger sales in 2004. This signifies that *X1* has entered the maturity stage in the above two markets, whereas other markets are still in growth phase. Figure 5.6, 5.7 and 5.8 however show that *X5, X11, X12* are all in growth phase. In fact, *X5* is introduced in Czech, Nordic, Spanish and Russian markets in 2004 and is estimated to grow in massive scale thus requiring huge production planning adaptability. In 2003, *X5* had only one large market, Italy, whereas in 2004, *X5* sales are estimated to grow in all the countries. Same situation holds for products *X11* and *X12*.

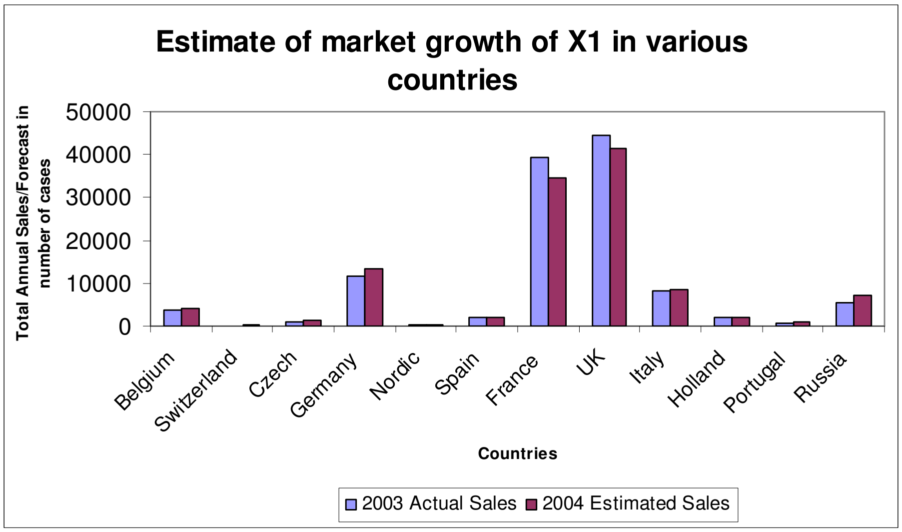


Figure 5.5: *X1* market growth in different countries in 2004

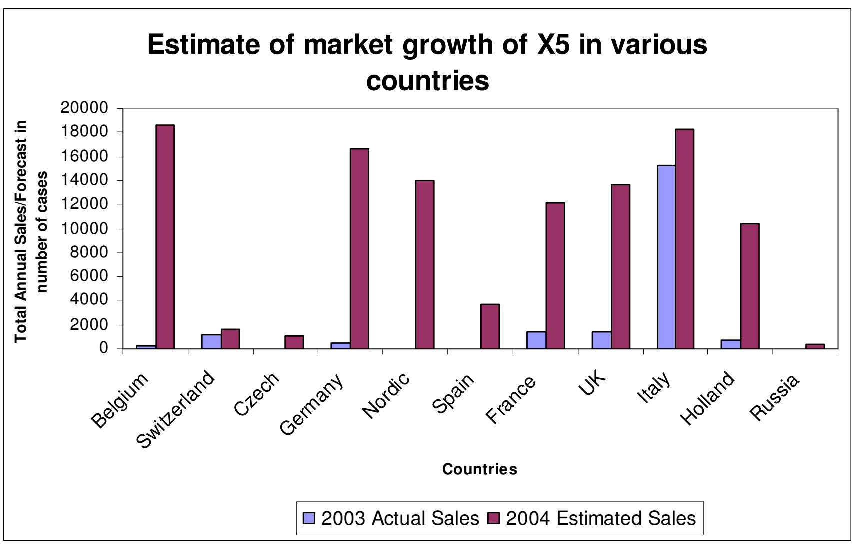


Figure 5.6 *X5* market growth in different countries in 2004

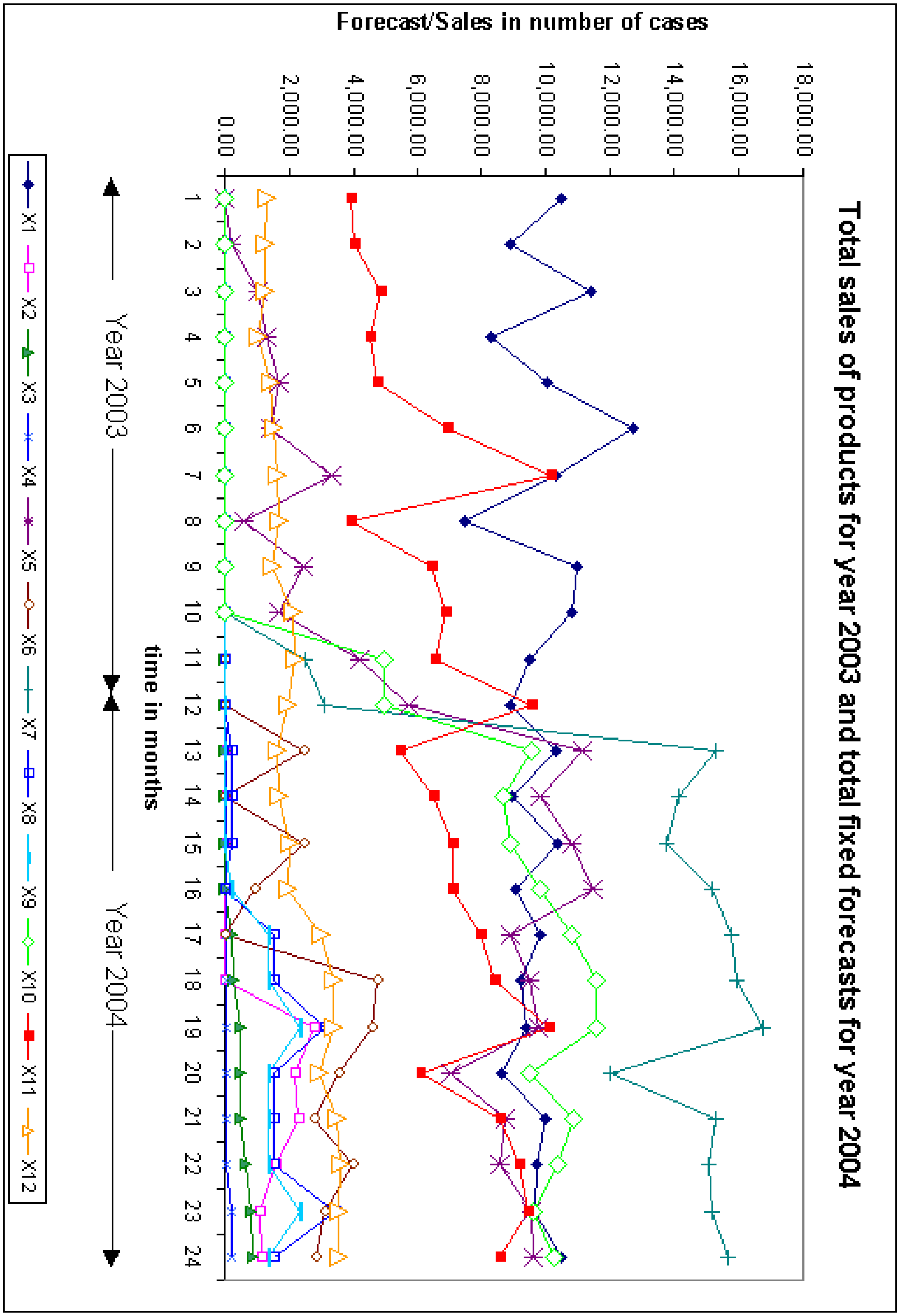


Figure 5.4: Total fixed forecasts for the different products for years 2003 and 2004

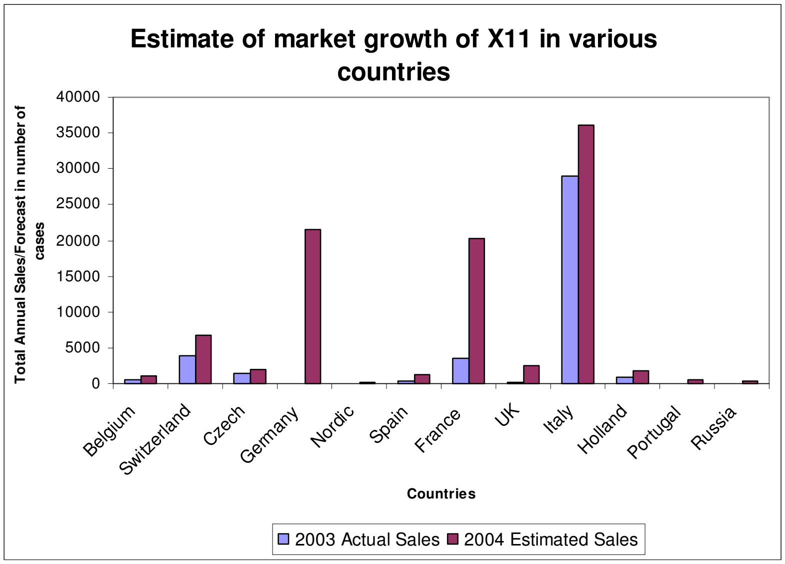


Figure 5.7: *X11* market growth in different countries in 2004

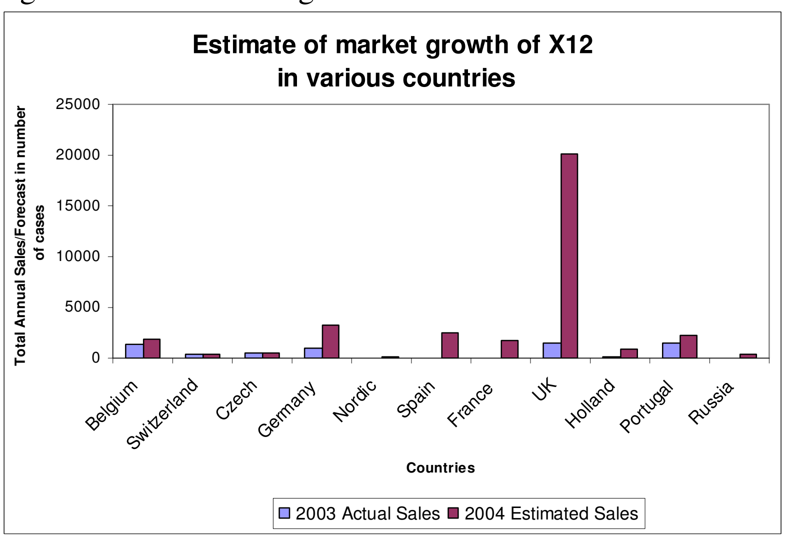


Figure 5.8: *X12* market growth in different countries in 2004

Figure 5.9 shows the total annual fixed forecast volume per country for the year 2004 for the eight products sold in more than one market. It can be envisaged, Britain is expected to be the largest market for the product codes *X10, X1, X12*. Germany is the largest market for products *X2* and *X6*; Italy is the largest market for products *X5* and *X11*; France is the largest market for product *X7*. So from this figure, the largest markets for the products are France, Germany, Italy and UK.

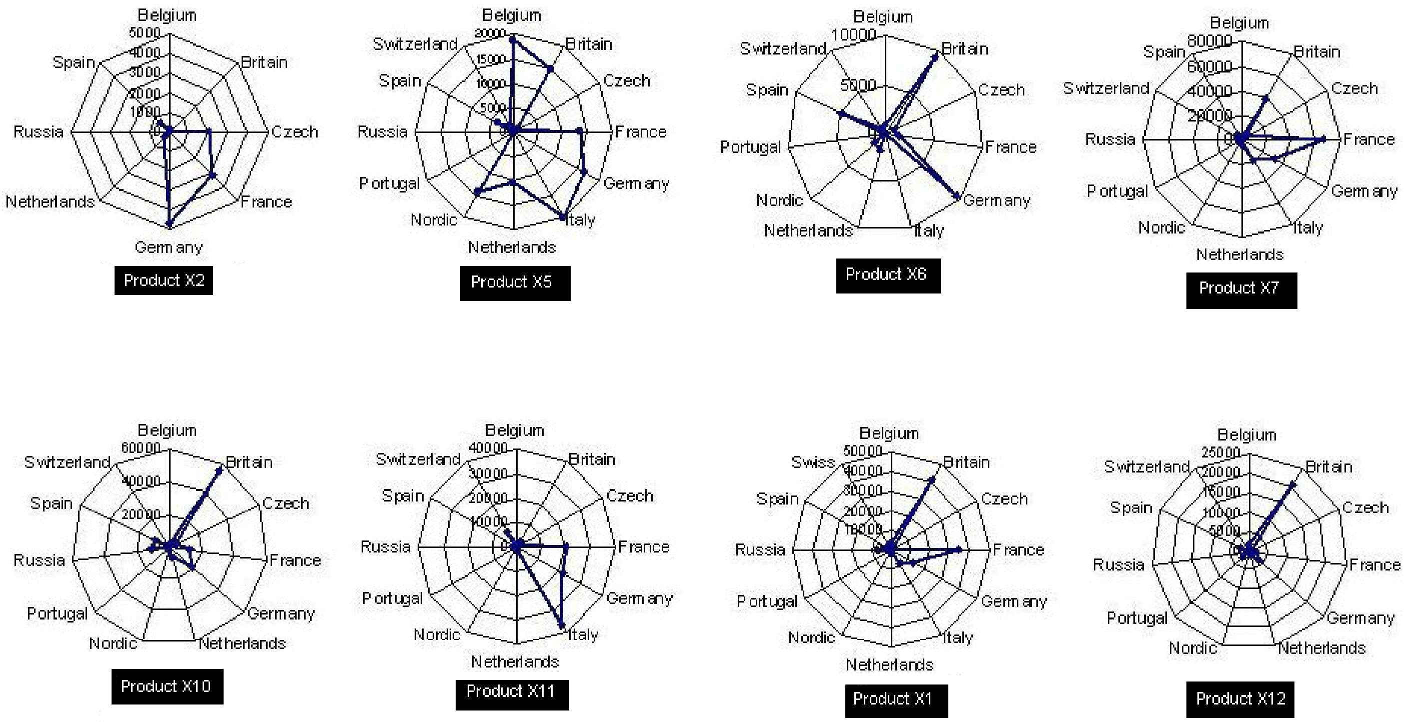


Figure 5.9: Annual Fixed Forecast Volumes per country for each code

Data preparation for experimental scenarios –

The main data set for analysis is the daily sales history of the twelve products in each of the RDCs and the central warehouse at Germany (Product *X13* is not included in the analysis as it is used to compare the performance of actual system with the agent based model). This analysis is crucial in order to determine the appropriate demand distributions at each country market.

The appropriate theoretical demand distributions are determined using distribution-fitting software, Stat::Fit™ (Geer Mountain Software Corp, 1996). The Anderson Darling (A-D) test for goodness of fit is used. The reason for selection of the A-D test is the difficulty associated with the other two tests - the Chi-square and Kolmogorov-Smirnov (K-S) tests for goodness of fit. The real difficulty in using a Chi-square test is the troublesome problem of interval specification. The decision of how to specify the intervals is specifically difficult for continuous distributions in the Chi-square test. K-S tests tend to be more powerful than the chi-square tests, they also have some drawbacks. Most seriously, their range of applicability is limited to few distributions. Also the K-S test is valid only if **all** the parameters of the hypothesized distribution are **known** and the distribution is continuous. The parameters cannot be estimated from the raw data. The A-D test is designed to detect discrepancies in the tails and has higher power than the K-S test against many alternative distributions, since most distributions are different in their tails (Law and Kelton, 2000).

The appropriate theoretical distribution for each country and their relative goodness of fit are shown in Table 6. In situations where no theoretical distribution is found to fit the data, empirical distributions are determined using the raw data points. If $X_1, X_2, \ldots X_n$ be the actual values of demand at n time periods. The piecewise linear distribution function F is defined for each i, $F(X_{(i)}) = (i-1)/(n-1)$, which is approximately the proportion of the X_j's that are less than $X_{(i)}$ (the ith smallest of the X_j's, so that $X_{(1)} \leq X_{(2)} \leq \ldots \leq X_{(n)}$).

Table 6: Theoretical Distribution Fitting to the historical demand data

	X1	**X2**	**X5**	**X10**	**X11**	**X7**	**X6**	**X12**
France	Pearson6 min 0 beta 571.5 p 1.39 q 11.14 pValue 0.444 adstat 2.49 (at 0.005) adstat = 0.853	Beta min 0 max 315.54 p 0.589835 q 3.62644 p Value 0.425 adstat 2.49 (at 0.005) adstat = 0.883	Weibull min 0 alpha 0.930674 beta 47.446 p Value 0.651 adstat 2.49 (at 0.005) adstat = 0.597	Weibull min 0 alpha 1.24066 beta 65.0995 p Value 0.409 adstat 2.49 (at 0.005) adstat = 0.909	Beta min 0 max 612.066 p 0.684728 q 3.88996 p Value 0.23 adstat 2.49 (at 0.005) adstat = 1.31	Beta min 0 max 1200 p 1.154 q 9.413 p Value 0.42 adstat 2.49 (at 0.005) adstat = 0.891	Beta min 0 max 129.152 p 0.656633 q 5.1559 p Value 0.141 adstat 2.49 (at 0.005) adstat = 1.67	Weibull min 0 alpha 1.28232 beta 23.9272 p Value 0.246 adstat 2.49 (at 0.005) adstat = 1.26
	X1	**X5**	**X6**	**X10**	**X11**	**X12**	**X7**	
UK	Weibull min 0 alpha 1.68265 beta 187.552 p Value 0.357 adstat 2.49 (at 0.005) adstat = 1	Weibull min 0 alpha 1.36153 beta 64.4731 p Value 0.643 adstat 2.49 (at 0.005) adstat = 0.605	Pearson6 min 0 beta 3519.07 p 0.716988 q 56.301 pValue 0.378 adstat 2.49 (at 0.005) adstat = 0.962	Beta min 0 max 2617.65 p 2.8728 q 34.1202 p Value 0.632 adstat 2.49 (at 0.005) adstat = 0.617	Beta min 0 max 215 p 1.20139 q 14.9117 p Value 0.378 adstat 2.49 (at 0.005) adstat = 0.962	Weibull min 0 alpha 1.16757 beta 102.672 p Value 0.937 adstat 2.49 (at 0.005) adstat = 0.301	Pearson6 min 0 beta 419.382 p 2.11824 q 6.84759 pValue 0.375 adstat 2.49 (at 0.005) adstat = 0.967	
	X1	**X5**	**X11**	**X7**				
Italy	Weibull min 0 alpha 0.86041 beta 41.6885 p Value 0.566 adstat 2.49 (at 0.005) adstat = 0.692	Weibull min 0 alpha 0.841547 beta 80.5614 p Value 0.225 adstat 2.49 (at 0.005) adstat = 1.32	Pearson6 min 0 beta 200.734 p 1.06842 q 2.62625 pValue 0.233 adstat 2.49 (at 0.005) adstat = 1.3	Pearson6 min 0 beta 28.4015 p 1.1221 q 1.26744 pValue 0.311 adstat 2.49 (at 0.005) adstat = 1.09				

Table 6 (contd.): Theoretical Distribution Fitting to the historical demand data								
Ede	**X8** LogNormal mu 3.91574 sigma 1.06415 p Value 0.542 adstat = 0.721	**X9** Pearson6 min 0 beta 9.09162 p 5.29414 q 1.51345 pValue 0.604 adstat = 0.647						
Belgium	**X1** Beta min 0 max 299.739 p 0.91661 q 2.44143 p Value 0.375 adstat 2.49 (at 0.005) adstat = 0.968	**X5** NO FIT	**X7** Beta min 0 max 167.182 p 0.828948 q 3.99218 p Value 0.219 adstat 2.49 (at 0.005) adstat = 1.34	**X10** Beta min 0 max 96 p 0.689462 q 2.19812 p Value 0.157 adstat 2.49 (at 0.005) adstat = 1.59	**X11** Beta min 0 max 130 p 0.784563 q 1.88272 p Value 0.537 adstat 2.49 (at 0.005) adstat = 0.726	**X12** NO FIT		
France Koblenz Supply	**X1** Weibull min 0 alpha 1.29731 beta 150.317 p Value 0.401 adstat = 0.921	**X2** Weibull min 0 alpha 1.38902 beta 53.2774 p Value 0.228 adstat = 1.31	**X5** Weibull min 0 alpha 1.12096 beta 140.871 p Value 0.227 adstat = 1.32	**X6** Power Function min 0 max 96 alpha 0.462848 p Value 0.448 adstat = 0.846	**X7** LogLogistic min 0 p=1.89576 beta=136.142 p Value 0.457 adstat = 0.834	**X10** Weibull min 0 alpha 1.56928 beta 80.7103 p Value 0.601 adstat = 0.652	**X11** LogLogistic min 0 p=1.93573 beta=108.404 p Value 0.497 adstat = 0.779	**X12** Rayleigh min 0 sigma 34.9857 p value 0.411 adstat = 0.906
Germany	**X1** NO FIT	**X2** LogNormal min 0 mu=2.02432 sigma=1.49709 p Value 0.444 adstat = 0.854	**X5** LogNormal min 0 mu=3.30102 sigma=1.80697 p Value 0.129 adstat = 1.74	**X6** NO FIT	**X7** Weibull min 0 alpha 1.10227 beta 147.901 p Value 0.355 adstat = 1	**X10** Weibull min 0 alpha 0.668527 beta 82.0396 p Value 0.377 adstat = 0.964	**X11** LogNormal min 0 mu=3.46777 sigma=1.76339 p Value 0.273 adstat = 1.18	**X12** NO FIT
Holland	**X1** Pearson6 min 0 beta 15.0627 p 1.60537 q 2.33246 pValue 0.315 adstat = 1.09	**X2** Beta min 0 max 80.96 p 0.739457 q 2.55218 p Value 0.46 adstat = .831	**X5** JohnsonSB min 0 lambda 152.625 gamma 1.03488 delta 0.544003 p Value 0.148 adstat = 1.63	**X6** Beta min 0 max 37 p 0.483675 q 0.512836 p Value 0.165 adstat = 1.55	**X7** LogNormal min 0 mu=2.45098 sigma=1.21409 p Value 0.276 adstat = 1.18	**X10** Beta min 0 max 249.796 p 0.826429 q 5.21969 p Value 0.201 adstat = 1.4	**X11** Beta min 0 max 418.77 p 1.08316 q 19.515 p Value 0.106 adstat = 1.89	**X12** LogLogistic min 0 p=1.17585 beta=9.22714 p Value 0.249 adstat = 1.25
Nordic	**X1** Beta min 0 max 40 p 0.943048 q 1.0975 p Value 0.893 adstat = .353	**X5** Weibull min 0 alpha 1.04612 beta 125.907 p Value 0.348 adstat = 1.02	**X7** NO FIT	**X10** NO FIT	**X11** NO FIT	**X12** NO FIT		
Swiss Koblenz Supply	**X7** LogNormal min 0 mu=4.3875 sigma=1.01785 p Value 0.593 adstat = 0.66	**X10** Weibull min 0 alpha 1 beta 32 p Value 0.789 adstat = 0.459	**X11** Rayleigh min 0 sigma 49.0775 p value 0.151 adstat = 1.62					

Table 6 (contd.): Theoretical Distribution Fitting to the historical demand data								
Niederbipp	**X1** Pearson6 min 0 beta 0.252823 p 16.9963 q 1.61015 pValue 0.919 adstat = 0.324	**X3** NO FIT	**X4** Power Function min 0 max 63.1842 alpha 0.593971 p Value 0.792 adstat = 0.456	**X5** LogLogistic min 0 p=1.11608 beta=13.8812 p Value 0.237 adstat = 1.29	**X7** Weibull min 0 alpha 0.823236 beta 24.1642 p Value 0.197 adstat = 1.42	**X10** Pearson6 min 0 beta 432046 p 1.15736 q 20002 pValue 0.363 adstat = 0.99	**X11** Beta min 0 max 263.974 p 0.808448 q 5.22913 p Value 0.146 adstat = 1.64	**X12** Beta min 0 max 32 p 0.948369 q 2.35116 p Value 0.677 adstat = 0.569
Russia	**X1** NO FIT	**X5** Loglogistic min 0 p 1.64576 beta 3.42842 p-Value 0.989 adstat 0.204	**X6** Weibull min 0 alpha 0.793344 beta 19.7243 p-Value 0.396 adstat 0.93	**X7** Pearson 6 min 0 beta 52.1109 p 1.40973 q 4.67701 p-value 0.136 ad-stat 1.7	**X10** Beta min 0 max 601.118 p 1.07255 q 9.79428 p-Value 0.228 adstat 1.31	**X11** Loglogistic min 0 p 1.93775 beta 3.60911 p-Value 0.36 adstat 0.994	**X12** Pearson 6 min 0 beta 1.36728 p 5.90056 q 2.05342 p-value 0.534 ad-stat 0.731	
Czech	**X1** Chi-squared min 0 nu 7.05058 p Value 0.971 ad stat 0.249	**X5** LogLogistic min 0 p=1.74328 beta=6.31933 p Value 0.538 adstat = .725	**X7** Weibull min 0 alpha 1.27944 beta 11.4341 p Value 0.556 adstat = 0.704	**X10** Pearson6 min 0 beta 211.259 p 2.07942 q 32.7712 pValue 0.698 adstat = 0.549	**X11** Chi-squared min 0 nu 5.46464 p Value 0.984 ad stat 0.22	**X12** Weibull min 0 alpha 1.57373 beta 5.66302 p Value 0.977 adstat = 0.236		
Spain	**X1** Rayleigh min 0 max 33.7611 p-Value 0.169 adstat 1.53	**X5** Power Function min 0 max 8 p Value 0.977 adstat 0.236 alpha 0.980305	**X6** Inverse Weibull min 0 alpha 0.766643 beta 0.21451 p-Value 0.95 adstat 0.283	**X7** Inverse Weibull min 0 alpha 1.94206 beta 0.207909 p-Value 0.897 adstat 0.349	**X10**	**X11** Weibull min 0 alpha 1.88714 beta 27.574 p-Value 0.769 adstat 0.479	**X12** Pearson6 min 0 beta 6.74813 p 8.24697 q 2.7695 adstat 0.876 p-Value 0.429	
Portugal	**X1** Beta min 0 max 151.636 p 0.703557 q 3.30046 p Value 0.183 adstat = 1.47	**X5** Loglogistic min 0 p 0.913455 beta 16.7743 p Value 0.318 adstat 1.08	**X6** Pearson 6 min 0 beta 107.385 p 0.90101 q 2.81841 p Value 0.452	**X7** Beta min 0 max 72 p 1.00535 q 2.15564 p Value 0.457 adstat = 0.834	**X10** Loglogistic min 0 p 1.49027 beta 23.7831 p Value 0.784 adstat 0.464	**X11** Inverse Weibull min 0 alpha 0.885559 beta 0.244332 p Value 0.121 adstat 1.79	**X12** Weibull min 0 alpha 0.935618 beta 33.2491 p Value 0.301 adstat 1.12	

5.4 Verification and Validation of the agent based model

Model verification is concerned with whether the conceptual framework in terms of agent behaviours represented by algorithms and mathematical expressions is reflected correctly in the agent based model. Model validation is concerned with whether the model is an accurate representation of the real-world system (Kleijnen, 1995). The model developed in this research work is verified and validated via the following ways. First, the flow diagram of entities, the decision making and functioning stages of each agent in the system are verified through multiple discussions held with the company staff. The simulation model is found to operate as intended. Next, the model output is examined for reasonableness under a variety of settings of input parameters. For instance, the customer service levels are set at different values for a particular RDC and safety stock levels, factory requests, timing of factory requests, the receipt of factory requests after stipulated lead time are generated from the model. These are then compared with manual calculations using MS Excel. No discrepancies are found between the two results.

The initial conceptual model should have high *face validity*. Input is sought from as wide a range as possible of people knowledgeable about the system. This is done prior to developing the model by talking to the production planners and material deployers. There are at least three reasons for this. Primarily, people who work with the system in different ways have different knowledge about the system. Some of this knowledge overlaps with others, but some are unique to a particular perspective. The unique perspectives complete the system concept and correct misconceptions. Secondly, the overlapping areas of knowledge provide crosschecks of the various inputs for consistency. Thirdly, participation in the modelling process reinforces confidence in the simulation. It provides the users the opportunity to question and critique the conceptual model. Involvement enhances acceptance and understanding among the users of the real system being modelled.

5.4.1 The Model of the Baseline Case

The assumptions are listed below,

1) Raw material variability is not considered and infinite raw material stock is assumed in all the models,

2) All orders are assumed to be rush orders,

3) No transport constraints are present. If enough inventories are present at source, replenishment orders are satisfied immediately by sending materials,

4) No materials are stored in the factory and there is no delay in transit from the factory to the store.

The structure of the model used to represent the current operating supply chain follows the structure shown in fig. 4.2(a) of Chapter 4. It consists of a central planning agent, which decides on the actions taken by all the other agents. Appendix B.4 lists the program depicting central planning agent, the factory, central warehouse and the RDC agents used to replicate the actual system. The central planning agent has full visibility of all the operations in the network. First the central planning agent decides on the planning horizon to guide the factory on how much to produce every planning horizon. In the current case, this horizon is one month. At the beginning of every month, the central planner has information on the current month's budgeted production days set by the operations group, the stock levels of each product at the central warehouse, the next month's total forecasted sales in each product throughout the entire network. Then the central planner decides on the amounts to be produced in each product by the factory based on the above information.

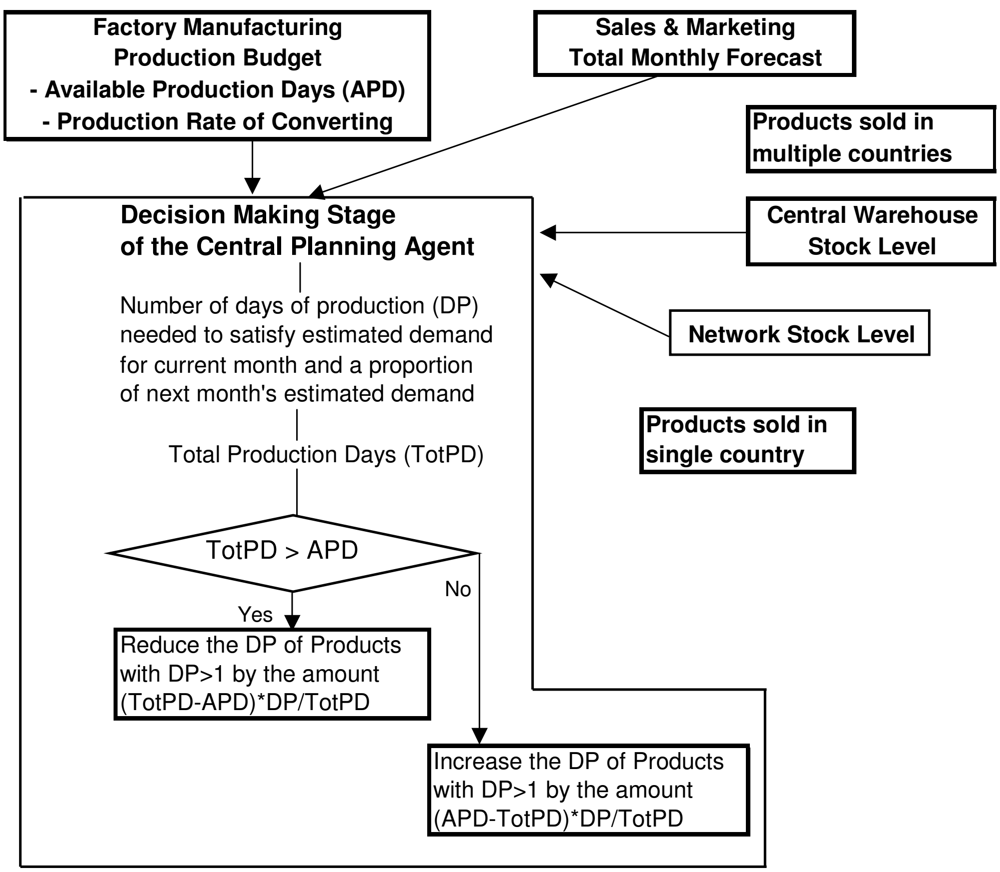


Figure 5.10: Central Planning Agent making decisions on production amount

The budgeted production days per month may be smaller than the actual number of days in a particular month. This may be due to unavailability of labour or due to essential maintenance work to be carried out. However this agent has only one stage structure to make decisions on which product to produce and by how much amount (shown in figure 5.10).

In the current case, the central planning makes an aggregate target inventory plan first, which sets the basis for the production amount decisions for each product in the factory. The central planning decides a target aggregate inventory cover for central warehouse sufficient to cover the total aggregate forecasted demand. This is set at 5.5 weeks in the model representing the base-case (after having discussion with the central planning manager of the company). In order to achieve the target inventory cover, the central planning agent calculates how many days of production are needed based on the production rates of each product (fixed by the factory manufacturing department), the opening stock level in each product in the central warehouse at the start of each planning month. If the number of days' production is less than 1, the central planning normally decides to produce the product for one full day in order to avoid any efficiency problems or fine production planning problems faced by production schedulers. After finalizing the number of days each product needs to be produced to achieve a target aggregate inventory cover at the central warehouse, the central planning agent aggregates the total number of production days (TotPD) in the converting machine. If TotPD is greater than the available days of production already decided by the factory manufacturing, the central planning agent scales down the production days in all products excluding those to be produced for a day only. This reduction is done on the basis of their respective days of production calculated before by the central planning agent. In the same way, the number of production days is increased if TotPD is less than the available days of production.

At the start of every month the factory agent receives from the central planning agent the amounts to be produced for each product. The main task of the factory agent in this case is to decide on the sequence of production and also to decide on the palletisation and delivery of products from factory to central warehouse.

Palletisation & Delivery

This stage of the factory agent determines what fraction of the amount produced ($fr_{i,p}$) is to be stored in a particular type of pallet ($p \in \{E3, E5, S2\}$). The total demand of finished product i is $FD_{t,i}$ and those requested in pallet type p is given by $FD_{t,i,p}$. The total forecast of finished product i is $FF_{t,i}$ and those requested in pallet type P is given by $FF_{t,i,p}$. This function actually assumes that the factory produces a particular type of product only if either its sales are non-zero at the downstream customer end or its forecast is non-zero. This can be expressed algorithmically as,

$\forall i$, *if* $AP_i>0$

$$FD_{t,i} = \sum_{p=E3}^{S2} \sum_{c=1}^{C} fd_{c,p,t,i}$$

$$FF_{t,i} = \sum_{p=E3}^{S2} \sum_{c=1}^{C} ff_{c,p,t,i}$$

if $FD_{t,i} >0$

$$FD_{t,i,p} = \sum_{c=1}^{C} fd_{c,t,i,p} \qquad \forall p$$

$$fr_{i,p} = FD_{t,i,p}/FD_{t,i} \qquad \forall p$$

else

$$FF_{t,i,p} = \sum_{c=1}^{C} ff_{c,t,i,p} \qquad \forall p$$

$$fr_{i,p} = FF_{t,i,p}/FF_{t,i} \qquad \forall p$$

end

$$AP_{i,p} = AP_i \times fr_{i,p} \qquad \forall p$$

end

After palletisation, the factory agent dispatches the products in different types of pallets immediately to the next stock point, which is the central warehouse. The production planning and control function is carried out in the same manner as described in section 4.1.3, chapter 4. The factory agent gets the information on the inventory at the central warehouse and based on the inventory covers produces a ranking list. The factory starts production with the top ranked product in the list if the central planning department makes a plan for production of that product during that month and there is some portion of planned production amount left to be produced. If the top ranked product has already been produced its planned amount, the factory then switches over to the next top ranked product with the second lowest inventory cover at the central warehouse. When the factory agent decides on the stop time of production of any product, it first looks at two things: firstly, the time to produce the planned amount and secondly, the time left in the month for which the production is carried out and the planning is made. This is shown in figure 5.11.

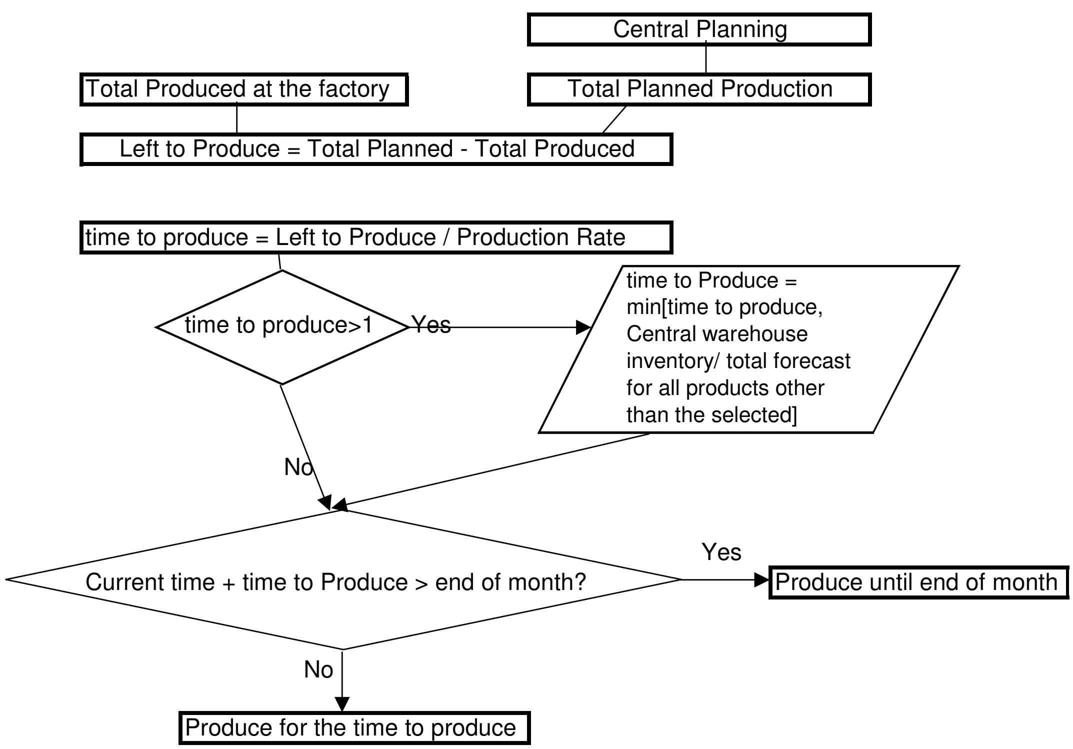


Figure 5.11: Factory Agent decision making

Once the product is selected for production, it is checked for the amount left to be produced in comparison to the planned production. If there are amounts left to be produced in the selected product, the time to produce that amount is estimated by the factory agent. If this time is less than one day, the factory agent checks whether producing for this time would result in moving the current month's plan into next month. Since whatever production is planned for the current month needs to be produced in the current month, the factory would produce only until the end of the month instead of carrying forward to the next month. If however, the production is not found to continue until end of the month, the factory produces for the estimated time for production. The same is true for production time greater than 1. In that case, however the factory looks at the inventory position of other products and finds the minimum of the estimated time to produce the selected product and the time the stock levels of all other products are going to last.

The entire modelling is adapted to represent the current functioning and decision making of the paper tissue manufacturer. The entire process is inflexible because any changes in the product demands with respect to the forecast can only be reacted to after the entire planning horizon of one month.

The RDCs and central warehouse agents are modelled to be consisting of just the functioning stage with no decision making stage. The RDCs place orders on the central warehouse when their stock levels fall below the target stock level. The target stock levels, in weeks' cover, for each RDC and each product are set by the central planning agent at the start of each year, based on each product's demand pattern given by average annual demand, standard deviation of actual demand over the lead time and target customer service level. So each RDC has different target inventory covers for different products it deals in. For example UK RDC and Niederbipp RDC might need inventory to satisfy 2 weeks' forecasted demand in products X11, whereas France and Italy might need 5 weeks' cover depending on the fluctuation of demand in those markets or target service levels. In general for products, which are not sold in the past year, the RDCs use two weeks' target inventory cover. These ordering policies are inflexible because they do not react to real market changes. Some products might be forecasted to sell more in a country but due to certain reasons its sales drop suddenly. But since the ordering policy followed currently by the company assumes fixed target weeks' cover of inventory based on annual forecasted sales without any mechanism of adjusting, the RDCs will continue to order when the stock level falls below the target level and the central warehouse would continue to supply materials even though the real demand might have vanished.

5.4.2 Validation Results

Representing the input data by theoretical distributions might pose some problems as some distributions as the Weibull, LogNormal and LogLogistic have no upper bound on the generated data. So to make realistic representations, these data need to be capped at the observed maximum from the past historical data available. To validate the model input data, the datasets for products, which are initiated in many markets at the middle of the year, are generated accordingly. Also to see the model performance, all the replications of the model, under different sets of strategies, are done with sales data generated from the theoretical distributions with the same mean values. The parameters relevant to that distribution are estimated from the sampled data. Finally the fit of the selected distribution to the data can be verified by applying appropriate statistical tests (Table 6).

Table 7a: Validation Results - Inventory Figures

Product Code	RDC	RDC Average Inventory		
		Actual	Model	Difference
X5	UK	741	751	1.35%
X10	Koblenz	19784	19879	0.48%
X5	Niederbipp	195	175	10.26%
X2	France	309	312	0.97%
X7	Italy	4032	3487	13.52%

Table 7b: Validation Results - Production Figures

Product Code	Average Production Amounts		
	Actual	Model	Difference
X5	298	290	2.68%
X6	94	94	0.00%
X7	533	473	11.26%
X9	44	48	9.09%
X10	366	322	12.02%
X11	343	308	10.20%
X12	117	131	11.97%

The most conclusive test for the model is the simulation of the system under conditions where the outputs of the real system are known. The focus during this process is on the overall transformation of the inputs into outputs. The outputs of the simulation can then be compared with the historical data. This testing can only be made for situations where historical data of key performance indicators are available for a range of input conditions. Though these are not available in the present case study for all the products and also the rules are not explicitly disclosed in carrying out the regular operations in real life. However, the model is validated with respect to certain products' average inventory level over a specific time period ranging from 93rd day to 303rd day. These are then compared with model output values. Since only one set of historical data is available (year 2004), the model is run for validation purpose with this set of data. The exact conditions under which the orders are raised are very difficult to gauge from past set of data. There might have been different incidents, which might have initiated a substantial push of materials from one place to another. To avoid the effect of such events, I have taken a few products and their inventory levels at various RDCs and Koblenz for validation. A difference in average inventory level of approximately 15% is considered to be acceptable, since it is very difficult to replicate the actual inventory profile for all the products. The model outputs for average RDC stock levels and Koblenz stock levels are compared with actual historical data. These are presented in Table 7a and Figure 5.12a. The model validation indicates the capability of the model to represent reality. Since the actual customer service levels are unavailable, the model is validated only with respect to the inventory information obtained from initial stock levels given and the order delivery information provided. Another validation test is performed with respect to the amount produced for various products during the specified time interval. The results are tabulated in Table 7b. As can be observed, most of the production figures fall within 15% of the actual production amount figures. Figures 5.12a – 5.12b show that the modelled inventory patterns follow the actual stock patterns.

From the above study, it can be said that, with the incorporation of central planning agent, the fixed safety stock policies adopted by the RDCs without any heed for actual sales, the model can be claimed to be a valid representation of reality. This model is termed as the **baseline model,** which will be discussed in Chapter 6. In the next section, the performance measures are presented, on which the efficacy of the proposed decentralized, learning agent based model (described in Chapter 4) is judged with respect to the **actual** supply chain performance.

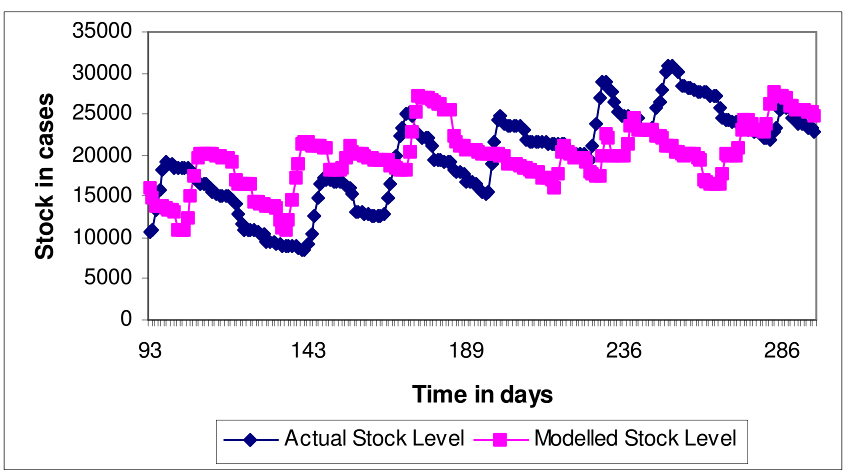


Figure 5.12a: Actual and Modelled Stock Level at Central Warehouse for *X10*

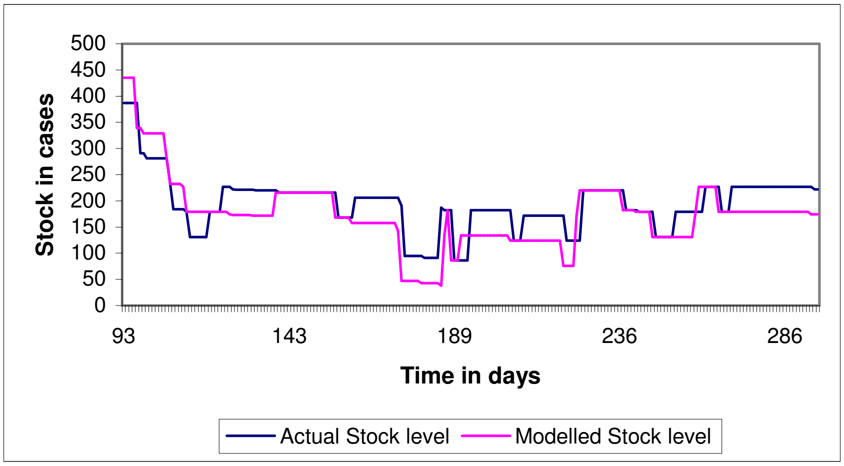


Figure 5.12b: Actual and Modelled Stock Level at Niederbipp RDC for *X5*

5.5 Performance Measures

The performance of the supply chain will be judged in terms of the following performance measures for each product in each distribution centre and the factory.

- Customer Service Level (CSL) is taken to be the fill rate, which is the total quantity sold to the end customer over the total quantity ordered, for that product market for the entire time horizon of the simulation. When the stock level is lower than the order quantity, only the stock available is sold and remaining is backlogged. So CSL for each product, each distribution centre is given by the following mathematical expression and expressed in either fraction or percentage,

$$CSL = \frac{\sum_{t=1}^{T_H} AS_{n,t}}{\sum_{t=1}^{T_H} D_{n,t}} \quad \text{and} \quad AS_{n,t} = \min\,(I_{n,t-1}, D_{n,t})$$

Where, $AS_{n,t}$ *= actual sales in simulation n at time instance t*
$D_{n,t}$ *= demand in simulation n at time instance t*
$I_{n,t}$ *= ending stock level in simulation n at time t*
n = simulation number
T_H *= simulation time horizon*

- Production change over time (CO) & Average Production Run-Length (APR) in days

- The average inventory (AVI) is the on-hand stock level of the products at each distribution centre averaged over the time horizon of each simulation run and is given by, $\frac{1}{n \times T_H} \sum_{t=1}^{T_H} I_{n,t} \quad \forall\, i,\ \forall dc$
- The total average network inventory (NAVI) is the total on-hand stock-level in the whole network across all distribution centres averaged over the time horizon of each simulation run and is given by, $\frac{1}{n \times T_H} \sum_{t=1}^{T_H} \sum_{dc} I_{n,t,dc} \ \forall\, i,\ \forall dc$

In addition to these performance measures, other measures are also identified to understand the improvements in disturbance management. Disturbance here means any unwanted deviation from expected. This may be demand deviating widely from forecasts or process plant breakdown or defective process outputs from the converting machines. Also there may be totally unexpected incidents not in immediate control of the supply chain network, such as terror attacks or strikes impairing important truck routes or natural hazards forcing shutdown of plants or RDCs. Several potential sources of disturbances in the current case are discussed before in section 5.2. Since, it is very difficult to get real data on process breakdown or defective process outputs (because of confidentiality requirements from the company), there is no way to explore such situations to judge the effectiveness of the different intelligent rules employed by the different agents under such situations. These will be dealt with in the next chapter, where I would design certain possible experimental scenarios with different events and would discuss the results of applying the agent based framework discussed in Chapter 4. So some other performance measures are required to ensure that the decision making rules or control procedures incorporated in Chapter 4 do not give rise to disturbances in exchange of enhanced customer service levels or reduced inventory levels or improved production efficiency. In this chapter, in order to compare the performances of the actual system with the modelled system, I have only used disturbances generated by huge deviation of real sales from forecasts, which result in changed ordering patterns by the different country RDCs on the central warehouse and create problems in production plans. Hence, some additional measures are needed to understand whether the framework with intelligent rules is effective in managing the disturbance and improving the resilience through adaptive interconnecting informational linkages. These measures are:

- Time (in days) taken to return to steady state after disturbances in the form of sudden spikes or falls in demand compared to the forecasts. The ideal response of the system would be the speed of reaction of the inventory levels at various stockpoints in the network to the new demand without falling below the safety level for a long time. This is determined by calculating the time the system takes to attend to a large drop in inventory (when inventory is below its target level and the drop is significantly large taken as 10%). This would help in identifying the agility of the systems (especially in next chapter, where use of different strategies are investigated) to detect and act to the faintest signal of huge disturbances.
- The average variation in replenishment orders. This is expressed by the bull-whip effect (calculated by the ratio of variance of weekly replenishment order to the variance of weekly customer demand). This would reflect the ability of the system to timely act to any disturbance without damaging the over-all performance. And this should be kept as low as possible.
- Number of emergency orders, which shows the ability of the supply network to react adequately to any disturbance.
- Number of stock outs through out the time of simulation. Risk of stock out should be kept low to highlight consistent customer service level and reduced vulnerability of the system.

5.6 Application of the Agent based model with improvements (described in Chapter 4.1.1, 4.1.2 and 4.1.3) – Different Settings

The outcomes (in the form of different performance measures discussed in 5.5) of applying the agent based framework are compared with the actual supply network's performance in the face of actual uncertain demand figures in 2004. The factory agent described in Chapter 4, section 4.1.3 represents the converting factory in Koblenz responsible for converting the basesheet reels into a variety of paper tissue rolls of various lengths, widths and diameter. The central warehouse agent (Chapter 4, section 4.1.2) represents the central store in figure 5.1, responsible for deploying all customer orders to markets directly served by central store in Germany and replenishment orders to RDCs serving different countries. The individual RDCs are represented by the distribution center agents (Chapter 4, section 4.1.1) with different product-market combinations and lead times. The settings of different parameters used in the improved model are first discussed.

5.6.1 Settings for applying the improved agent based model

First, the categories of the different products are decided on the basis of their total annual forecast. Products are assigned approximate cycle times for production. Although, Table 8 shows fixed cycle times for a number of products, the central warehouse agent uses these for estimation of the target stock levels (see eq. 18, Chapter 4). The actual cycle time over the year however is guided by actual sales and the intelligent rules of production discussed in previous chapter. So the actual cycle times are quite different from the approximate cycle times, which will be shown later when the results are presented.

Table 8: Approximate production Cycle Times from Historical Forecast Data

15 days for SKU Total Annual Forecast above 75000, ***Products X7, X10, X5, X1, X11***
30 days for SKU Total Annual Forecast 40000 to 75000, ***Products X12, X6, X13***
60 days for SKU Total Annual Forecast 20000 to 40000, ***Products X2, X8***
90 days for SKU Total Annual Forecast 20000 and below, ***Products X3, X4, X9***

The distribution centre agents while deciding on the ordering amount to avoid any unwanted disturbances arising out of uncertain demand make another categorisation of products based on their total annual forecasts. This is shown in Table 9. Based on this categorization, the learning parameters are chosen and altered. These categorizations both at the RDC and the central warehouse levels help in accumulating knowledge of the product life cycle. Each distribution centre agent also has the knowledge of the products, which are newly introduced around the year (for example, *X2* and *X6)* and which are sold in the market through out the year. So throughout the supply chain, these two products are estimated to start selling at various times of the year. From earlier discussion on the product types, it is seen that all the products except *X1, X10, X11* are introduced in 2004.

Table 9: Different Learning Parameters for different products in different RDCs

	Total Annual Forecast	*err*	*limit*	*learnRate*	*ex*	*ey*	*incRate*	*decRate*
Category 1 (Low selling)	>0 & <5000	3	*5*	*10*	*0.5*	*1*	*2*	*0.5*
Category 2 (Medium Selling)	<30000	3	*2*	*2.5*	*1*	*0.5*	*2*	*0.5*
Category 3 (High Selling)	>30000	1	*2*	*1*	*1*	*0.1*	*2*	*0.5*

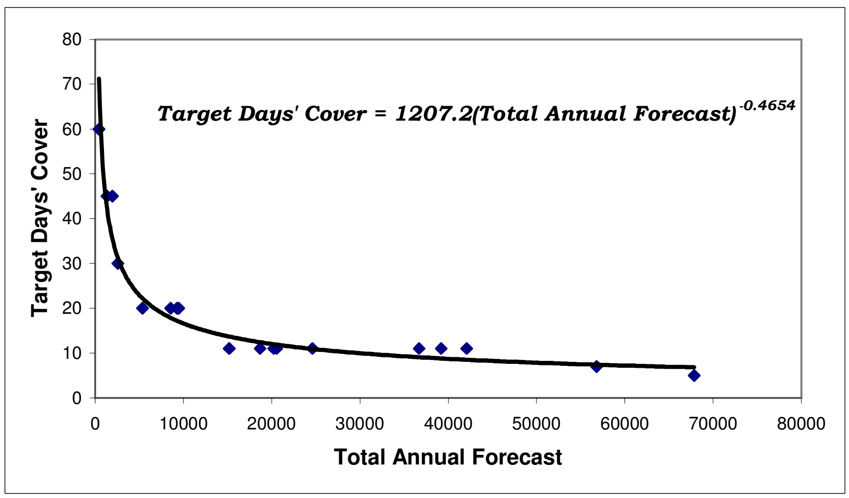
The above learning parameters and categories are hand-tweaked to arrive at the best possible results. Experiments with different parameters and the results are summarised in Chapter 6. The RDC agents are assumed to be more inclined towards lean and efficient operation and hence *satPeriod* is set at 5 for all the RDCs. Although the RDCs increase the target covers for high selling products as soon as the customer order exceeds the forecast value but in order to avoid large inventory build-up in these products, the period of continued increase is limited to 2 and also the *incRate* is increased by a smaller proportion in comparison to the low selling products.

The distribution centres assume a non-linear relationship between total annual forecast and the target days' cover. The best fit function $\phi(\,)$ (eq.14, chapter 4) is determined after running the simulation several times with different target days' cover for different products in different RDCs and noting the days' cover values that give the best customer service level. However, this is done to give the function a form, which can be used in any other supply network for any other demand patterns. The idea behind this is, products with low annual forecast will have higher target days' cover and products with very high forecast will have low target days' cover.

This is to ensure that the RDCs do not accumulate huge stocks of highly demanded products unless needed to. Also, this relationship avoids selecting arbitrary days' cover for different products. So each product will have its initial target days' cover, which is then varied to adjust to the real demand, basing on the different learning parameters given in Table9. Table 10 shows the different target days' cover used for different total annual forecast values for different products across different RDCs to achieve a target customer service level of 96%. These are used to determine the best-fit function. The best-fit function is also shown in the accompanying graph.

Table 10: Best-fit function determination

Total Annual Forecast	*Target Days' Cover*
24630	*11*
1941	*45*
9289	*20*
1326	*45*
67861	*5*
5356	*20*
15200	*11*
437	*60*
36704	*11*
8570	*20*
20219	*11*
18696	*11*
42068	*11*
15194	*11*
9463	*20*
56800	*7*
2561	*30*
39209	*11*
20552	*11*



The factory agent is modelled as risk-averse with the values of *c, c1, k1* set at 0,0 and 4 respectively. Three different least production times are set based on the categories of products, described in Table 8 (Approximate production cycle time = 15, 30 and greater than 30). Initially all these are set at 1 and each time a product in one category is produced this time is incremented by a fixed value of 0.05 (days) and the least production times for other product categories are decreased by a fixed value of 0.01 (days). Again these parameters are all hand-tweaked to provide the best possible performance in terms of increased production run-length and improved customer service throughout the network. Also the factory is assumed to consider both global and local information to decide which product to produce when and for how long. Everyday the factory agent does the production planning autonomously after receiving daily information on sales, forecast and stock levels from different members of the supply network.

5.7 Results & Discussions

The agent based simulation model is run for one full year and its performance is compared with respect to same set of performance measures obtained from the actual system during that period for the same set of demand data. The same set of assumptions used to model the baseline case for validations holds for this model also. The improvements obtained in the performance measures in each product in each RDC and the central warehouse are shown in Tables 10a and b. It can be seen that, in all the products, the agent based computational framework has been able to improve upon the actual performance with reduced average network inventory level and improved customer service levels. Most importantly, for the products X3, X4, X8, X9 demanded in single markets the agent in the model has pushed the materials fully to the country RDCs rather than keeping them in Koblenz, where there is no demand. This has not only improved CSL but also reduced the overall average network inventory level for these products. As can be seen for products X3 and X4, in the real case, central warehouse actual average stock level is higher than the RDC stock level. This is particularly prone to disruption if there are sudden spikes in demand in the country markets. So in the model, to improve resilience, materials not directly sold from the central warehouse are pushed to the markets as soon as they are produced. This would not only make the system more resilient to uncertain demand but would also reduce the number of times these materials are produced because in this configuration, the factory will consider the entire network inventory position rather than just the central warehouse stock position for making decision to produce. So these products are produced on a pull basis and just when the RDCs need them.

This will enable the factory to produce highly demanded materials for longer time and reduce the number of costly machine set-ups (from 120 to 80). The total changeover time (CO) is found to be 9.5 days, which is less than the actual 11.3 days. The intelligent decision rules used by the agents definitely provide improved operational resilience in terms of the network-wide performance measures. It is also observed that, the overall customer service level for all the RDCs for all products are 100% except the product X7 in the UK RDC. In no case is the service level performance in the real case better than the modelled performance output. Though the stock levels are higher for one or two products compared to the real case, the overall average network inventory is reduced.

Table 10a: Actual and Modelled Stock and Customer Service Levels

	Actual Stock	Actual CSL	Model Stock	Model CSL
Product Code X2				
Central Warehouse	5176	100%	4327	100%
France	311	100%	200	100%
NAVI	5487		4527	
Product Code X3				
Niederbipp	810	100%	1272	100%
Central Warehouse	1583		80	
NAVI	2393		1352	
Product Code X4				
Niederbipp	151	100%	846	100%
Central Warehouse	719		17	
NAVI	870		863	
Product Code X5				
Italy	3321	100.0%	1036	100%
France	656	99.8%	601	100%
Britain	625	100.0%	631	100%
Central Warehouse	15315	100.0%	17738	100%
Niederbipp	249	100.0%	369	100%
NAVI	20166		20375	
Product Code X6				
Britain	625	100.0%	776	100%
Arceniega	269	95.8%	544	100%
France	215	100.0%	351	100%
Central Warehouse	8753	100.0%	6124	100%
NAVI	9862		7795	
Product Code X7				
Britain	3369	98.3%	1146	98.3%
France	1879	99.0%	1954	100.0%
Central Warehouse	30103	100.0%	25794	100.0%
Italy	3717	100.0%	1022	100.0%
Niederbipp	299	100.0%	364	100.0%
Arceniega	221	94.3%	599	100.0%
NAVI	39588		30879	

Table 10b: Actual and Modelled Stock and Customer Service Levels

Product Code X8				
Ede	2061	100.0%	2404	100.0%
Central Warehouse	727		116	
NAVI	2788		2520	
Product Code X9				
Ede	1327	96.6%	2763	100.0%
Central Warehouse	1030		861	
NAVI	2357		3624	
Product Code X11				
Central Warehouse	13841	100.0%	16260	100%
Britain	621	100.0%	351	100%
France	953	99.5%	930	100%
Italy	6802	100.0%	1624	100%
Niederbipp	547	97.6%	736	100%
Arceniega	199	84.0%	532	100%
NAVI	22963		20433	
Product Code X10				
Central Warehouse	12034	98.9%	16218	100%
Britain	5921	100.0%	1134	100%
France	493	99.7%	433	100%
Niederbipp	72	100.0%	148	100%
Arceniega	119	71.0%	332	100%
NAVI	18639		18265	
Product Code X12				
Central Warehouse	4662	95.7%	8458	100.0%
France	100	98.9%	172	100.0%
Britain	440	92.2%	725	100.0%
Niederbipp	55	100.0%	191	100.0%
Arceniega	235	88.8%	436	100.0%
NAVI	5492		9982	

Table 10c: Actual and Modelled Stock and Customer Service levels

	Actual	Modelled
Over-all NAVI	130605	120615
Over-all CSL	97.57%	99.95%

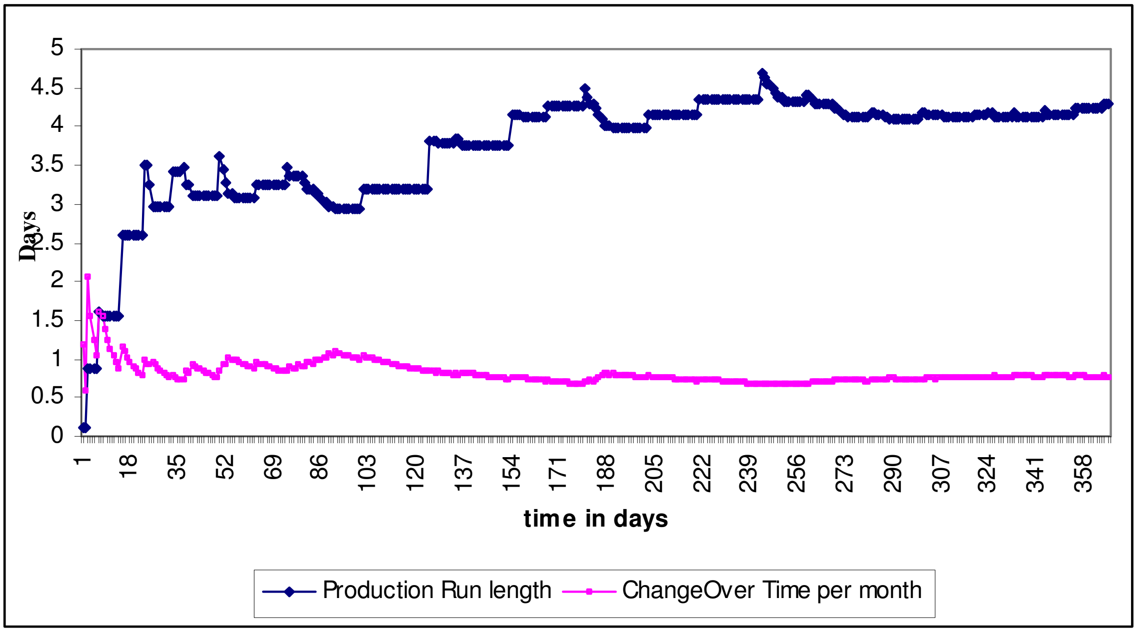


Figure 5.13: Variation of Modelled Change-Over time per month (actual change-over time per day projected over a month) and average run-length with time

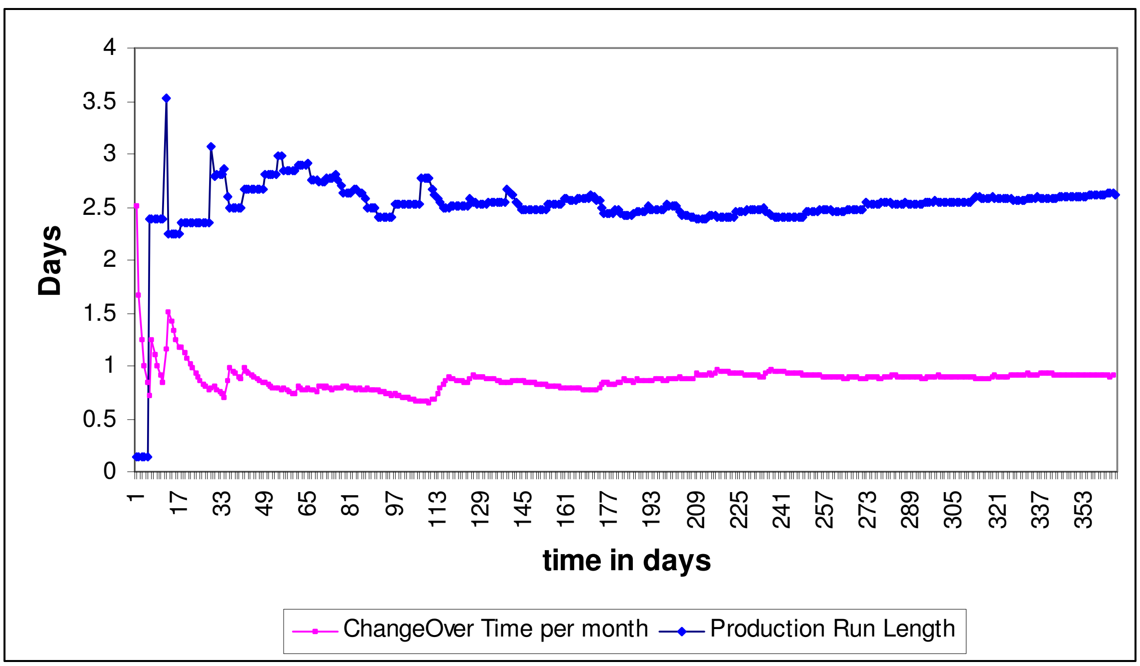


Figure 5.14: Variation of Actual Change-Over time per month (actual change-over time per day projected over a month) and average run-length with time

At the very start of the model, when central warehouse stock levels are low, the products are produced for very small runs, resulting in large changeover times per month (rising up to 2 days per month at times as shown in figure 5.13). After the product stock levels reach their maximum limits, production is carried out in such a way that the number of changeovers gets reduced (to less than 1 per month) and run-lengths get increased (from near zero to 4.5 days). At times, the products are produced for quite long spells and since the factory adjusts the scheduling based on real time inventory, sales and forecast information across the network the run length changes throughout the year modelled. This gives rise to a flexible and integrated production-distribution system capable of responding to changes in time. On the other hand, Figure 5.14 shows the variation of average production run-length and the changeover time per month in the actual factory. As can be seen, the average production run-length (instead of increasing with time as in the model) starts decreasing and the total changeover time goes on increasing with time (instead of decreasing). This reduces the production efficiency and the total number of changeovers increase.

The impact of implementing the agent based simulation modelling framework on the over-all network CSL and NAVI is summarised in Table 10c. Both the performance measures have improved. At the same time, the productivity in terms of average run length also increased over the year (4.3 days as opposed to actual of 2.4 days) thus signifying more utilisation of capacity and more productive days. In order to understand how the agent based framework manages disturbance to improve the performance with respect to the real system, I will now present the performance of the system in more details.

First, the performance of the system after applying the above agent based framework is discussed at the RDC level. For each product, the performance of the modelled system is compared with that of the actual under disturbances in the form of huge demand spikes. First the performance of the three major RDCs, Italy, France and UK are analysed. The ability to successfully manage disturbance is evident in the number of days required for the inventory level to reach a steady state signifying normal operation without any risk of being out of stock after a huge dip in inventory level. The number of emergency or large orders generated due to huge mismatches between demand and forecast depicts the disturbance caused by the resilience enhancing strategies adopted by the RDCs. The variation of replenishment order volumes, measured by the bullwhip effects, compares the disturbance managing capability of the designed system with respect to the actual system. The maximum and minimum stock levels actually describe the "latent pathogens" (Chapter 2) of the system. These signify cases where the stock-out might have been avoided but the stock level either dipped to a minimum point, which can be vulnerable to any uncertain spikes, or the stock level rose to a very high level when actually the demand might have died down. Finally the production performances are compared with respect to number of changeovers or set-ups.

5.7.1 UK RDC

X7: Figure 5.15 shows the UK RDC's performance for product X7. Both the modelled and actual systems suffer stock-outs. The initial stock level is zero for both the cases and since the transportation lead-time is six days, so any demand occurring during that period is backlogged and results in stock-out in UK RDC. The circle on the X-axis on the top-right hand graph shows the stock-out zone in both cases. The fixed forecasted demand is shown by the bold continuous line running across the entire period in the top right hand graph showing actual and modelled stock variation with time. Most of the time the real demand exceeds the forecast.

After stock out, the model builds on stock to avoid any further risks of stock-outs keeping in view the rising mismatches between demand and forecast. But in actual case, the replenishment orders are not properly generated by the RDCs after the first stock out and the inventory level dips to another near stock-out point within 20 days. So the reaction time to the disturbance is 29 days in actual case as compared to only 6 days for the modelled system. Although in the actual case, the reaction time is very large, but the RDC over-reacts at later stage whenever a huge forecast error occurs. This results in 6 large orders in comparison to 4 in the model. This has impact in system wide disturbance resulting in faster deterioration of central warehouse stock in X7, forcing frequent production and hence frequent changeovers thus reducing production efficiency.

Product X7	Actual	Modelled
Average Inventory	***2731***	***1146***
Average CSL	***98.3%***	***98.3%***
Number of Stock-out situations	***1***	***1***
Number of Emergency or Large Orders	***6***	***4***
Average weekly Bullwhip-effect*	***8.29***	***4.87***
Time taken for inventory to return to normal	***29 days***	***6 days***
Maximum Stock Level	***4146***	***4803***
Minimum Stock Level *(without stock-out)*	***0*** *170*	***0*** *365*

*Bullwhip Effect = Variance of weekly Replenishment Order / Variance of actual weekly demand

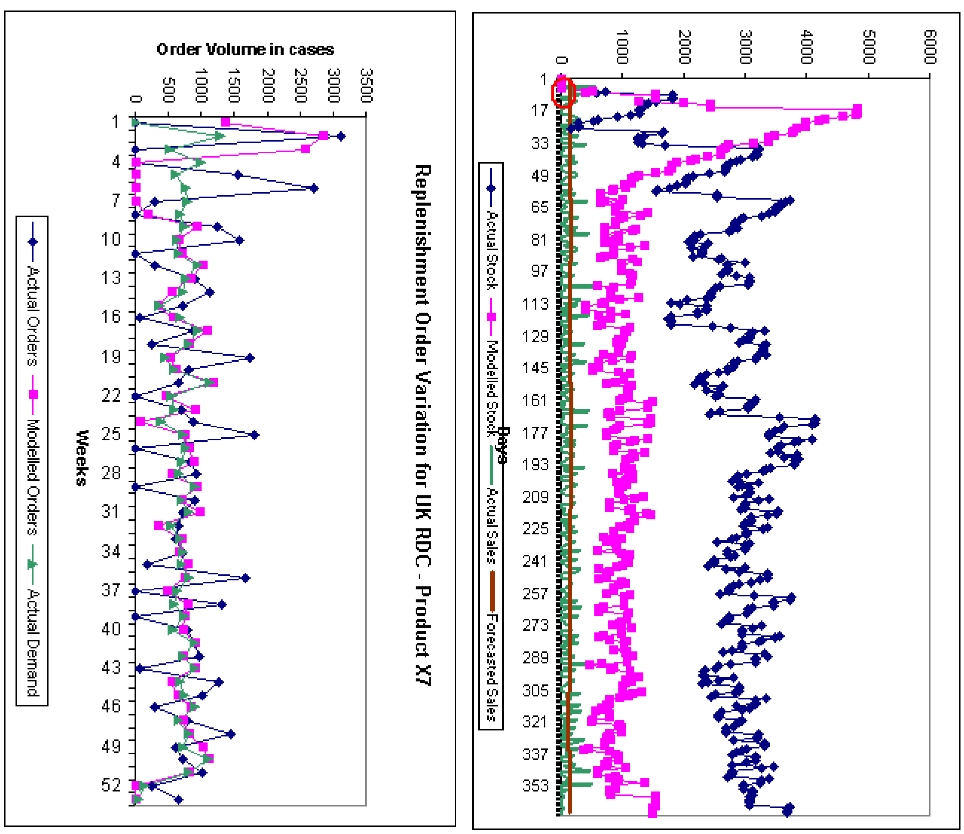


Figure 5.15: Modelled and actual system performance for UK RDC for product X7

Naturally this raises the weekly bullwhip effect (8.29), which is much less (4.87) for the model in spite of initial large orders placed. Although the maximum stock level in the model is higher than the actual case, the lower minimum stock level in actual case shows the vulnerability to higher demand-forecast mismatch and imminent risk of stock outs. The bottom right hand graph shows the weekly actual and model replenishment orders along with the real demand. Apart from the initial emergency orders, the model follows the actual demand pattern almost exactly, whereas the orders placed in reality are of much larger amplitude in comparison to the weekly demand volumes.

X10: UK is the largest market for this product and so in actual case, the distribution centre orders as much as possible without any consideration for huge inventory increase. But this results in huge inventory accumulation in UK RDC for the real case, as shown in figure 5.16 and the accompanying maximum and minimum stock figures (10603 and 2204 respectively). In the model, the distribution centre agent aims more towards achieving greater efficiency by having lower inventory but higher customer service level. So, although the modelled case achieves lower average inventory (1134 in comparison to 5921) and 100% customer service level, yet the inventory drops to very low values (minimum 258) which is prone to stock outs in case excessive demand occurs. The performance for higher demand will be tested in next chapter. Although, the model depicts a risky inventory profile in *X10,* the reaction to disturbance is very fast (only 3 days). The slightest positive deviation of demand from forecast results in huge accumulation of inventory in real case (sometimes the inventory level rises to around 100 times the actual sales per day). Thus the inventory never returns to normal after any disturbance in the form of uncertain demand in the real case. This is depicted in the lower right hand side graph showing the weekly replenishment order pattern in comparison to actual weekly demand variation. The actual replenishment orders register more peaks and huge deviations from the actual demand pattern thus resulting in large average weekly bullwhip effect (12.93).

X11: The demand for this product in UK market is very low but is characterized by occasional spikes in demands (average forecasted daily demand is only 7, whereas on the 106^{th} day, a customer order of 216 units is faced by the RDC, shown in Fig. 5.17). The

RDC can take totally risk-averse attitude and build on stock for such one-off uncertain spiky demands or they can adapt their replenishment ordering patterns to just meet such spikes otherwise maintaining average inventory to satisfy the normal orders. The ordering rule used by the RDC agents in the model does the latter and that is reflected in the inventory behaviour. The model RDC's stock level drops to a minimum of 16 on the 106th day unlike the actual RDC's stock pattern (which attains a maximum of 1201 at one time). But the agent in the model with the knowledge of very low total annual demand of the product does not build stock in anticipation of any more of such spikes. The agent in the model sets a parameter (*err)* for deciding to increase order-size when the order exceeds the forecast. In case of such one-off spiky orders, the order-size does not increase considerably. However, the parameter can be adjusted by the RDC based on its attitude towards risk (discussed before in Chapter 4). After the stock-out the real system generates huge replenishment order due to over-reaction to the disturbance but the weekly replenishment orders of the modelled system follows the weekly actual demand pattern closely after the disturbance. This is reflected in the low bull-whip effect of 2.23 in comparison to 4.73 in actual case.

X12*:* The actual system here suffers from severe service level issues satisfying only 92.2% of all customer demands due to massive stock outs at the very beginning of the year. After that, the UK RDC could not recover from the disturbance for 150 days and 3 stock-out situations arise (as shown by the three circles on the top right hand side graph of fig.5.18). The modeled system through adaptive adjustment of ordering mechanism restores stability in 3 days inspite of inventory dropping to 26 on the 91st day. Most importantly, there are no stockout situations in the model and only one emergency order after the stock drops to 26. On the other hand, the management of disturbances is sluggish in real case and in fact, at times, the RDC is found to over-react to any near stock-out situation and over-orders resulting in raising the maximum inventory to 1517 and bullwhip effect to 3.46 in comparison to the maximum inventory of 1214 and bull-whip of 1.45 for the model respectively.

Product X10

	Actual	Modelled
Average Inventory	*5921*	*1134*
Average CSL	*100.0%*	*100.0%*
Number of Stock-out situations	*0*	*0*
Number of Emergency or Large Orders	*1*	*0*
*Average weekly Bullwhip-effect**	*12.93*	*3.58*
Time taken for inventory to return to normal	*infinity*	*3 days*
Maximum Stock Level	*10603*	*3889*
Minimum Stock Level	*2204*	*258*

*Bullwhip Effect =
Variance of weekly Replenishment Order /
Variance of actual weekly demand

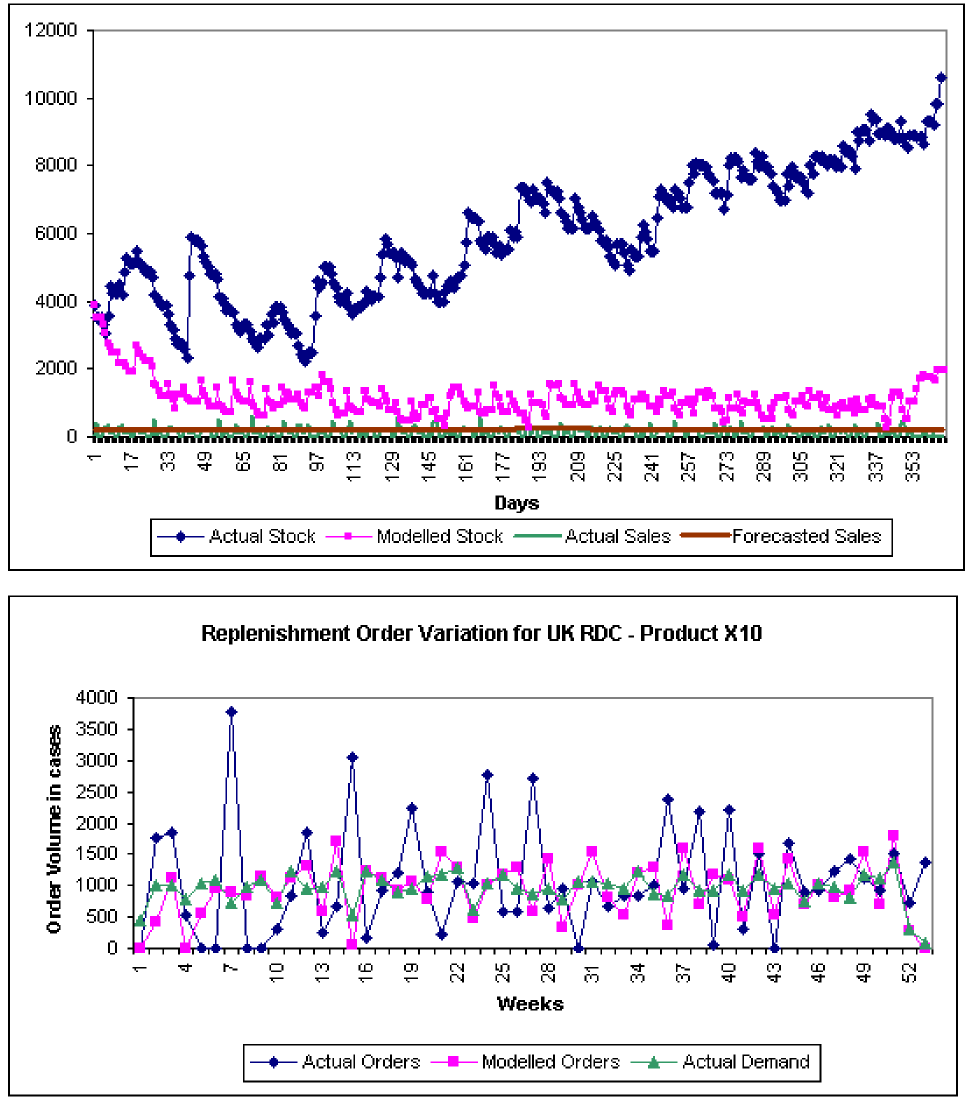


Figure 5.16: Performance of modelled and actual system for UK RDC for product X10

X6: The higher average inventory for the modelled system is due to the stock sitting at the RDC for a long time. This is because of the forecasted sales during the second month although there are no actual sales. In the actual system, the stock is accumulated just before actual sales occur. This is a very risky way of operating RDCs. If there have been sales during the period when they are forecasted, stock out situations would have arisen. In the actual case, although stock build-up occurs late but when there are forecasts later, the RDC over-reacts and over-orders materials. This lack of consistency in generating orders results in large bullwhip effects (4.51) in comparison to the modelled system (2.43). Also the stock level rises to its maximum of 1695 in the actual case, when there is practically no demand. The maximum stock level for the modelled system is 1295, in response to a spike in demand. The response time for the inventory level to recover from a disturbance is 3 days in both the cases. Although the minimum inventory for the model is 90, but it is actually at the time when the RDC is stocking materials for forecasted sales at the start. From the inventory pattern (Fig.5.19), there are no signs of risk in the modelled system as it accumulates stocks in the right amount when they are needed (in the form of forecasted sales).

X5: The agent based model improves all aspects of disturbance management ability of the RDC in this product. The model achieves 100% CSL with lower average inventory (fig. 5.20). The modelled system reduces the bullwhip effect from 4.28 to 1.84 by generating replenishment orders following the actual weekly demand pattern more closely. The maximum inventory level is reduced. Although the minimum inventory level in the model is less than the actual case, but the response time to the disturbance is 4 days as compared to 7 days in actual case.

So in UK RDC, for all products with different demand patterns, the intelligent decision making framework employed by the RDC agent improves the over-all resilience of the entire UK RDC in terms of improving the CSL with lower average inventory [where resilience is defined as maintaining control over performance variability in the face of disturbances in the form of huge demand-forecast mismatches (both cases when forecasts are more or less than the actual demand)]. We have seen that for products *X12* and *X10* the actual system goes out of control while responding to disturbances.

Product X11	***Actual***	***Modelled***
Average Inventory	***621***	***352***
Average CSL	***100.0%***	***100.0%***
Number of Stock-out situations	***0***	***0***
Number of Emergency / Large Orders	***1***	***0***
Average weekly Bullwhip-effect*	***4.74***	***2.23***
Time taken for inventory to return to normal	***6 days***	***6 days***
Maximum Stock Level	***1201***	***597***
Minimum Stock Level	***99***	***16***

*Bullwhip Effect = Variance of weekly Replenishment Order / Variance of actual weekly demand

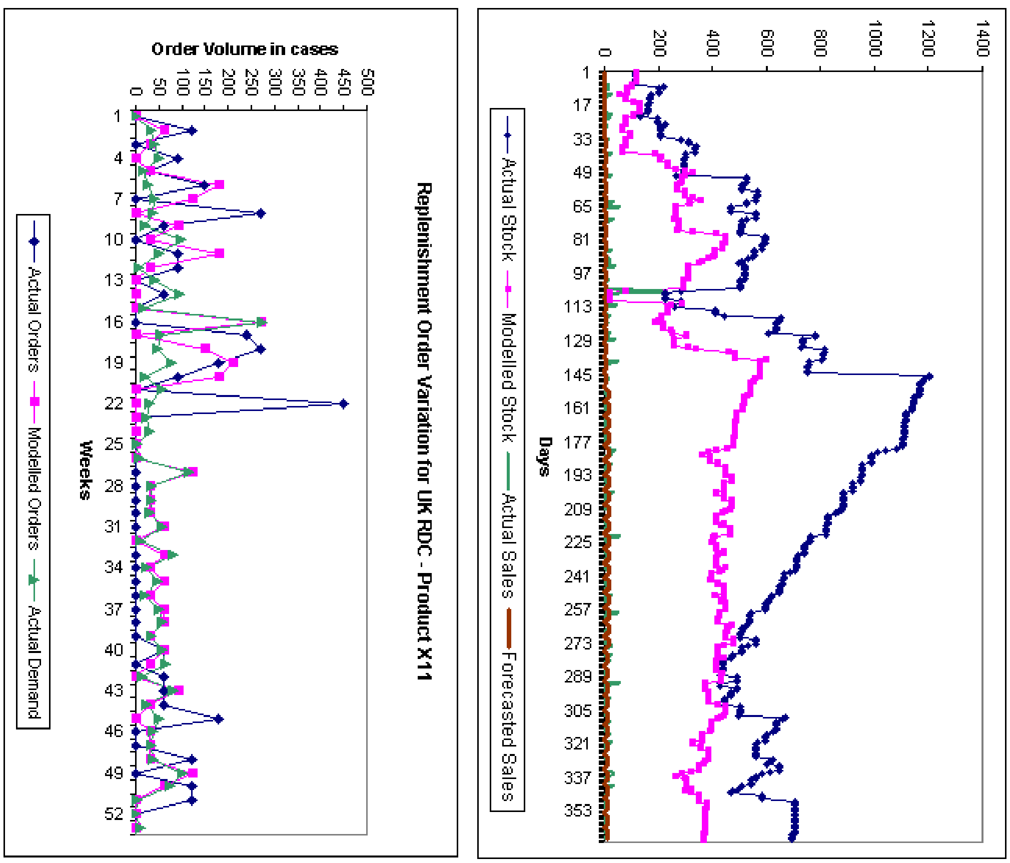


Figure 5.17: Performance of modelled and actual system for UK RDC for product X11

Product X12

	Actual	Modelled
Average Inventory	***530***	***725***
Average CSL	***92.2%***	***100.0%***
Number of Stock-out situations	***3***	***0***
Number of Emergency / Large Orders	***5***	***1***
Average weekly Bullwhip-effect*	***3.46***	***1.45***
Time taken for inventory to return to normal	***150 days***	***3 days***
Maximum Stock Level	***1517***	***1214***
Minimum Stock Level	***0***	***26***

*Bullwhip Effect =
Variance of weekly Replenishment Order /
Variance of actual weekly demand

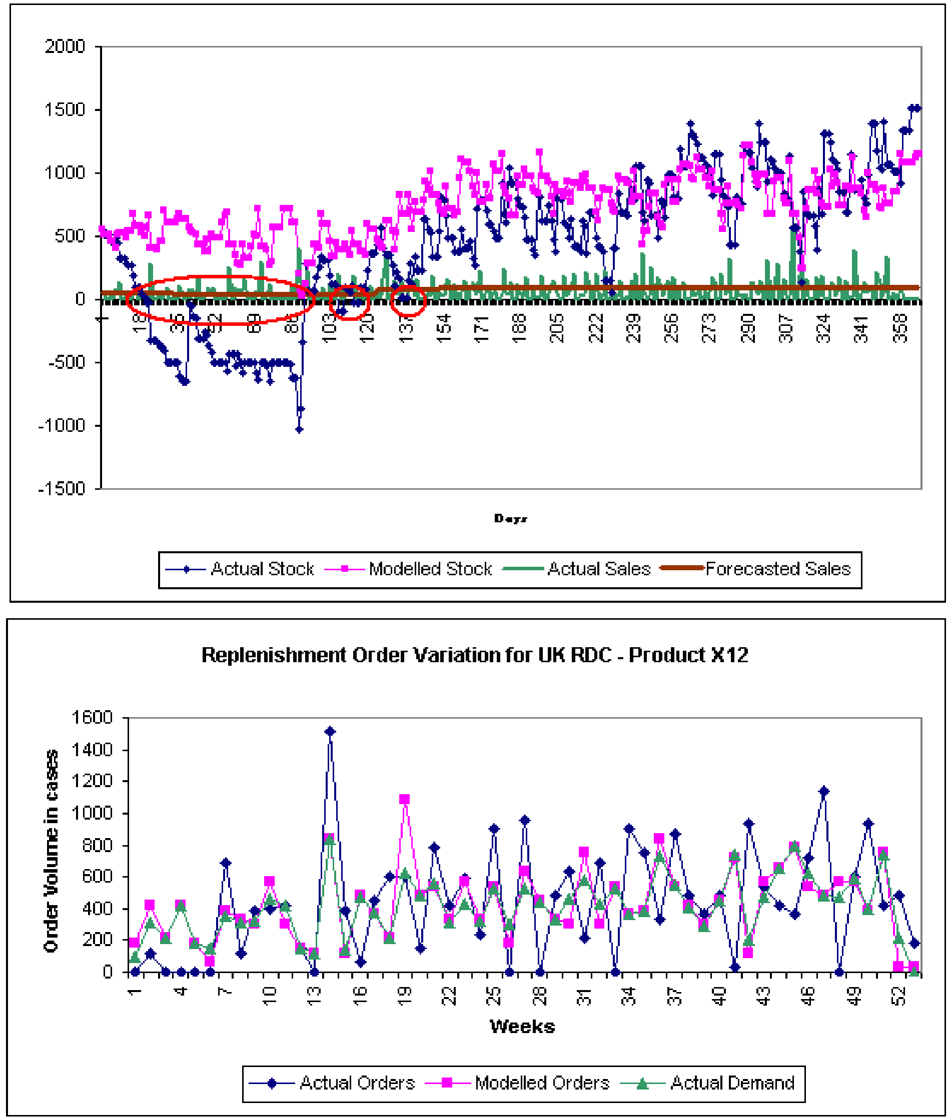
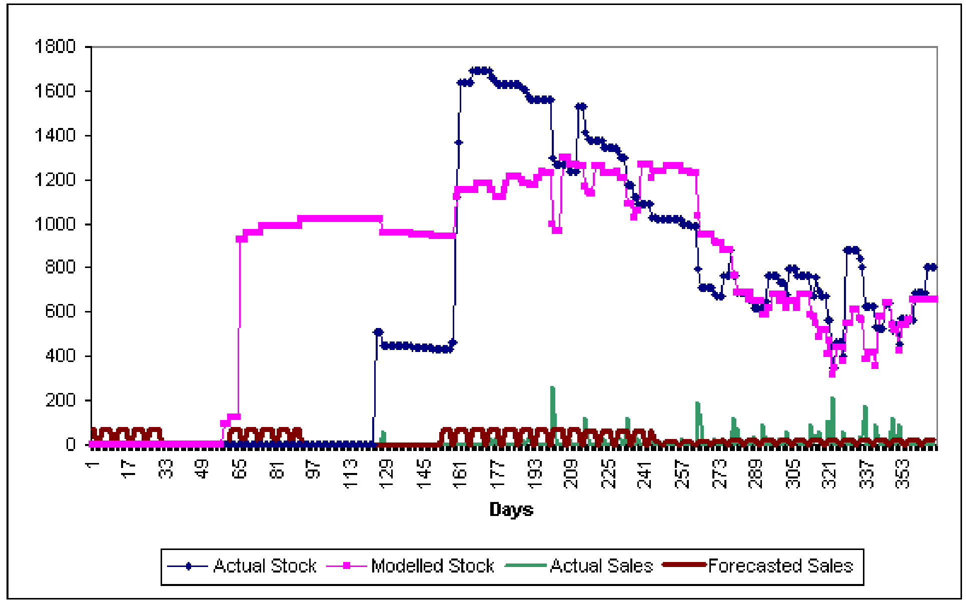


Figure 5.18: Performance of modelled and actual system for UK RDC for product *X12*

Product X6

	Actual	Modelled
Average Inventory	***625***	***775***
Average CSL	***100.0%***	***100.0%***
Number of Stock-out situations	***0***	***0***
Number of Emergency / Large Orders	***1***	***1***
Average weekly Bullwhip-effect*	***4.51***	***2.43***
Time taken for inventory to return to normal	***3 days***	***3 days***
Maximum Stock Level	***1694***	***1295***
Minimum Stock Level	***347***	***90***

*Bullwhip Effect =
Variance of weekly Replenishment Order /
Variance of actual weekly demand



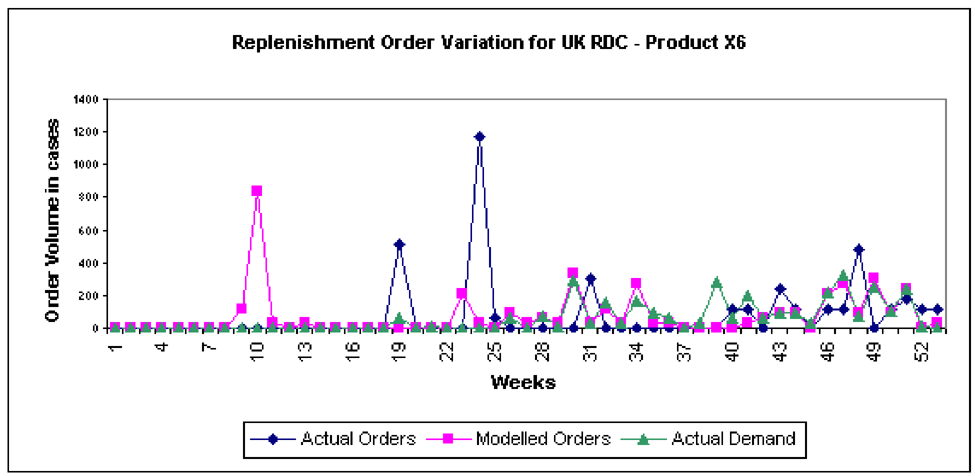
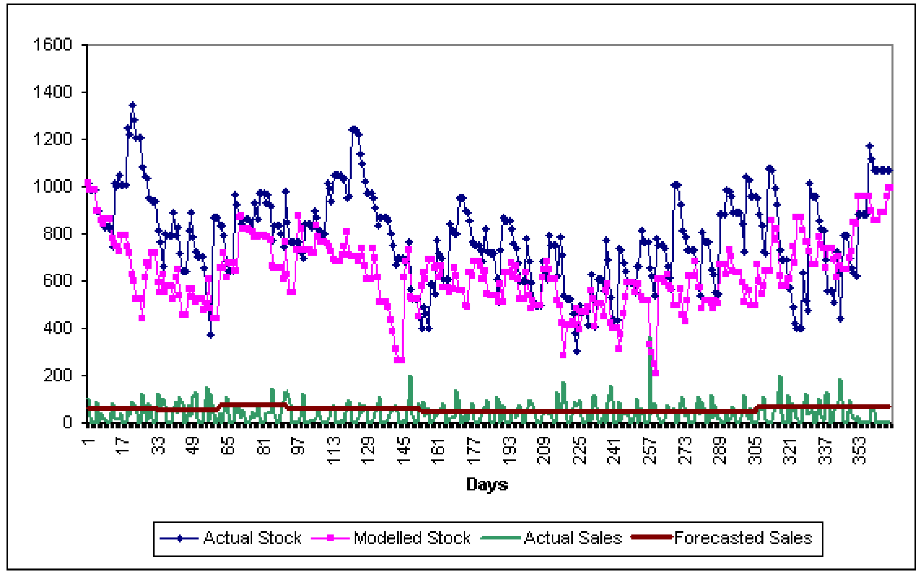


Figure 5.19: Performance of modelled and actual system for UK RDC for product *X6*

Product X5

	Actual	*Modelled*
Average Inventory	***784***	***631***
Average CSL	***100.0%***	***100.0%***
Number of Stock-out situations	***0***	***0***
Number of Emergency / Large Orders	***0***	***0***
Average weekly Bullwhip-effect*	***4.28***	***1.84***
Time taken for inventory to return to normal	***7 days***	***3 days***
Maximum Stock Level	***1348***	***1015***
Minimum Stock Level	***304***	***206***

*Bullwhip Effect =
Variance of weekly Replenishment Order /
Variance of actual weekly demand



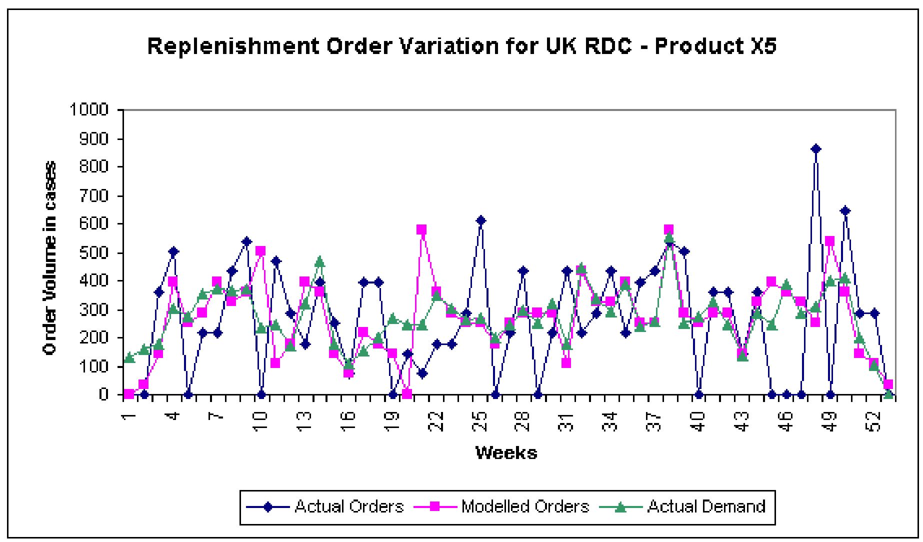


Figure 5.20: Performance of modelled and actual system for UK RDC for product *X5*

5.7.2 Italy RDC

X5: The actual inventory level for this product never really attains a steady state after the first demand spike (fig.5.21). It actually keeps on increasing to a maximum of 4365 and oscillates around the 3000-4000 levels throughout the entire year. This results in higher weekly bullwhip effects (2.96) in comparison to the model (1.83). This is also reflected in the weekly replenishment order patterns compared to the actual weekly demand patterns for both actual and modeled case. Again as before, the RDC agent here focuses on efficient operation through inventory minimization and so the RDC achieves 100% CSL with a very low average inventory. But the inventory at times drops to precarious positions of 224 only making it vulnerable to high demands. But the fast response of the model to any disturbance almost nullifies this risk.

X7: Exactly similar uncontrolled situation arises for this product as well (fig. 5.22). The inventory keeps on rising, although demand remains quite flat except for few occasional peaks. The model however maintains the inventory at an average level of 1022 without a single stockout situation as opposed to the average actual inventory level of 3717. However, the model's inventory level drops to a minimum of 127. But Italy RDC agent in the model never allows the inventory to rise to uncontrollable levels (a maximum of 5771 attained in the actual case) and maintains it within a manageable limit. The maximum inventory attained in the model is 1563. The weekly bullwhip effect also gets reduced in the model from 2.11 to 1.86.

X12: This is another example, where the real system could not control the inventory after any disturbance. The demand is again characterized by less frequent spikes and so the RDC in actual case adopts a safe procedure to manage this occasional disturbance by accumulating huge volume of stock (fig. 5.23). This is a costly proposition in today's competitive world. Although in the case, the paper tissues are low value products, so huge stock accumulation may not affect the costs much in comparison to customer service issues. But in case of costly products (e.g., electronic goods), this may not be a feasible strategy. In the model, the agent maintains a controllable level of inventory with only 2 large volume orders in comparison to 3 such orders for the actual case. The higher bullwhip effect (5.24), huge maximum inventory (12587) accounts for instability in the inventory control procedure in response to uncertain spikes in demand in this product.

Product X5	Actual	Modelled
Average Inventory	3323	1036
Average CSL	100.0%	100.0%
Number of Stock-out situations	0	0
Number of Emergency / Large Orders	1	0
Average weekly Bullwhip-effect*	2.96	1.83
Time taken for inventory to return to normal	infinite	3 days
Maximum Stock Level	4365	2243
Minimum Stock Level	1774	224

*Bullwhip Effect =
Variance of weekly Replenishment Order /
Variance of actual weekly demand

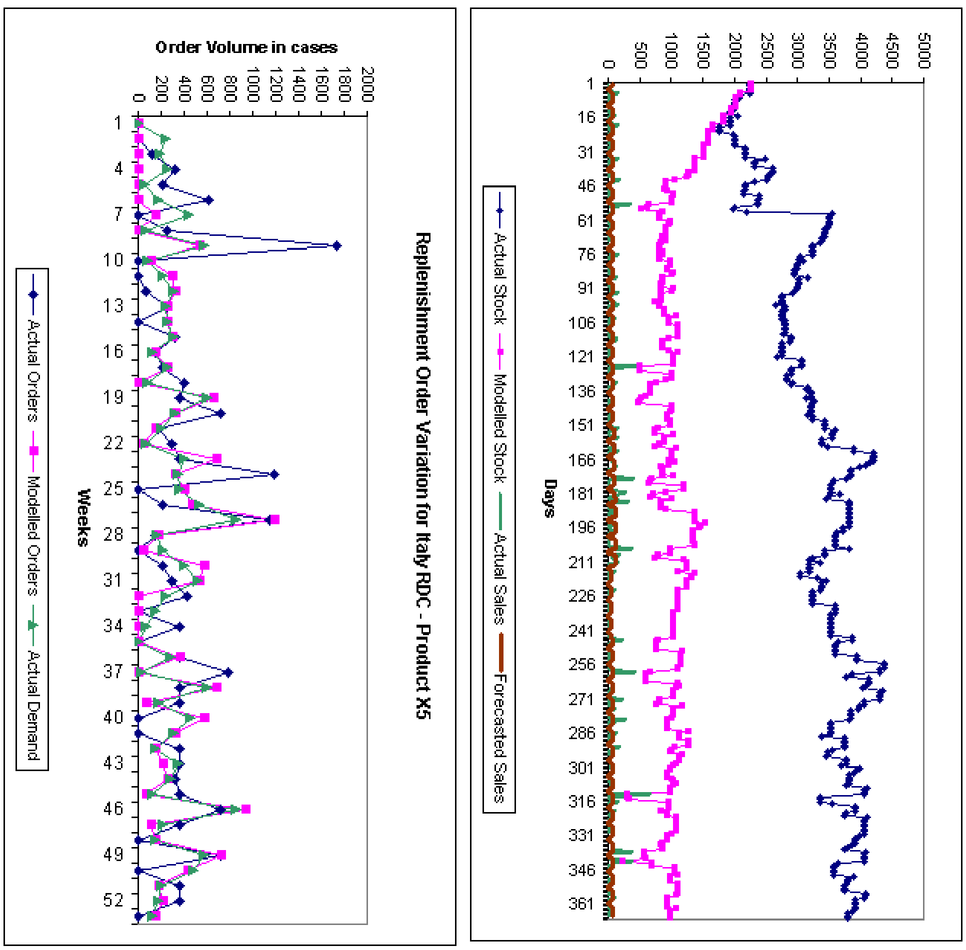
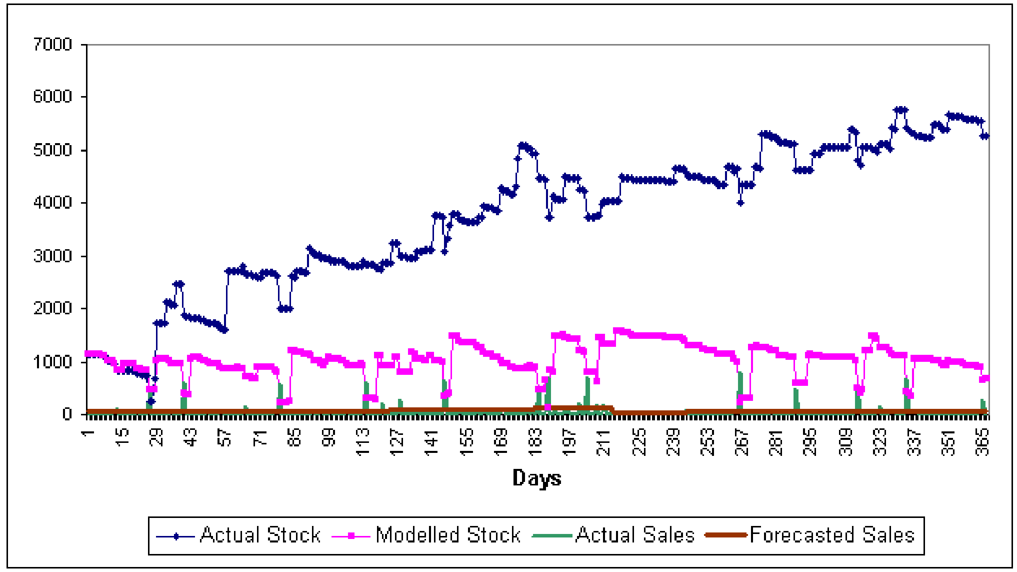


Figure 5.21: Italy RDC performance comparison for product *X5*

Product X7

	Actual	Modelled
Average Inventory	*3717*	*1022*
Average CSL	*100.0%*	*100.0%*
Number of Stock-out situations	*0*	*0*
Number of Emergency / Large Orders	*1*	*0*
Average weekly Bullwhip-effect*	*2.11*	*1.86*
Time taken for inventory to return to normal	*infinite*	*5 days*
Maximum Stock Level	*5771*	*1563*
Minimum Stock Level	*253*	*127*

*Bullwhip Effect =
Variance of weekly Replenishment Order /
Variance of actual weekly demand



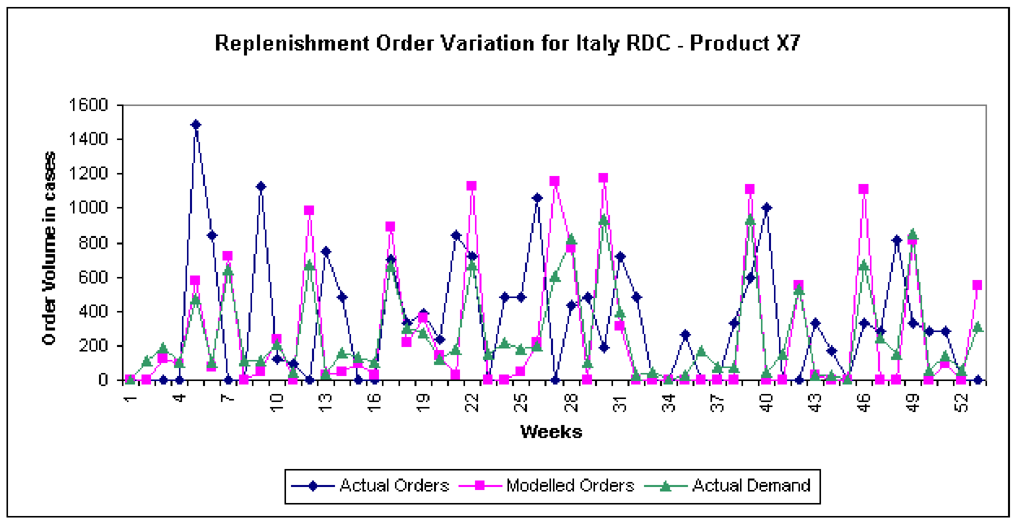
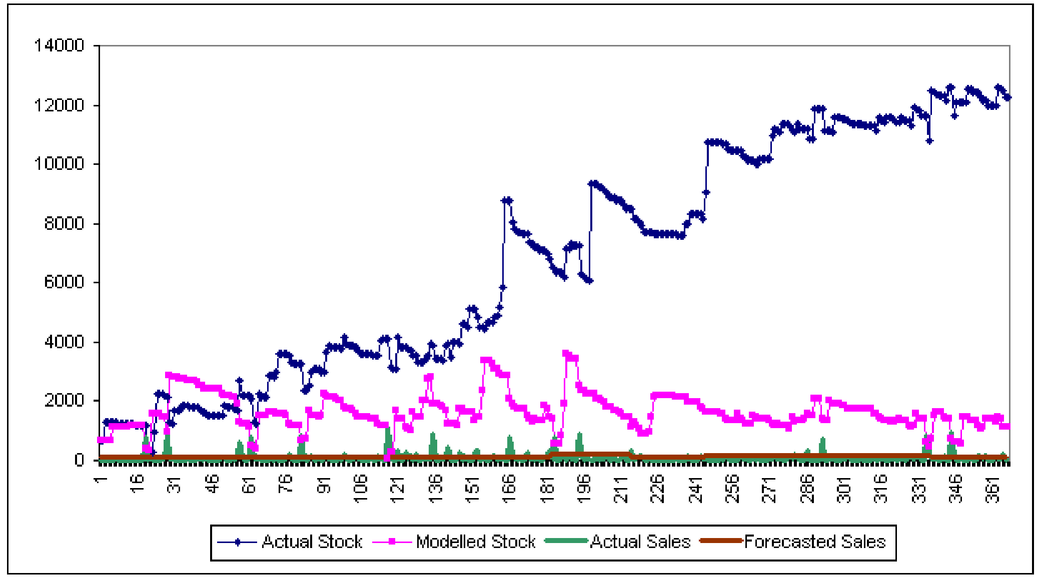


Figure 5.22: Italy RDC performance comparison for product *X7*

Product X11

	Actual	Modelled
Average Inventory	*6802*	*1624*
Average CSL	*100.0%*	*100.0%*
Number of Stock-out situations	*0*	*0*
Number of Emergency / Large Orders	*3*	*2*
Average weekly Bullwhip-effect*	*5.24*	*3.99*
Time taken for inventory to return to normal	*infinite*	*3 days*
Maximum Stock Level	*12587*	*3571*
Minimum Stock Level	*282*	*84*

*Bullwhip Effect =
Variance of weekly Replenishment Order /
Variance of actual weekly demand



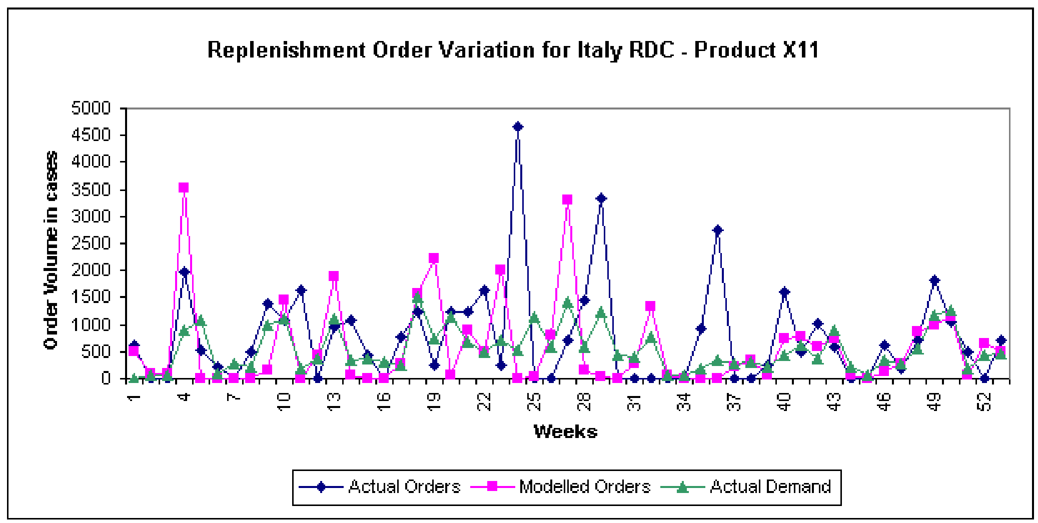


Figure 5.23: Italy RDC performance comparison for product *X12*

So, in Italy RDC also, the agent based framework application improves the resilience through better management of disturbances.

5.7.3 France RDC

X2: This product is introduced in the French market in the middle of the year. But since the product is produced at the factory during the second month, a little amount is stocked at the RDC. This accounts for the small amount of stock held in the modelled RDC. The RDC satisfies 100% of all demands with less average stock level in comparison to the actual RDC (200 as opposed to 311). At the end of the year, the actual system stocks a large amount of *X2* in France RDC in response to slight disturbance (raising the maximum stock level to 1344). The modelled system puts a check on the maximum stock accumulation but responds to disturbances at the same pace as the real system (Figure 5.24).

X5: Fig. 5.25 shows another example of the inability of the RDC to manage disturbances. Inspite of the actual average and maximum inventory (656 and 1208) is higher than the modelled values (601 and 1007), the actual RDC suffers one stockout which takes 4 days to respond and the inventory drops to near stockout situation within 2 days. The RDC agent in the model faces no stockouts and responds swiftly without generating very large emergency orders (low bullwhip of 1.23 only).

X6: The model achieves 100% CSL with higher average inventory because of carrying inventory from the moment it is available at the central warehouse. However, the maximum inventory and the bullwhip effects are considerably less than the actual case (Figure 5.26).

X7: Fig. 5.27 depicts the forecast and the actual sales and it can be seen that the actual sales exceeds the forecast by very small amount. The actual stock level in the RDC could not even cope with such small amount of variation of actual sales from the forecast and results in 3 stock out situations. The negative value of actual inventory indicates the amount of backlogged sales during this period. Also it can be seen that when not needed, the actual inventory rises to a maximum level of 3917 on the 315th day of the year. The inventory level for the RDC in the model stays comparatively stable and oscillates between a maximum of 2736 and minimum of 1058 units. The model also reduces the bullwhip effect of replenishment order generation.

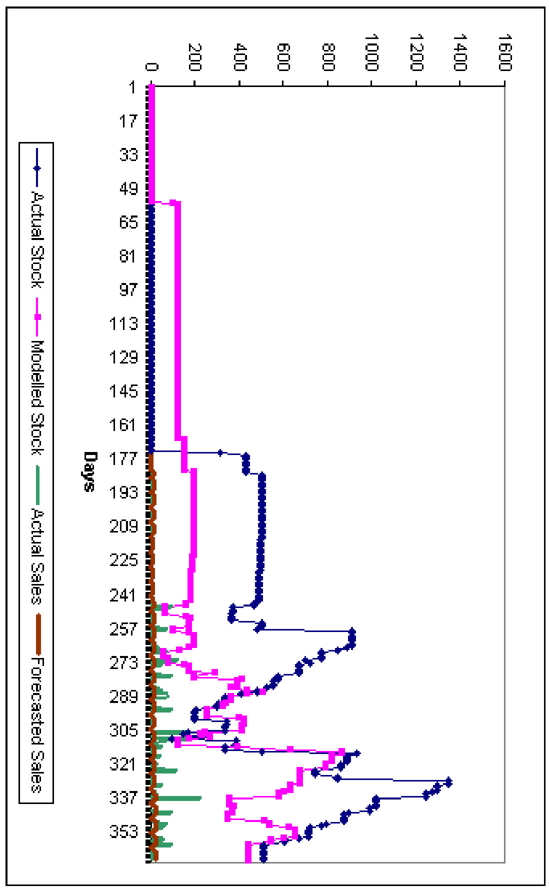
X10: The demand pattern and forecast of this product (Fig. 5.28) shows that the fixed forecast per day is wrong in most of the instances and the actual demand exceeds the forecast in most of the cases, which creates huge instability in the actual inventory pattern resulting in 2 stockouts, disproportionate response in terms of huge orders when actually demand is less (high bullwhip of 3.21, increased maximum stock level of 1229, increased time of 8 days for the inventory to return to normal level after stockout). The modelled stock level maintains much more stable performance and swift recovery from large deviations of customer orders from forecasts as compared to real case.

X11: The modelled RDC suffers no stock out (figure 5.29) in this product during the year but operates at a lower average inventory than the actual case. In reality, the RDC suffers one stockout and takes 14 days to recover to normal. The average weekly bullwhip effect, maximum stock levels are all higher than the modelled distribution centre's corresponding values.

X12: The modelled RDC achieves 100% customer satisfaction with higher average stock value, higher weekly bullwhip effect and higher maximum stock level compared to the actual case. This is mainly due to the long period of stock out in the real case and also the long time period taken to recover from the disturbance. In spite of the prolonged stockout situation, no emergency orders are issued to the factory. It is unknown why the orders are not generated, or why the product is not produced in the factory during the period. But the agent in the model generates proportionate emergency orders at correct time to avoid stock outs and improve the swiftness of response to such disturbances. Although the model's stock level rises to a high of 348 after the initial sales deviation, it gradually restores normalcy by controlling further accumulation of stock above this level by generating lower volume replenishment orders in this product (Fig. 5.30).

Product X2	Actual	Modelled
Average Inventory	311	200
Average CSL	100.0%	100.0%
Number of Stock-out situations	0	0
Number of Emergency / Large Orders	1	1
Average weekly Bullwhip-effect*	1.86	2
Time taken for inventory to return to normal	3 days	3 days
Maximum Stock Level	1344	861
Minimum Stock Level	96	50

*Bullwhip Effect = Variance of weekly Replenishment Order / Variance of actual weekly demand



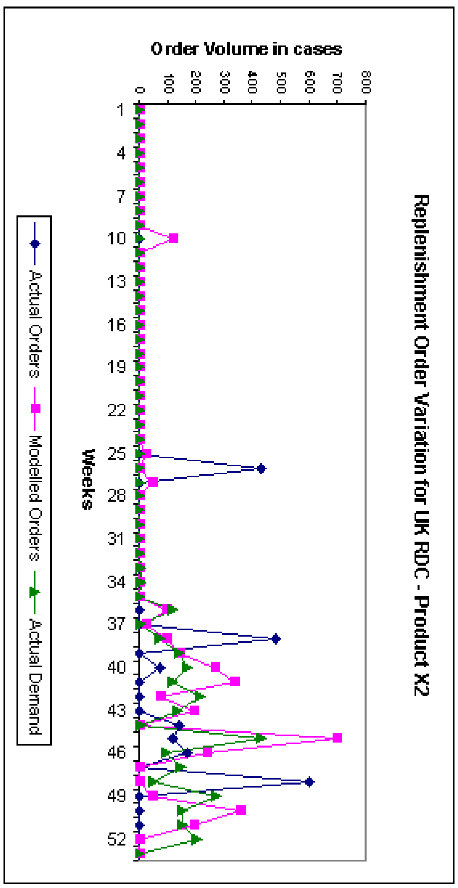


Figure 5.24: France RDC performance comparison for product *X2*

Product X5

	Actual	*Modelled*
Average Inventory	***656***	***601***
Average CSL	***99.8%***	***100.0%***
Number of Stock-out situations	***1***	***0***
Number of Emergency / Large Orders	***2***	***1***
Average weekly Bullwhip-effect*	***1.71***	***1.23***
Time taken for inventory to return to normal	***4 days***	***3 days***
Maximum Stock Level	***1208***	***1007***
Minimum Stock Level	***0***	***167***

*Bullwhip Effect =
Variance of weekly Replenishment Order /
Variance of actual weekly demand

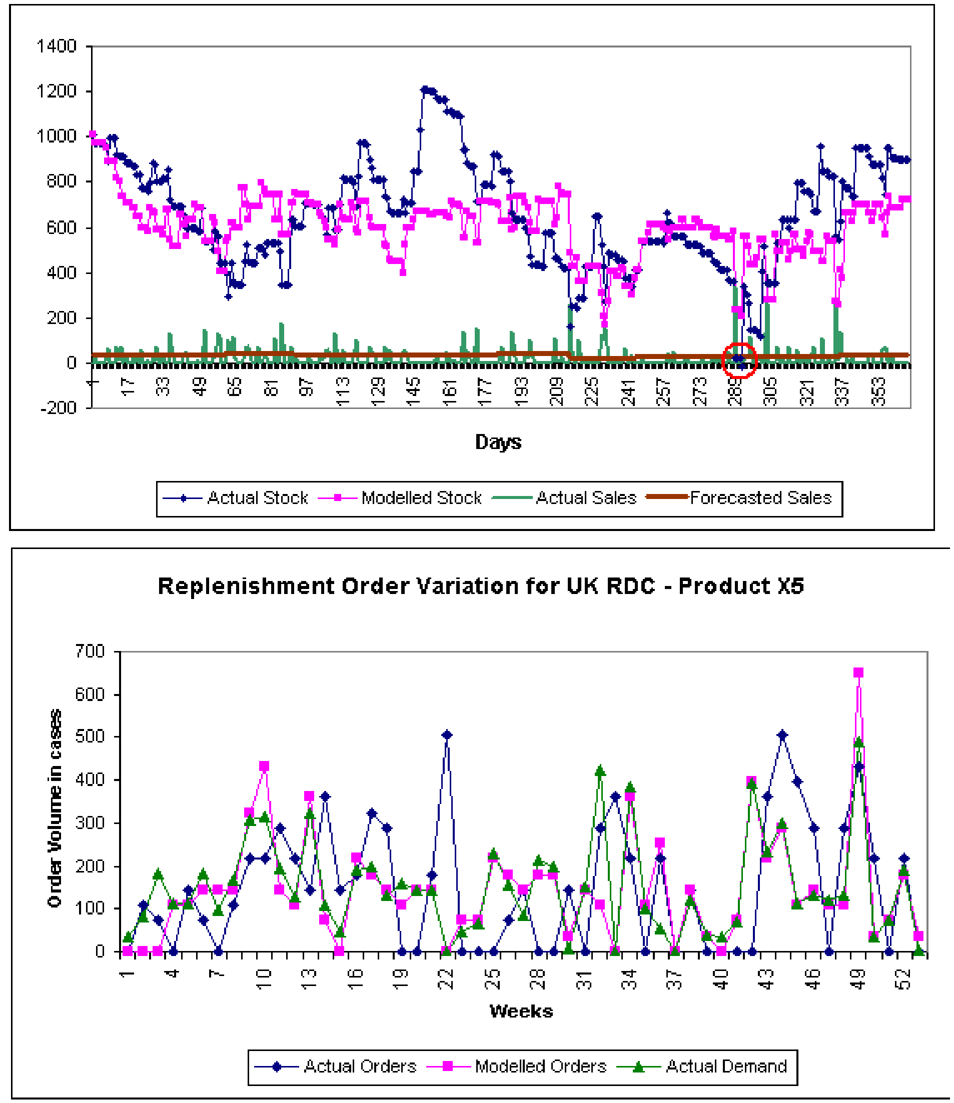
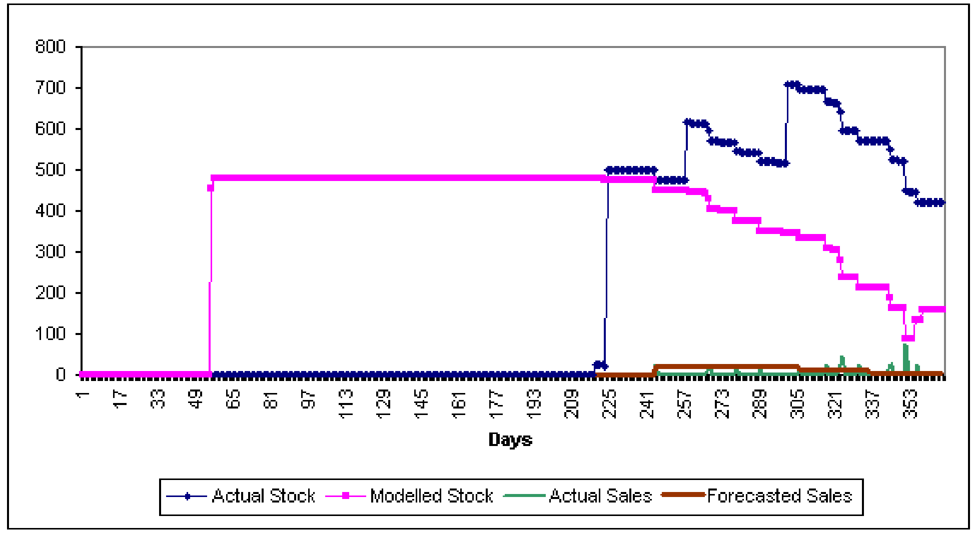


Figure 5.25: France RDC performance comparison for product *X5*

Product X6

	Actual	Modelled
Average Inventory	***215***	***351***
Average CSL	***100.0%***	***100.0%***
Number of Stock-out situations	***0***	***0***
Number of Emergency / Large Orders	***1***	***1***
Average weekly Bullwhip-effect*	***17.4***	***13.4***
Time taken for inventory to return to normal	***5 days***	***4 days***
Maximum Stock Level	***707***	***480***
Minimum Stock Level	***20***	***87***

*Bullwhip Effect =
Variance of weekly Replenishment Order /
Variance of actual weekly demand



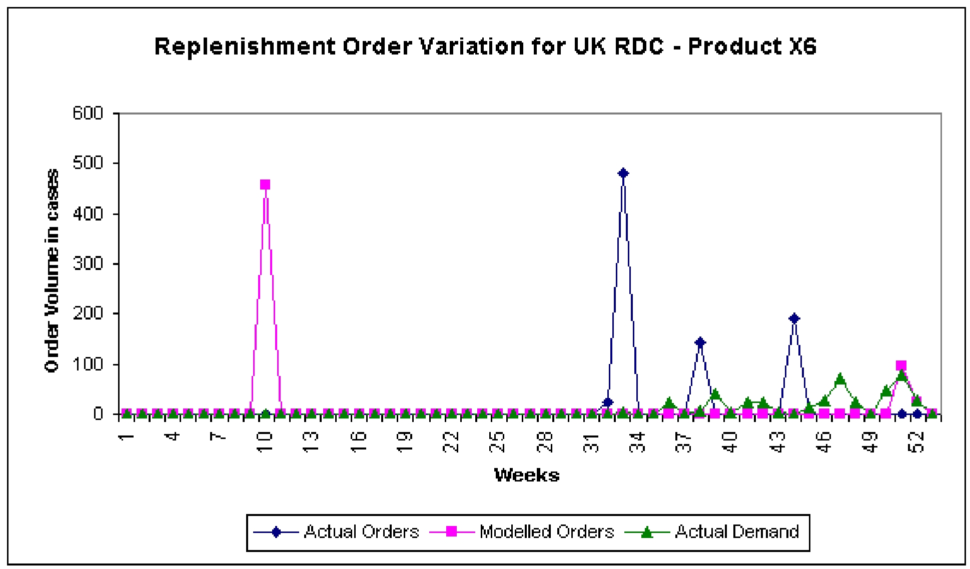
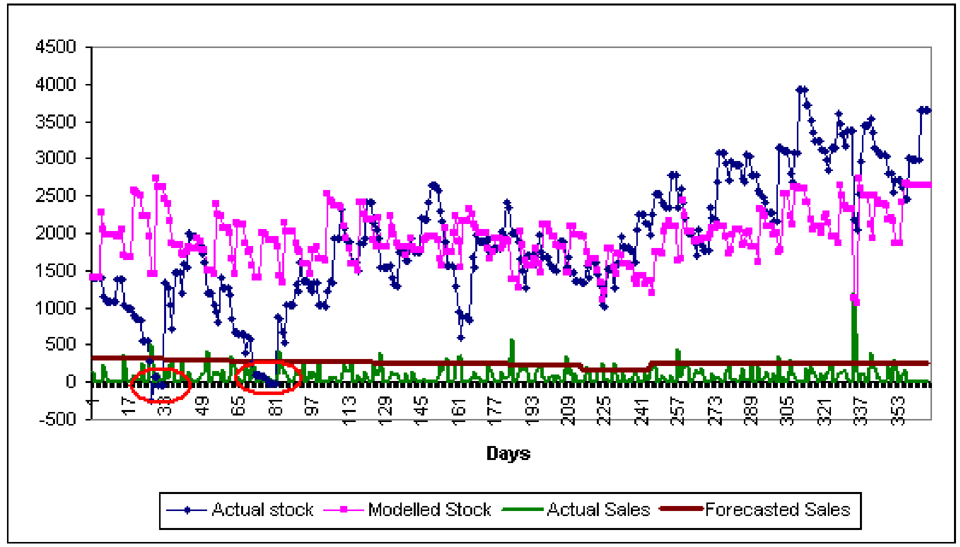


Figure 5.26: France RDC performance for product *X6*

Product X7

	Actual	Modelled
Average Inventory	***1879***	***1954***
Average CSL	***100.0%***	***100.0%***
Number of Stock-out situations	***3***	***0***
Number of Emergency / Large Orders	***3***	***3***
Average weekly Bullwhip-effect*	***3.19***	***2.88***
Time taken for inventory to return to normal	***10 days***	***2 days***
Maximum Stock Level	***3917***	***2736***
Minimum Stock Level	***0***	***1058***

*Bullwhip Effect =
Variance of weekly Replenishment Order /
Variance of actual weekly demand



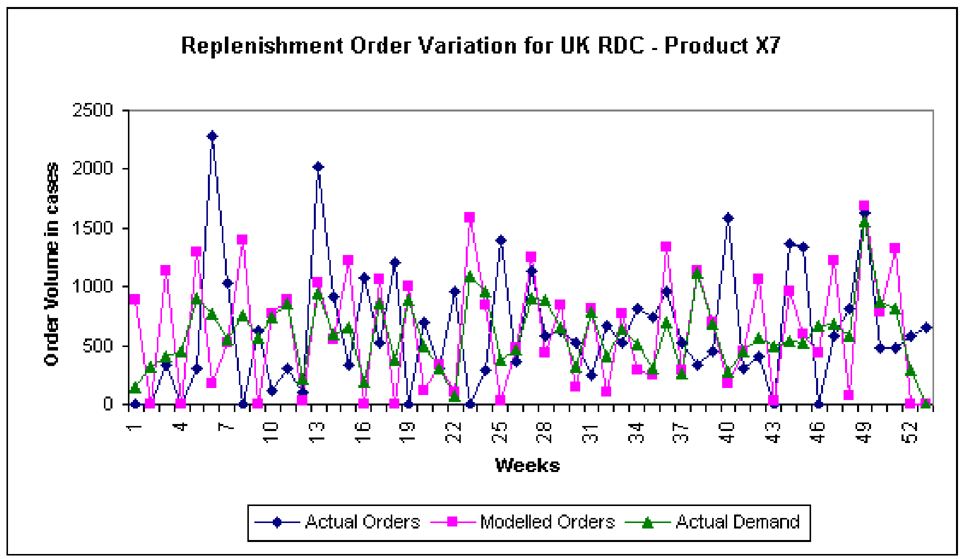
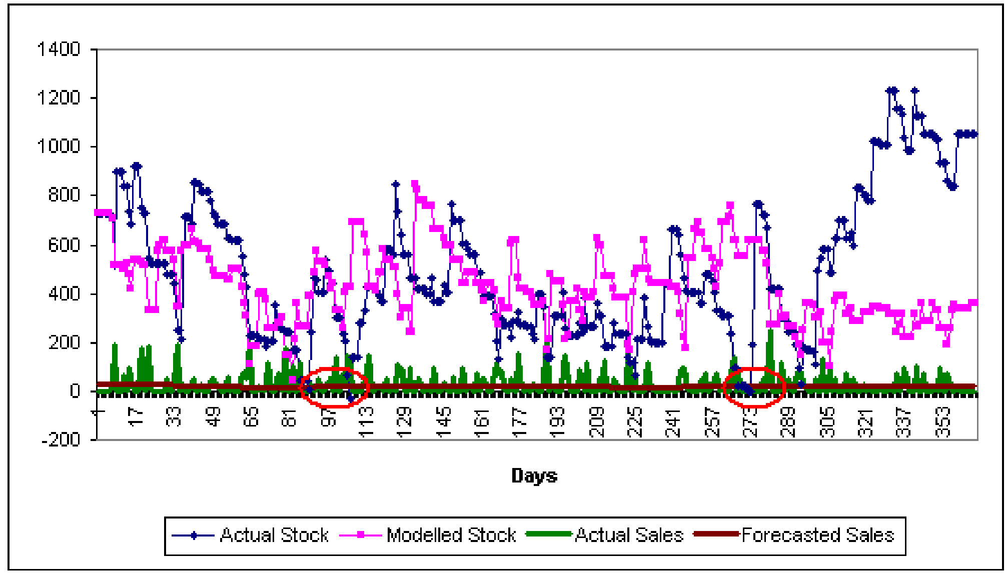


Figure 5.27: France RDC performance for product *X7*

Product X10

	Actual	Modelled
Average Inventory	493	432
Average CSL	99.7%	100.0%
Number of Stock-out situations	2	0
Number of Emergency / Large Orders	2	0
*Average weekly Bullwhip-effect**	3.21	2.65
Time taken for inventory to return to normal	8 days	2 days
Maximum Stock Level	1229	844
Minimum Stock Level	0	46

*Bullwhip Effect =
Variance of weekly Replenishment Order /
Variance of actual weekly demand



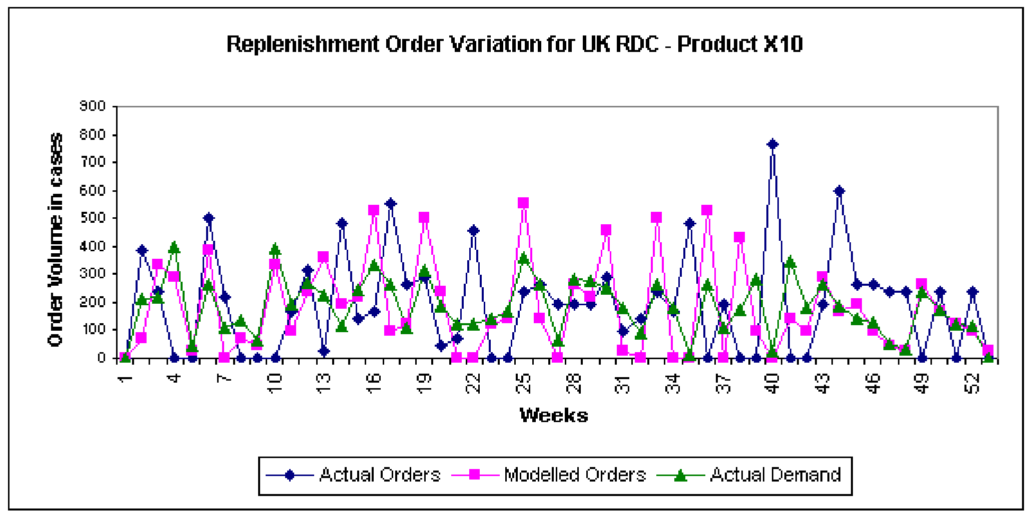
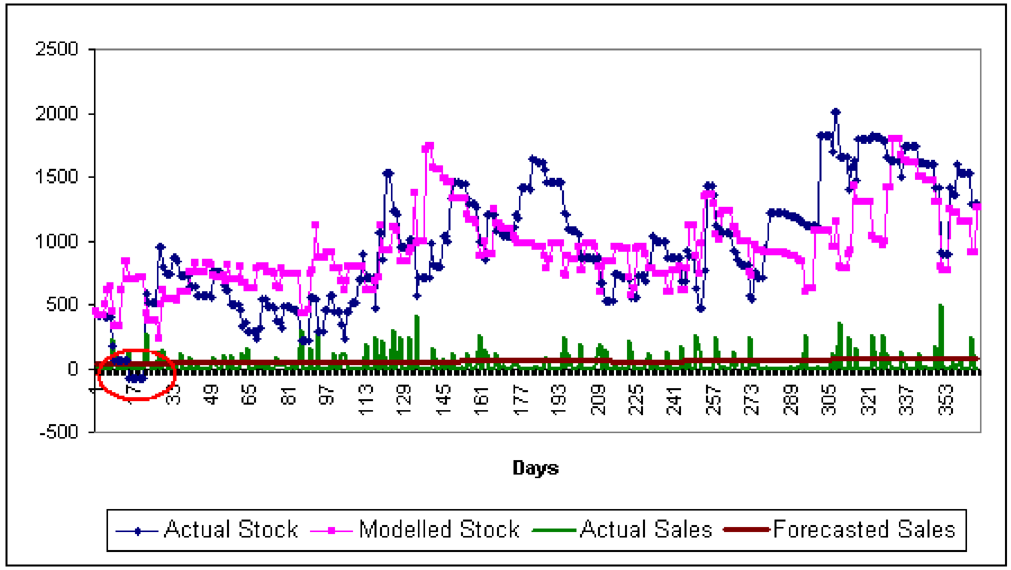


Figure 5.28: France RDC performance for product *X10*

Product X11

	Actual	Modelled
Average Inventory	***953***	***930***
Average CSL	***99.5%***	***100.0%***
Number of Stock-out situations	***1***	***0***
Number of Emergency / Large Orders	***1***	***0***
Average weekly Bullwhip-effect*	***3.21***	***2.95***
Time taken for inventory to return to normal	***14 days***	***2 days***
Maximum Stock Level	***2013***	***1796***
Minimum Stock Level	***0***	***234***

*Bullwhip Effect =
Variance of weekly Replenishment Order /
Variance of actual weekly demand



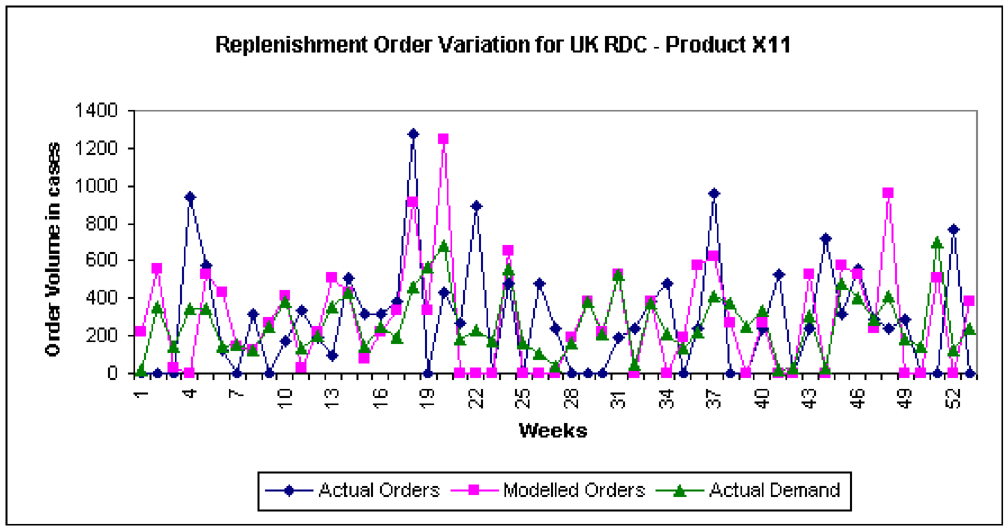
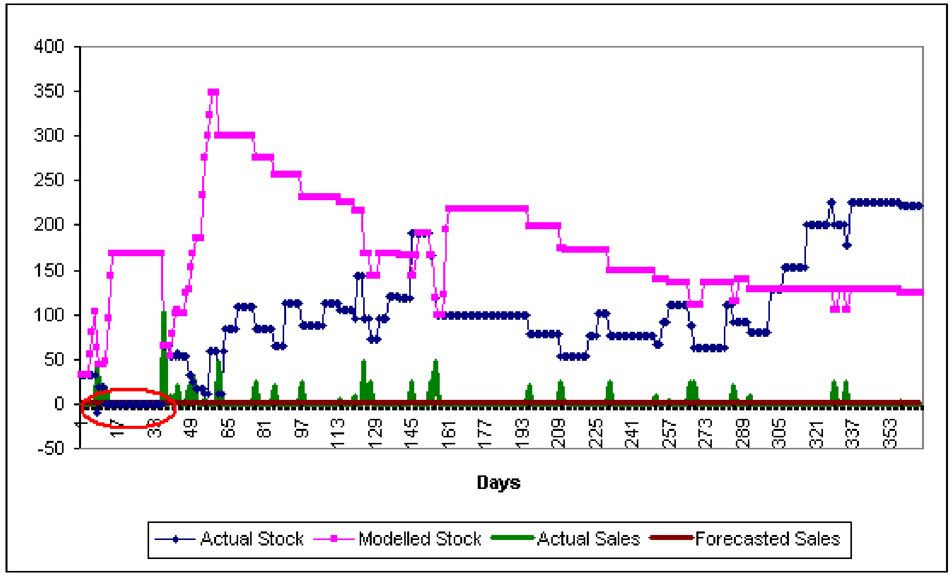


Figure 5.29: France RDC performance for product *X11*

Product X12

	Actual	Modelled
Average Inventory	*100*	*172*
Average CSL	*98.9%*	*100.0%*
Number of Stock-out situations	*1*	*0*
Number of Emergency / Large Orders	*1*	*0*
Average weekly Bullwhip-effect*	*1.65*	*2.24*
Time taken for inventory to return to normal	*28 days*	*5 days*
Maximum Stock Level	*225*	*348*
Minimum Stock Level	*0*	*32*

*Bullwhip Effect =
Variance of weekly Replenishment Order /
Variance of actual weekly demand



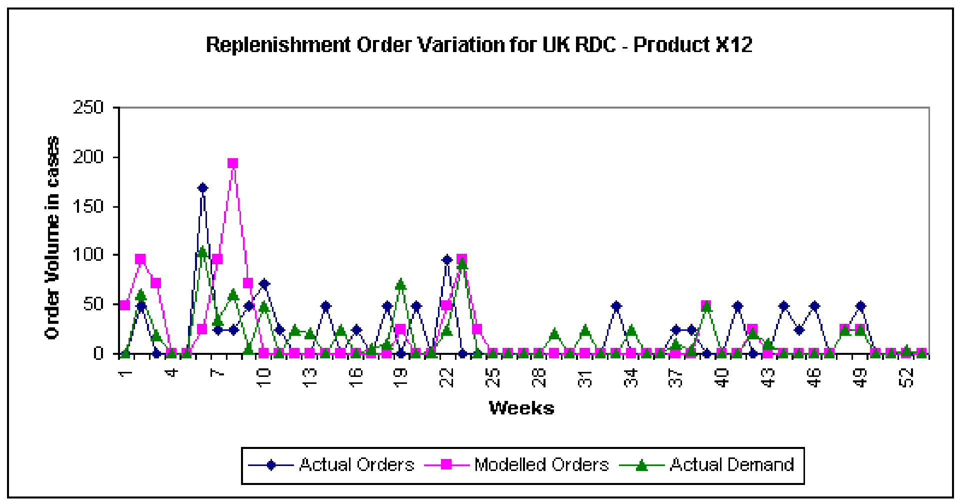


Figure 5.30: France RDC performance for product *X12*

5.7.4 Factory and the Central Warehouse

The response of the factory and the central warehouse to unwanted disturbances is reflected in its production performance and AVI, CSL respectively. The factory in the proposed model has full knowledge of each product's demand pattern and products with established sales, huge total annual estimated sales are produced in larger quantity for longer production run-lengths (*X1, X5, X7*). While products which are either new or have lower estimated sales throughout the year (*X2, X6, X3, X4*), are produced for shorter time-interval or not produced at all depending on actual sales. This is shown in Table 11b. Table 11a shows the actual total production time for each product, the average run-length, the number of runs requiring changeover at the start of each run. The modelled factory agent performs better than the actual factory in terms of the performance measures resulting in greater number of production days and average production run length, reduced idle time, reduced changeover time and number of changeovers. It is worth noting that although the model assumes approximate production cycle times before the start of the model but following the actual demand and the intelligent production rules, the production cycle times have changed from the assumed ones. It can be seen, the most highly demanded product *X7* though initially is in the category of 15 days cycle time but after running the model for one year, the cycle time increases to 58 days with average run-length of 11.67 days. In actual case, the cycle time is 16 but average production run-length is 4.79 days only with 16 runs (one single run as small as 0.14 day or 3.36 hours). Although the model produces the high demand products for long run-lengths but when need arises it can produce them for shorter duration. But in order to avoid excessive changeovers, the minimum time for production for all the products are not found to drop to as low values as in the real case. The minimum time of production is 0.86 days (20.64 hours) for low demand product *X3*. The lowest value of the minimum time of production is 1.2 days for the high demand product *X11*.

Table 11a: Actual Total Production, Average Run Length of different products produced by the factory throughout the year

	X1	*X2*	*X3*	*X4*	*X5*	*X6*	*X7*	*X8*	*X9*	*X10*	*X11*	*X12*	*X13*
Total Production	82320	12328	6524	0	111696	20192	187896	14784	15426	121920	119664	40824	51488
Average Run Length	3.81	2.42	1.08	0.00	3.42	1.62	4.79	1.01	0.63	3.14	3.52	1.34	2.55
Total Production Days	38.10	4.84	4.32	0.00	54.72	8.10	81.43	6.06	5.67	47.10	42.24	16.08	30.60
Maximum Run Length	5.09	3.25	1.35	0.00	8.43	3.06	9.99	1.35	1.14	8.89	5.72	1.97	4.20
Minimum Run Length	1.78	1.59	0.42	0.00	0.23	0.12	0.14	0.24	0.19	0.20	1.87	0.80	0.25
Number of Runs	10	2	4	0	16	5	17	6	9	15	12	12	12
Average Cycle Time	35	39	104	0	20	29	16	60	41	21	27	27	22

Table 11b: Modelled Total Production, Average Run Length of different products produced by the factory throughout the year

	X1	*X2*	*X3*	*X4*	*X5*	*X6*	*X7*	*X8*	*X9*	*X10*	*X11*	*X12*	*X13*
Total Production	136710	10710	5065	0	107441	25288	161327	15594	15052	122966	108503	44198	53537
Average Run Length	7.03	1.05	1.12	0.00	7.52	1.69	11.67	1.06	1.39	5.93	4.26	1.45	5.30
Total Production Days	63.29	4.21	3.35	0.00	52.67	10.13	70.02	6.37	5.55	47.44	38.31	17.37	31.83
Maximum Run Length	17.30	1.13	1.30	0.00	17.56	3.50	22.84	1.22	2.04	11.55	8.80	2.57	12.75
Minimum Run Length	2.13	0.98	0.86	0.00	1.51	1.09	6.94	0.93	1.26	1.55	1.20	1.05	1.48
Number of Runs	9	4	3	0	7	6	6	6	4	8	9	12	6
Average Cycle Time	37	65	81	0	44	43	58	54	92	39	34	25	43

Table 11c: Comparison of production performance between Model and Actual

	Actual	***Model***
Total Production Days	***339***	***351***
Average Run Length (Days)	***2.44***	***4.12***
Total ChangeOvers	***120***	***80***
Total ChangeOver Time (Days)	***11.3***	***9.5***
Total idle Time (days)	***16***	***6***

The number of runs in each product per month is tabulated in Table 12. Table 12a shows the data for actual system and Table 12b shows the result from the simulated model.

Table 12a: Number of Production Runs per product per month for the actual system

Product \ Month	1	2	3	4	5	6	7	8	9	10	11	12
X1	1	1	0	0	0	1	1	1	1	1	2	1
X2	0	0	0	0	0	1	1	0	0	0	0	0
X3	1	0	0	0	0	0	0	1	0	1	1	0
X5	1	1	1	2	0	1	2	1	1	1	2	1
X6	0	0	1	1	1	1	1	0	0	0	0	0
X7	1	1	3	1	2	2	1	2	0	1	1	1
X8	1	0	0	0	1	1	1	0	0	1	1	0
X9	0	1	1	1	0	1	1	0	1	1	1	1
X10	1	1	2	0	1	2	2	1	1	1	1	2
X11	1	1	1	1	1	1	1	1	1	1	1	1
X12	1	1	1	1	1	1	1	1	1	1	1	1
X13	0	0	1	2	1	1	2	2	1	0	1	1
Total	8	7	11	9	8	13	14	10	7	9	12	9

Table 12b: Number of Production Runs per product per month for the modelled system

Product \ Month	1	2	3	4	5	6	7	8	9	10	11	12
X1	2	0	3	0	0	0	1	0	0	1	1	1
X2	0	1	0	0	0	0	1	1	1	0	0	0
X3	0	0	0	0	0	1	0	0	1	0	0	1
X5	0	2	1	0	1	0	0	0	1	1	0	1
X6	0	1	0	0	1	1	0	0	3	0	0	0
X7	1	1	0	1	0	0	0	1	0	0	1	1
X8	0	1	0	0	0	1	1	0	1	0	2	0
X9	0	1	0	0	0	0	1	0	0	1	1	0
X10	1	0	2	0	1	1	1	0	1	0	1	0
X11	2	1	2	0	1	1	0	0	1	0	1	0
X12	2	1	3	0	0	0	1	1	3	1	0	0
X13	0	0	1	0	0	1	0	0	1	2	1	0
Total	8	9	12	1	4	6	6	3	13	6	8	4

The gray cells in the tables show the number of times a product is produced in a month. It can be seen that, in actual system, there are very few white cells. All the products except the less demanded ones (*X2, X3, X4, X8 and X9)* are produced all round the year. This creates large number of changeovers and higher total changeover time. Every month on average 10 changeovers take place in the actual factory, whereas in the modelled system in the 4th month only one changeover takes place. The average central warehouse stock positions for the actual and modelled system will be described next to understand whether the factory in the model is able to select the right products for production at the right time and produce them in correct amounts. Products *X3, X4, X8, X9* are pushed to their respective markets as soon as they are produced. So in the following figures, the inventory for these products are found to be zero, except during the period from their start of production to the delivery to respective country RDCs.

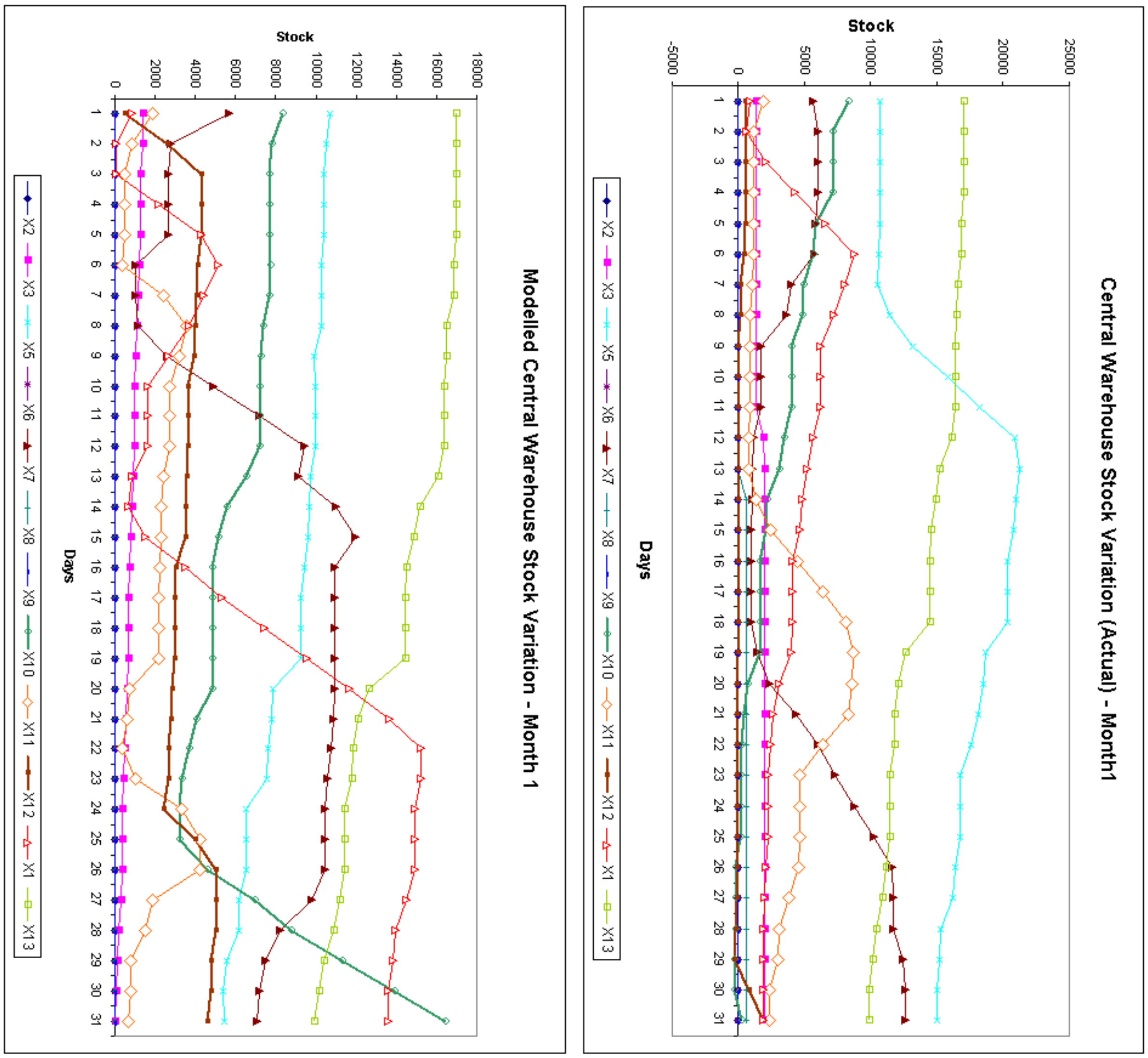


Figure 5.31: Actual and Modelled Central Warehouse Stock Variation – Month 1

In month 1 (Figure 5.31), the actual central warehouse suffers stockouts in products *X10* and *X12*. The factory manufactured products *X3, X5* and *X8,* which are not required to be produced in the first month. *X3* and *X8* have no sales (only forecast is there), whereas *X5's* stock position is not as precarious as *X10* and *X12*. But the factory neglects the production of these two products and allows stockouts for extended period, when sales are there. The factory in the model delays production of products such as *X3* and *X8* until there is absolute necessity or other products (specially high demand) are in safe inventory position to cater to the sudden emergency replenishment orders or direct sales from the factory. So although in the first month the number of changeovers is the same in both cases, but the model avoids any stockouts at the central warehouse by deciding intelligently on the sequence and duration of production for each product.

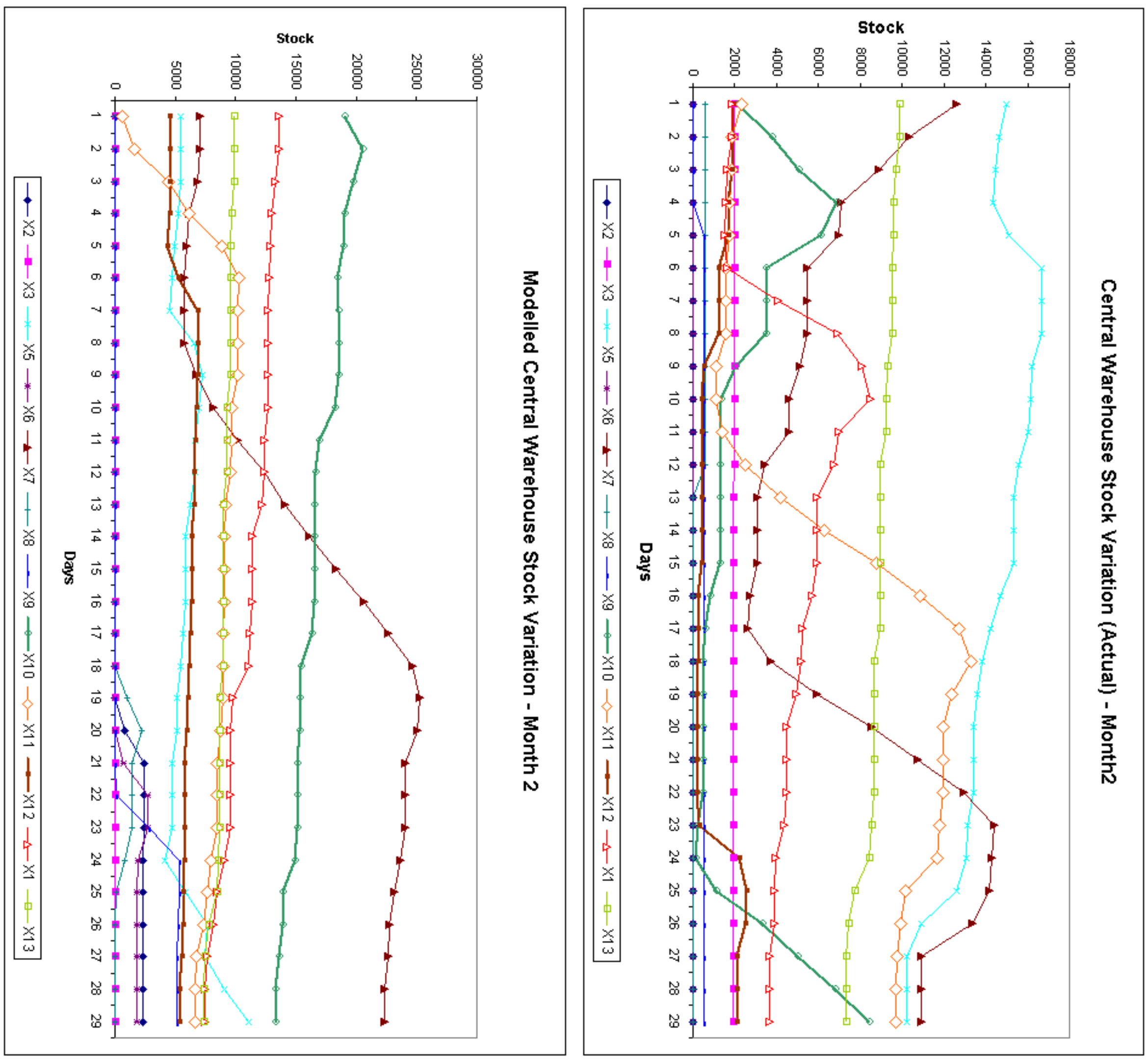


Figure 5.32: Actual and Modelled Central Warehouse Stock Variation – Month 2

In month 2 (Figure 5.32), though the actual system does not suffer any stockouts but it comes very close to stockout situations for both the products *X10* and *X12*. This is because of selecting the wrong products for production. For example, after *X10* is produced, the factory produces products such as *X5* and *X9,* but actual urgency for production is in products *X1, X12, X7*, which all have drooping inventory patterns. It can be seen that the factory takes a long time to react to the precarious inventory position of both *X10* and *X12.* Instead it continues to produce *X7* and *X11* for long periods when the central warehouse is operating with products *X10* and *X12* on the verge of stockout. Exactly reverse situation happens in the model. The increased number of changeovers compared to the actual is due to the production of products *X2, X6, X8* and *X9.* This is done after all the other products have achieved a safe inventory level. *X5* is produced twice as shown by the two peaks. This is to facilitate the production of high demand product such as *X7,* which is moving towards unsafe inventory zone. In the first run, *X5* is produced for a shorter run-length and in the second run it is produced for a longer duration. So the factory agent closely monitors all the different products' stock position and decides to changeover as soon as there are any undue disturbances resulting in large drops in the stock level of any product. The month 3 stock variations in Figure 5.33 clearly show lack of properly balancing the time of production of different products. *X7, X5* and *X11* are produced for long time intervals. Products *X1, X10 and X12* are once again neglected and their stock levels suffer deterioration resulting in network wide customer service level issues. Specially, throughout the third month, *X1* is not produced at all, when its inventory position has gone from bad to worse. The modelled system gives rise to 12 changeovers in this month. This is because of rapid reaction to stock level changes in different products at the same time and the factory's ability to switch production between products as soon as there is a signal of stock deterioration. This resulted in 2 changeovers for products *X10, X11* and 3 changeovers for products *X1, X12.* As can be seen from Figure 5.33, towards the second half of the month, the inventory levels for all these four products and *X5* are in precarious condition forcing frequent changeovers. In month 4 (Figure 5.34), the model produces only two products with one changeover from *X1* to *X7.* This is done because the inventory levels for all other products are within safe limits. On the other hand, the actual system starts functioning in an uncontrolled manner and faces stockout in product *X1*. It continues production in all other products, including *X5* whose stock is well above the safety limit.

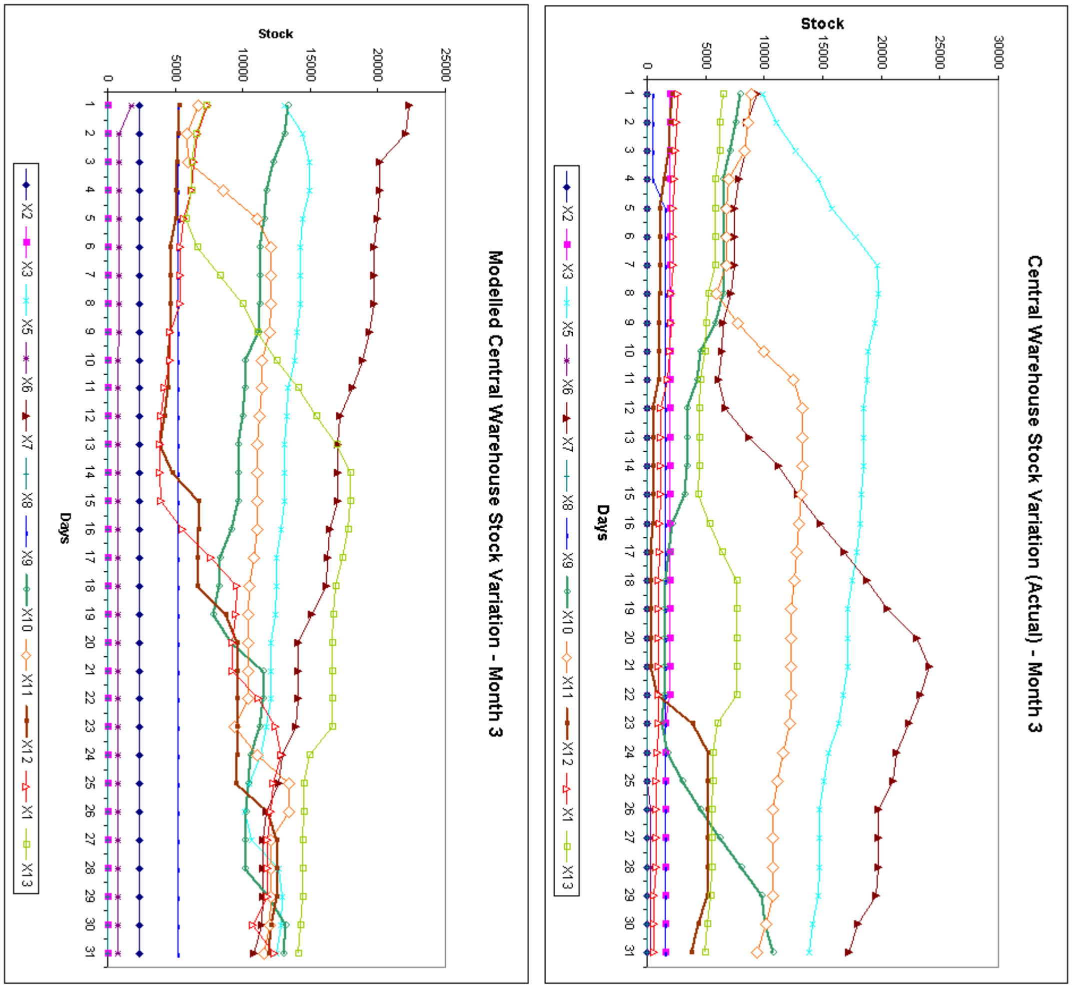


Figure 5.33: Actual and Modelled Central Warehouse Stock Variation – Month 3

In month 5 (figure 5.35), the factory in the model produces the three products, whose inventories were dropping in the previous month due to continued production of *X7*. In addition to this, the sales of product *X6* picks up during this period and so *X6* is also produced in this month resulting in only 4 changeovers. On the other hand, in the actual system, more products are produced, while *X1* still experiences stockout with backlogs mounting everyday. In month 6 (Figure 5.36), the actual system starts production of *X1* to reduce the backlogs. In the model, *X11* and *X13* are produced for long durations. Due to the long runs, *X10* inventory position deteriorates rapidly but the factory's intelligent rules are quick enough to respond to the variation and started production of the product at the end of month. Due to increasing sales, *X6* is produced again by the modelled factory agent for a longer time period. *X3* is produced for the first time because of reduction in RDC inventory signifying pull production. *X8* is produced to replenish the Ede stocks. In the actual system, 13 changeovers take place and all the products are produced during this month except *X3*. This is because, sales of all the newly introduced products start picking up from month 6. So *X2* is produced first, and production of *X6* continues this month also in anticipation of increased sales, *X8* and *X9* are also produced to replenish Ede RDC.

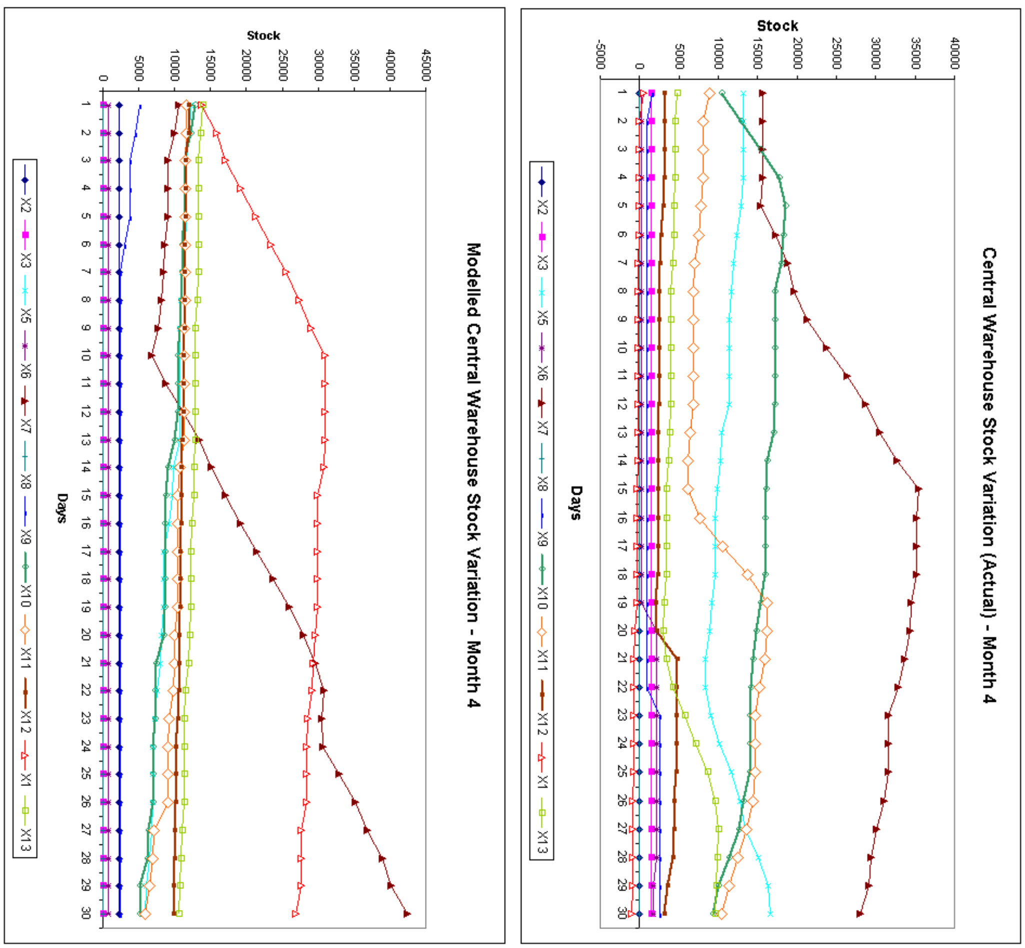


Figure 5.34: Actual and Modelled Central Warehouse Stock Variation – Month 4

Figure 5.37 shows the actual and modelled stocks at central warehouse for month 7. First time, the actual inventory of *X1* starts to become positive but the amount required to make the inventory well above safety limit is not produced during this month. Instead as before all the products are produced except *X3*. The warehouse is already carrying excess inventory in *X7,* but still the production in that product is carried out resulting in stockout situation once again for *X1*.

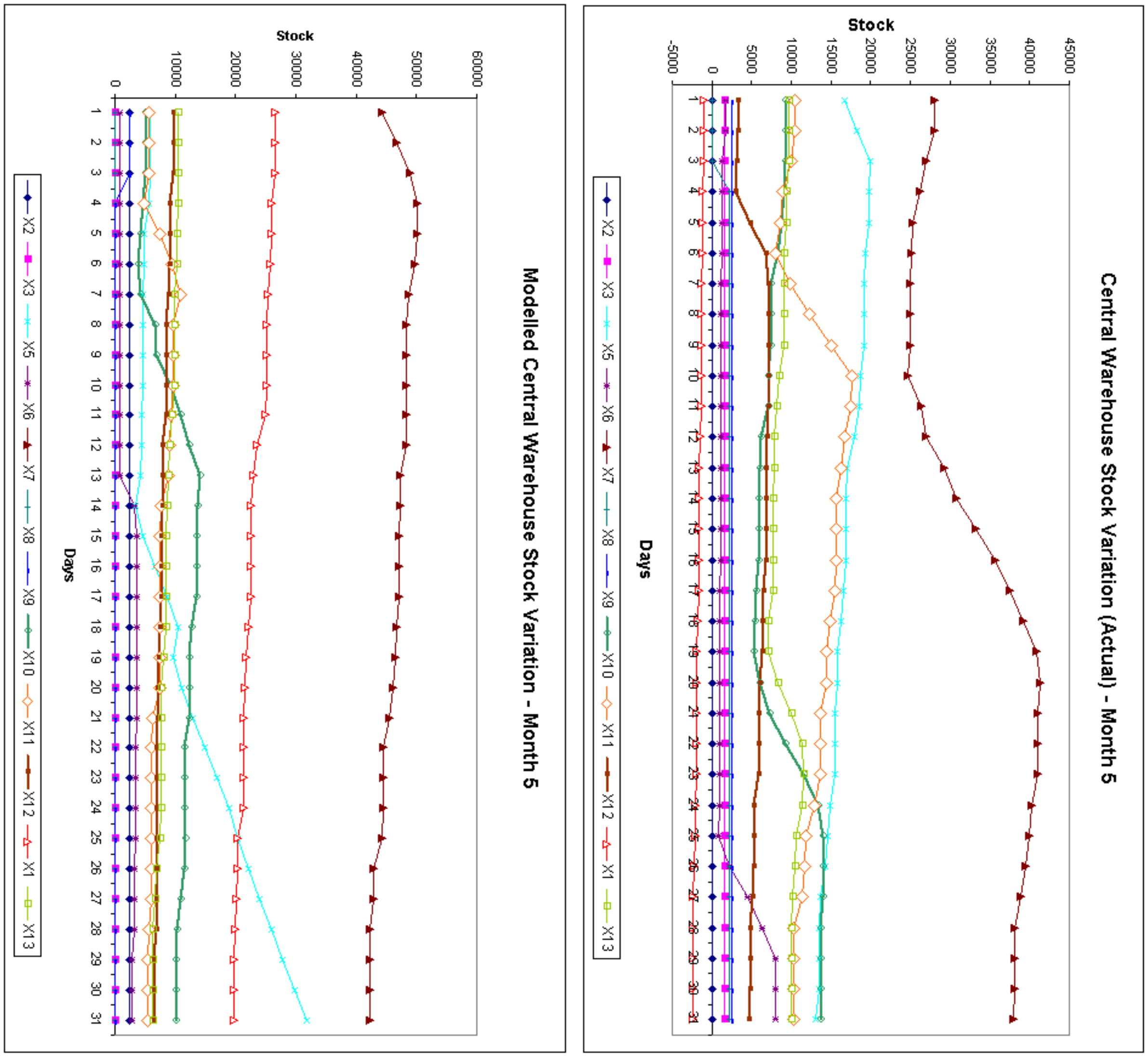


Figure 5.35: Actual and Modelled Central Warehouse Stock Variation – Month 5

In the modelled case, *X10* is produced for a long time to bring it out of critical stage. During this time, *X1* stock drops considerably, but the intelligent rules discussed in Chapter 4, spots the diminishing stock level and starts producing *X1* just before the stock level becomes critical. In order to reduce the possibility of Ede RDC falling out of stock, *X8* and *X9* are produced before *X12.* This is because of the lead time associated with transfer of these products. *X2* is also produced for long time in this month to cope with the increasing demand.

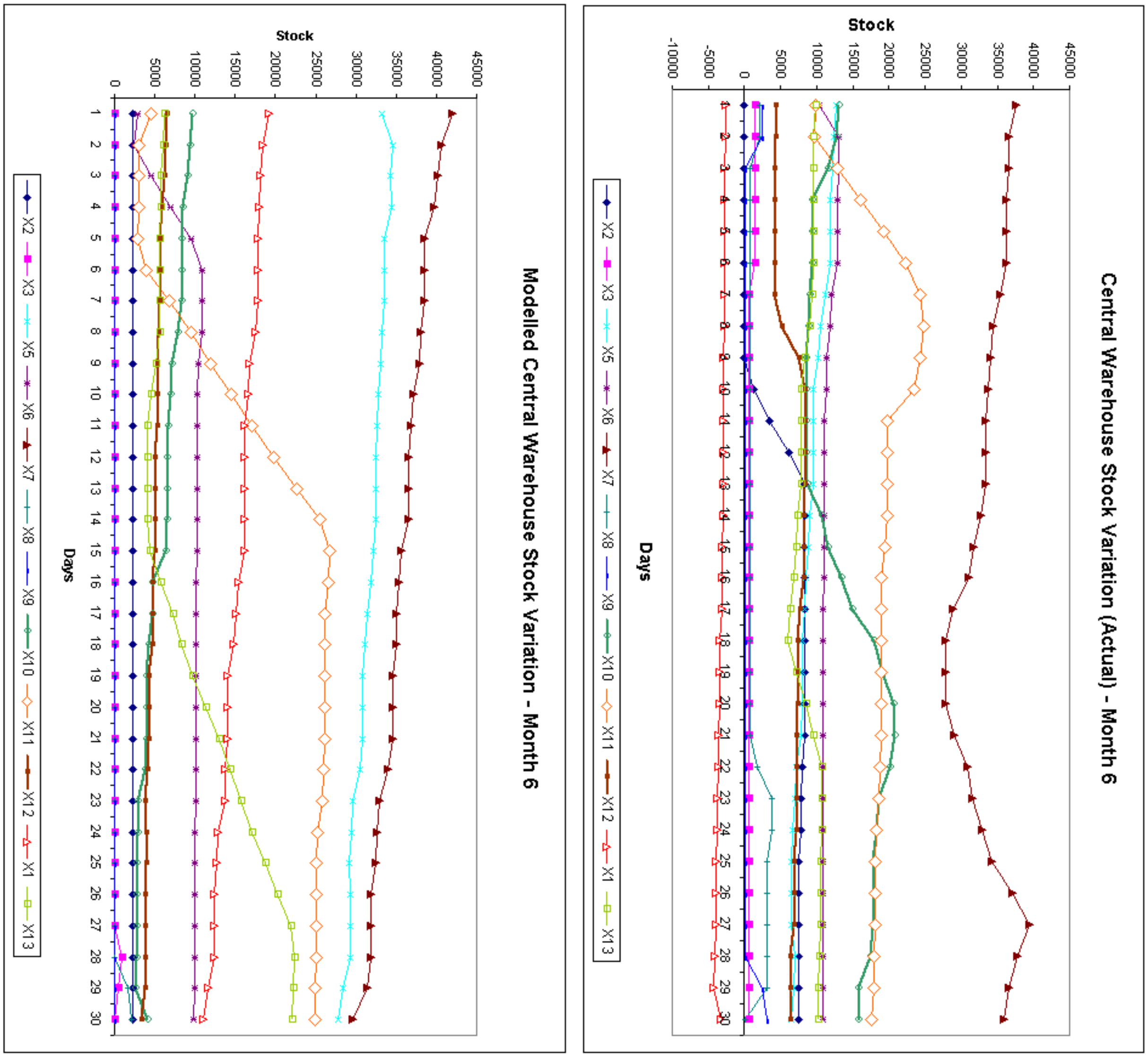


Figure 5.36: Actual and Modelled Stock Variation in Central Warehouse – Month 6

Month 8 is characterized by low sales for most products due to the seasonality in demand of the products (Figure 5.4). This is utilized by the modelled factory agent to produce X1, X7 for long periods. However, towards the end of the month, the factory (Figure 5.38) makes two quick changeovers to produce X2 and X12. But in the actual case, again 10 changeovers are made with most of the products produced once per month (except X2, X6, X8 and X9). X1 is now in a better inventory position compared to previous months with no stockout situations.

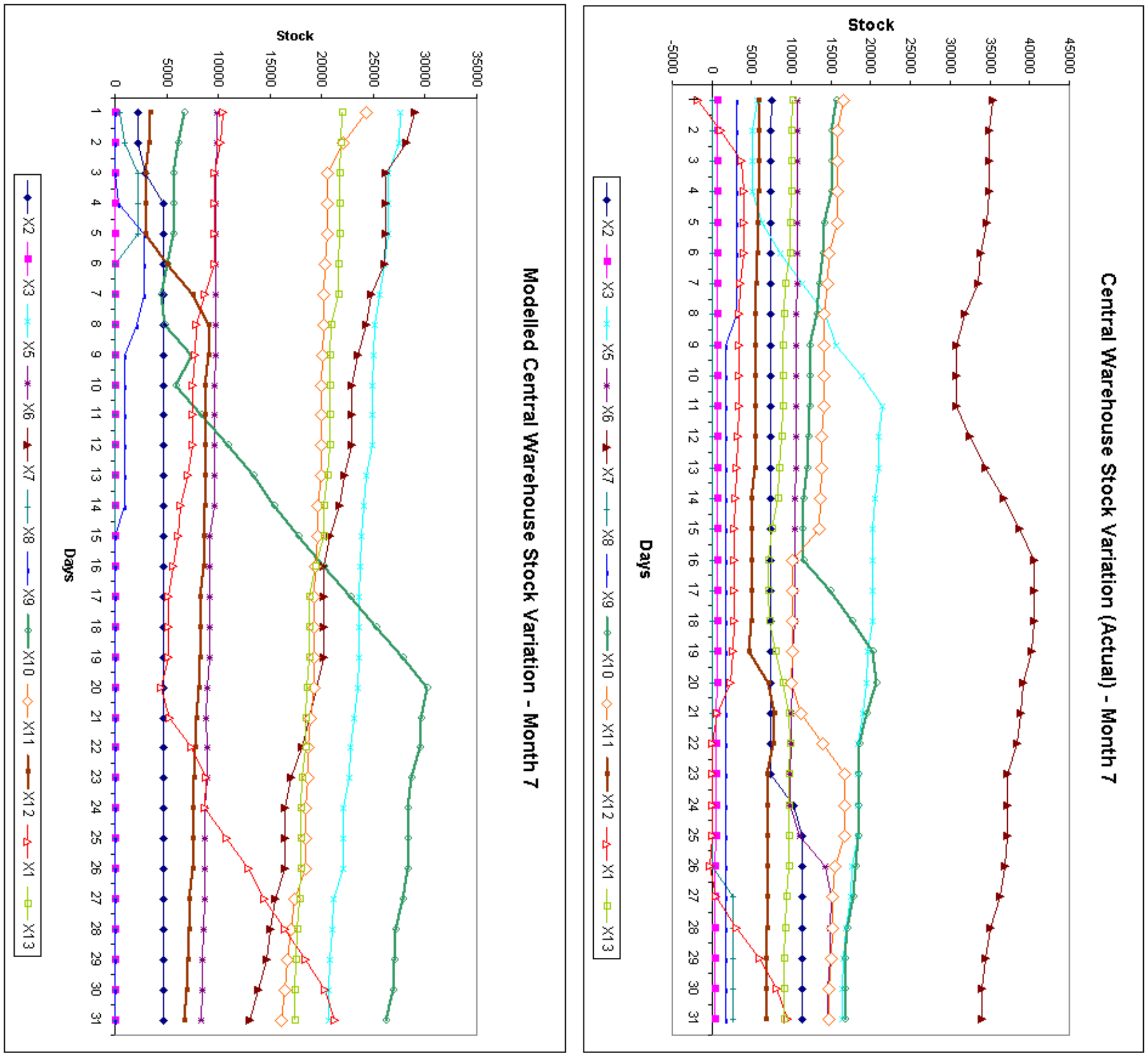


Figure 5.37: Actual and Modelled Stock Variation at Central Warehouse – Month 7

The 9th month (Figure 5.39) accounts for the largest number of changeovers (13) in the modelled system. This is because of the prolonged production of two products in previous month and from this month, the sales rise for almost all the products. So almost all the products are produced this month except X1, X7 and X9. X12 and X6 are produced thrice to bring the stock levels in these products to safe limits (Table 12b). The actual system however gives rise to lower number of changeovers but again does not produce X1 for sufficiently long period to raise the stock level to a safe zone.

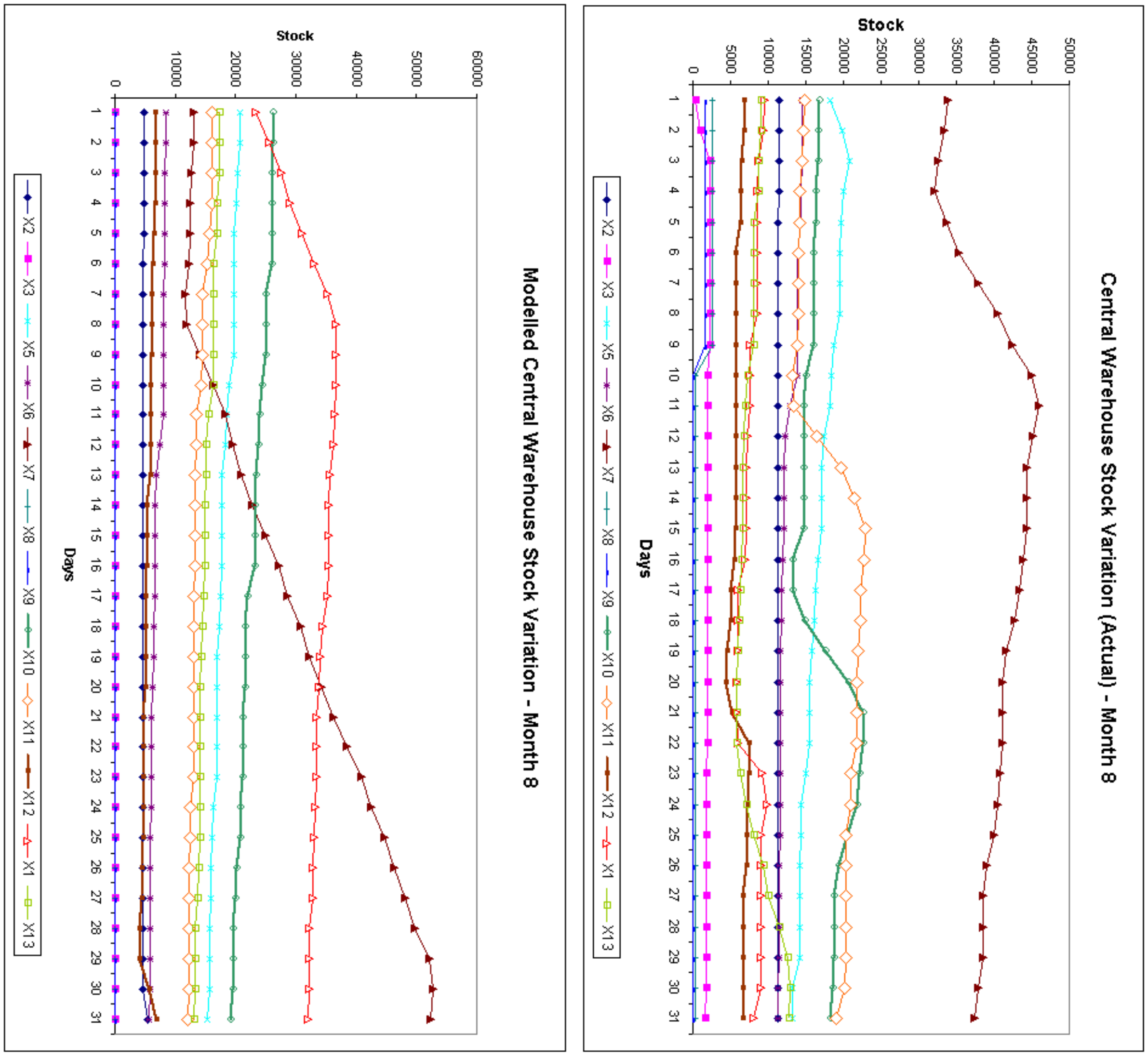


Figure 5.38: Actual and Modelled Stock Variation at Central Warehouse – Month 8

In month 10 (Figure 5.40), most of the products achieve improved stock levels in the modelled system. So *X5, X10* are produced for longer run-lengths. Almost all the products are produced this month in the actual system once, except *X2 and X6.* The notable point is, for the first time the factory in the actual system responds well to the stock variation in *X1*. In month 11 (Figure 5.41), the number of changeovers rises again to 12 for the actual system. This is due to the continued drop in the stock levels of most of the products, specifically *X1, X12*. Except *X2, X6* all the products are manufactured at least once this month in the actual system. In the model, *X11, X1 and X7* are produced for long durations as almost all the products are in safe inventory zone with very little chances of stockout. To be over-cautious at this stage, the factory in the model produces *X8* twice so that the country RDC does not get out of stock due to too much production of high demand products. An obvious effect of months 9, 10 and 11 on the production of month 12 in the model is a complete reduction in the number of products produced (Figure, 5.42, Table 12b). Only 4 products are produced during this month, *X7* is produced at the end. *X3* is produced for a small amount to replenish the country RDC. *X1, X5, X10* are produced for long time intervals. In the actual case, in month 12, almost all the products are produced. *X1* is produced for sufficiently long time to build a safe inventory and since demand is comparatively low towards the end of the year, *X1* stock level is first time well above the critical limit where possibility to go into stockout is high. *X10* is produced twice.

The purpose of showing the monthly inventory level variation at the central warehouse is to show the relative inflexibility and lack of responsiveness of the actual factory. The factory in actual system attempts to produce every product every month even if the inventory level is around 40000 (for example, product *X7* in month 9), but neglecting product *X1* even if there is no stock at Central Warehouse. On the other hand, the model only produces products for longer run-lengths when all other products have very little chance of getting out of stock. The factory agent in the model is able to shift production rapidly between different products as soon as there is a need. Most importantly, the factory in the model flexibly changes run-length of products from a maximum of 22.84 days to a minimum of 0.86 days without any adverse effects on the performance in the form of customer service or cost (production changeover). In fact, such flexibility and responsiveness to disturbances give rise to a resilient production factory and altogether a resilient supply chain.

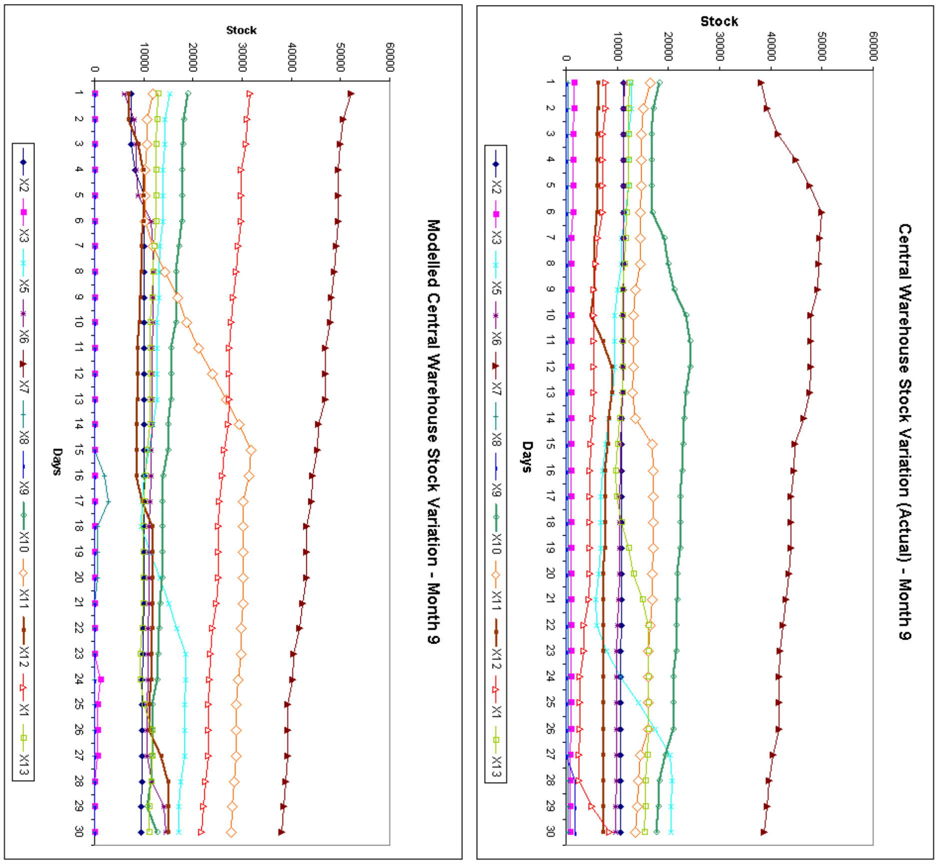


Figure 5.39: Actual and Modelled Stock Variation in Central Warehouse – Month 9

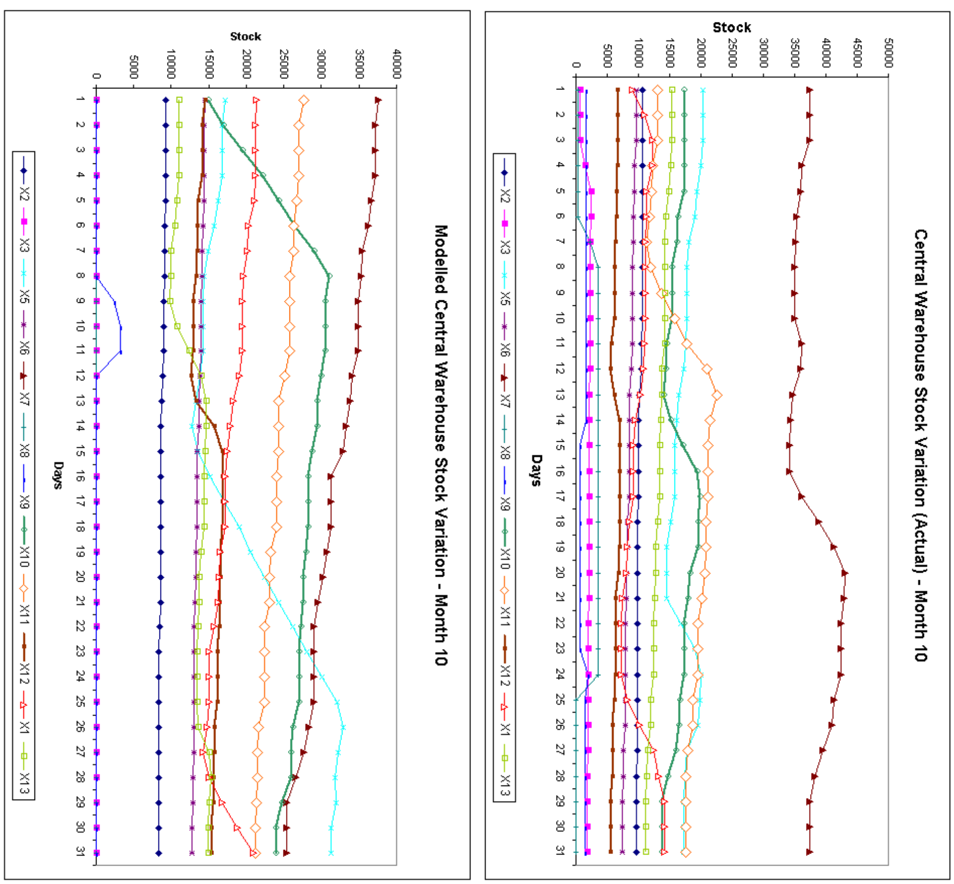


Figure 5.40: Actual and Modelled Stock Variation at Central Warehouse Month 10

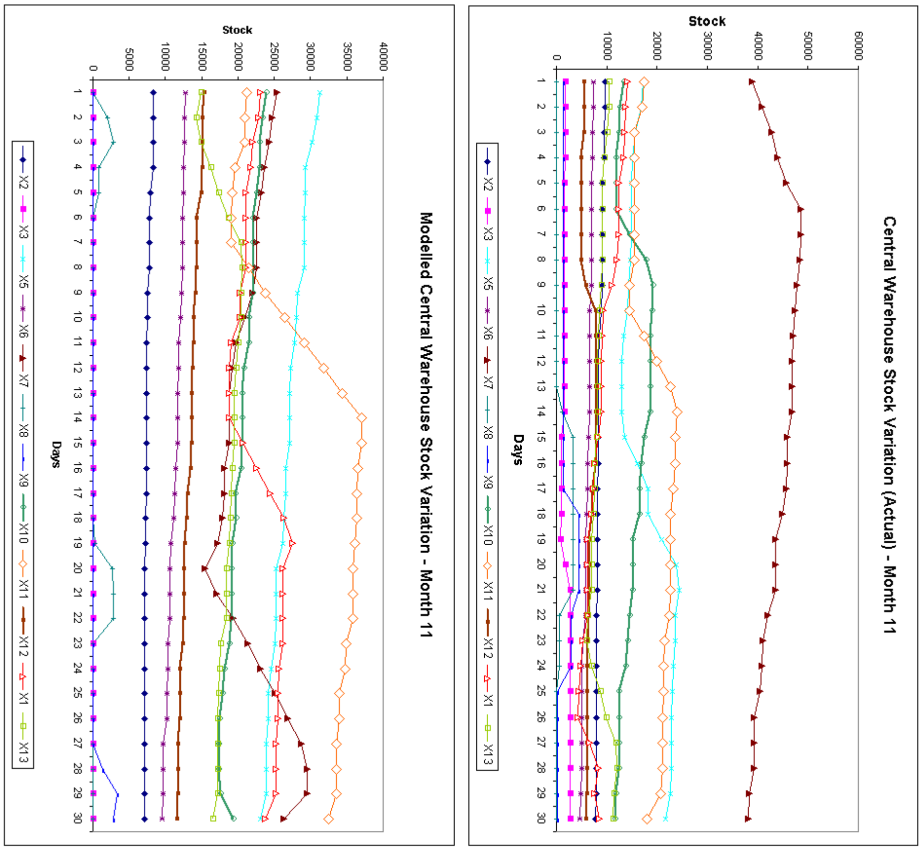


Figure 5.41: Actual and Modelled Stock Variation at Central Warehouse Month 11

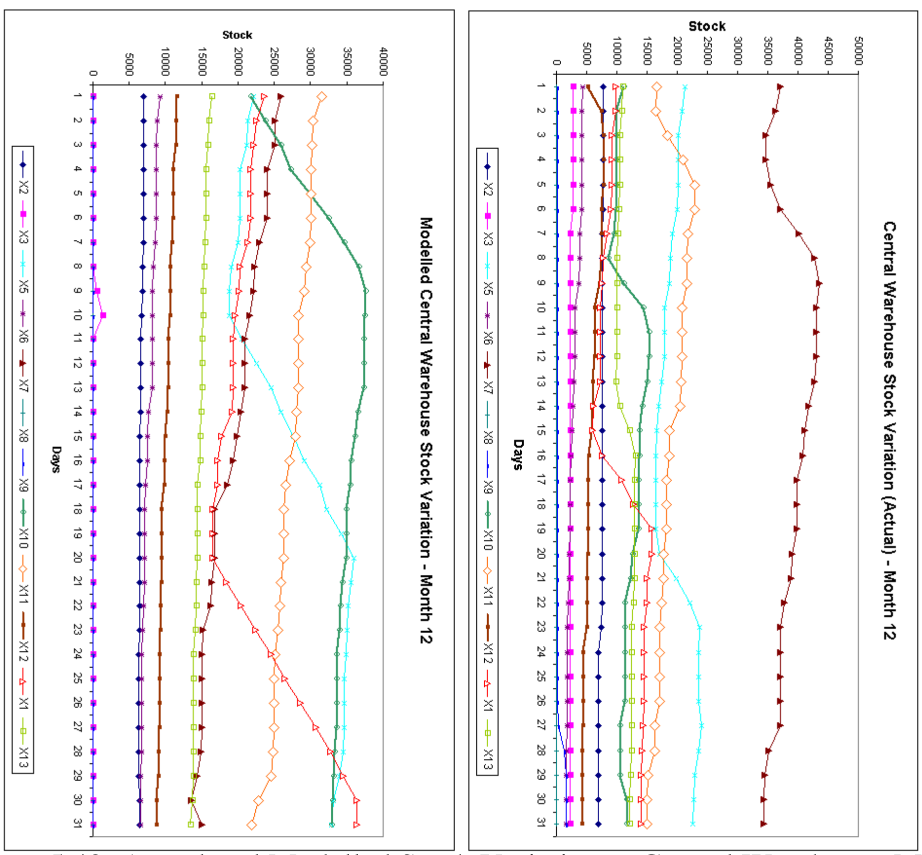


Figure 5.42: Actual and Modelled Stock Variation at Central Warehouse Month 12

5.8 Summary

This chapter first describes the real world supply network in details and shows the types of disturbances faced by the organisation. It was found that, for this organisation, the deviations of actual sales from the forecasts are a major source of disturbance and have huge impact on the performance measures of the entire supply network. Next, an agent based model is constructed to replicate the actual supply chain. All the different members of the actual supply chain, along with their decision making mechanisms, ways of functioning, are represented by different agents. This model is termed as the **baseline case** and would serve as the basis for carrying out several improvement experiments in the next chapter. Next, the model with all the improvements described in chapter 4 is run with the actual demand data faced by the actual supply network for the year 2004. This model is built in congruence with the informational and material flow structure depicted in Figure 4.2(b). All the different agents representing the different members of the supply chain are given full autonomy to make decisions. All the decisions made by different members are based on both global and local information. End-to-end visibility is ensured for all agents and the agents judge the relative usefulness of information. The factory has full control over deciding which product to produce and for how long. No central planning authority guides the different members on carrying out their regular activities. The performance of this improved model is then compared with the actual supply network's performance during the year 2004. The different performance measures are listed in section 5.5. These performance measures make sure that, although the actual supply network and the improved model have similar performance output but the actual system is more vulnerable to demand-forecast deviations. The actual system performs badly under uncertainty, which is evident from the increased number of stockouts, long response times to signals of disturbances, increased number of changeovers in production.

This chapter shows how the application of the intelligent decision-making rules used by the different agents representing the various elements in the supply chain can improve the management of disturbance by responding to them effectively without adversely affecting the performance of the system in terms of average inventory levels, production efficiency and customer service issues. This chapter shows how a decentralized, autonomous system capable of managing local disturbances through global information sharing and flexible, demand-led regular production planning system can give rise to increased supply chain resilience.

Chapter 6

Numerical Experiment Design

Chapter 2 (Table 1, conceptual model in Figure 2.4) shows the different possible capabilities and strategies to be adopted by the different agents of the supply network for enhancement of resilience. This chapter will enlist the different experiments with different combinations of these strategies and capabilities to understand the best possible strategies that can be adopted to manage disturbances effectively. This will help in understanding the trade-offs between different resilience enhancing strategies and at the same time in identifying those strategies, control procedures that can be sources of potential disturbance. Finally this chapter will evaluate the performance of the system under various uncertain scenarios.

6.1 Experimental Factors

6.1.1 Agent Attitude

Distribution Centre – The different attitudes of the distribution centres for the experiments are represented depending on the replenishment strategy adopted.

Safe (risk-averse) or Efficient (risk-neutral) – In case of adopting either KMSS or TMSS (please refer to chapter 4), the RDCs normally adopt a safe attitude towards inventory control. RDCs adopting a safe attitude would replenish at frequent intervals whenever the orders exceed forecasts (given by $G_{t,i}<0$ or $IP_{t,i} \leq F_{t,i}$ *or* $IP_{t,i} \leq D_{t,i}$ *or* $D_{t,i} \geq F_{t,i}$) and try building up as much inventory as possible to ward off uncertain demand. So the reorder point is set at a higher value equal to the sum of the cycle and safety stock and orders are generated more frequently.

In the instance, where the agents use learning mechanism, the various learning parameters and mechanisms will vary based on the attitudes of the agents (as discussed in section 4.1.1 of chapter 4). If an agent shows a safe attitude, it will opt for longer learning periods, *period* (period for updating the total days' cover based on real demand and the increase rates), *satPeriod (*during which the agent increases the target days' cover in case of any event of order exceeding the forecast), *limit (*during which the agent increases the learning rates based on significant deviation of order from forecast). Experiments can be conducted by varying the different learning periods to show the effects on the ability to improve resilience to uncertainties. In Chapter 5, *incRate* and *decRate* are assumed to be same for all the products irrespective of their demand. Focus towards safety would require higher *incRate,* while efficiency is preferred by the agents by selecting low values of *incRate*.

The agents can take both safety and efficiency focus by opting for a combination of both learned and adjustable safety stock figures to improve the service levels. The efficiency focus would encourage target days' cover expressed as an inverse function of total forecast. This will avoid generating excessive replenishment orders by the RDCs. On the other hand, the target days' covers are increased by a factor proportionate to the standard deviation of sales to take care of the safe attitude of the RDC agents (described in section 4.1.1, pp.115-116).

Self-centred (competitive) or Considerate (collaborate) – Each distribution centre can consider only its own stock position to place orders on the central warehouse. The decision to send materials to the respective RDCs is left upon the central warehouse. This portrays a self-centred attitude of the different agents. On the other hand, to explore the considerate or collaborative attitudes of different RDCs, they are made to share information on inventories of all stock-points in the chain (discussed in chapter 4.1.1 before). The RDCs decide on the order amounts after making provision for the central warehouse to keep average production run-length worth of stock for satisfying demands falling directly on the central warehouse.

Production Factory – Similar to the distribution centre agents, the factory can also act to be selfish or considerate and risk-averse or risk-neutral.

Safe (risk-averse) or Efficient (risk-neutral) – The different thresholds *c,c1 (*Flowchart 6, Chapter 4.1.3) are set at 0 for the safety focused agents. As the agent becomes more and more risk neutral, it increases the values of these thresholds.

The more safety focused factory agent aims at maintaining more stock-levels in the entire network. So factory agent considering either local or both local and global information for deciding on the priority of production, would be adopting a safe attitude by considering production cycle time worth of stock at each of the RDCs and the central warehouse while evaluating the inventory covers (Flowchart 5, chapter 4, pp 141). Risk-neutral agent would consider average production run-length (including average set-up time) and a contingency period (covering the uncertainty in supply of raw materials) worth of stock for evaluating the stock positions at various stock-points before making decisions. Risk-loving and more efficiency oriented factory agent would add no contingency period covering the supply uncertainty, even for products not directly sourced from the central warehouse.

Self-centred or Considerate – The factory agent's attitude can be to selfishly satisfy its own objective of improving production efficiency by trying to reduce the number of changeovers. The agent can be extremely self-centred by selecting the value of threshold *k1* to 0. The selfish attitude (*k1*=0) is considered in the cases described in Table 1 below, where the factory is marked as selfish. The factory agent might completely disregard the information on the stock positions of different products at different stock-points in the network and proceed with the ranking generated by the decision making stage. A self-centred factory agent can be simulated without the rule of avoiding the production of products with no sales, when other products are in precarious inventory condition.

A self-centred factory agent would continue producing the highly demanded products without any consideration for the inventory levels of other products across the network. This agent would not consider the inventory positions of different products even though the estimated production run-length obtained from the production planning and control function exceeds the average production run-length. Neither does the factory decides to change the product immediately if *y* and *y1* are found to be more than their respective thresholds.

The different agent type variations and their effects on the supply chain resilience will be investigated under the same environmental situation and under similar strategies. The learning parameter variation with the agent's attitudes will be tested only in the case where the agents use the learning mechanism. So all these experiments are to be carried out with a single set of demand data to compare the effects of having different types of agents.

6.1.2 Strategy Variation

This part of the experimentation process is based on exploring the utility of applying multiple resilience enhancing factors on the resilience of the system to unexpected rises or falls in demand across the network. This will also address the research questions in this thesis by identifying rules, control procedures that are not potential sources of disturbance. This will be discussed in the next chapter in further details after analysing the results from these experiments in this chapter and the results obtained from the case example in chapter 5.

Centralised planning V. Decentralised planning

A baseline model will be developed with the central planning agent, the factory agent, central warehouse agent and the different distribution centre agents. Section 5.4.1 in previous chapter describes the baseline model and its constituent agents in details. The characteristics of this model and the associated agent attitudes and strategies are listed in Table 1 at the end of this section. All these strategies are tested under the same set of disturbance characterised by the demand-forecast mismatch. The decentralised informational structure assigns autonomy to the factory agent to decide on both the amounts and the time of production of each product (both start and the duration). Not only this, but also the factory and RDC agent have the autonomy to learn the parameters needed to control the functions of inventory and production planning. The factory agent can either decide on the maintenance activities based on the inventory position of all products at the central warehouse or it can carry out the maintenance at stipulated fixed time intervals.

Information Sharing & Information Usage

Several stages of information sharing will be considered in the different experiments. First, the baseline case involving the central planning agent limits the information availability to the central planning agent alone with the factory, RDCs and central warehouse agents having no information shared among them. Only the factory uses the local information of central warehouse stock levels for basing its decision to produce products in a preferred sequence. This is termed as local information in Table 1. The details of global and local information are given in Chapter 4, where the formulation of the model is discussed. All other information sharing procedures will be tested in the decentralised informational structure of the system modelled to show the improvement in resilience. Since, in the decentralised informational structure all elements of the supply chain have complete access to the information, it is the usage of this information to make the decisions that matters in the final system performance. So there will be situations, where the factory agent might choose to use only local, only global or a combination of both local and global information for making decisions (section 4.1.3, Chapter 4). Similarly for the RDC agents, in the decentralised system, the effects of the choice to use the information on the standard deviation of actual sales during transit lead time in the traditional pull-based traditional safety stock based method of inventory planning or the information on the daily mismatch between sales-forecast, forecast bias will be investigated. Also the RDCs might choose to share information on each other's inventory levels, the central warehouse's inventory level and base their ordering decisions on that by collaborating amongst each other.

Pull-Push (Redundancy)

The strategy to pull materials from the central warehouse in case of need by the different RDCs will be tested. Also the case of push of materials, which are not sold at the central warehouse, will be tested. Although this is termed as push to the respective RDCs but actually this is production occurring by pull. The factory senses the time when these products need to be produced based on network information and produces them. Then the central warehouse immediately pushes them to the respective RDCs. Another case will be examined where excess materials available at the central warehouse are pushed to the RDCs demanding them. Pushing excess materials to the RDCs based on the absorption capacity of the RDCs (given by the sales to stock ratio) or the order volumes will be examined. These later two experiments will show how might the strategy to accumulate redundant resources nearer to customer order-points act beneficially or adversely to the entire network performance under uncertainty.

Flexibility & Visibility

The factory can decide to be flexible in its operations, first by incorporating flexibility in deciding the lower limit of production run-length and secondly by deciding to do maintenance at times when all products are being produced to a certain target level of inventory. Experiments with and without fixed lower limit for production run-length will be conducted to analyse the system performance under uncertain demand.

Flexibility in the number of available days for production will be considered while designing the experiments. Experiments will be conducted with fixed periods of maintenance at regular time intervals specified at the start of the year. Experiments with the factory deciding on the maintenance time (when to stop the production) based on actual demand across the network will also be conducted to examine the effects of flexibility of human resources.

Flexibility in the production process for enhancing resilience, to be tested in the experiments, would be the ability to decide intelligently the amount and the time of production of each product so that no product, at the time of intense demand in each of the products, gets produced excessively and thus limits the time of production of other products. So the ability of the production system, without hampering the production efficiency in the form of changeover time, to respond to rapid changes in demand would be tested in the experiments. Introducing full visibility of the network to the factory does this. The factory sets up control procedures to determine the exact time of production of products, which are not directly demanded from the central warehouse by looking at the network inventory of these products. Whereas, the factory uses the central warehouse stock information and forecast of direct demand from the central warehouse to determine the production time for all other products.

Formalisation vs. Improvisation

The different RDCs can adopt the traditional procedure of stock replenishment with the formalised periodic review process for safety stock estimation using standard deviation over the transit lead time. The RDCs could improvise the safety stock estimation procedure using the forecast error and bias as shown in Chapter 4. However, in order to ensure that it does not create unnecessary bull-whip effects, they can improvise the replenishment order amounts by limiting them by a target days' cover amount calculated as a function of total annual demand and standard deviation of demand. If the order is found to be more than this value, the RDCs order only the amount by which the stock levels fall short of the target days' cover. The factory can also improvise the minimum number of days' production by learning the production run-lengths to produce more frequently demanded products for longer duration.

6.2 Design of Experiments

In order to understand the importance of different strategies in improving resilience by managing disturbances and to identify the strategies that are not sources of disturbance, first a set of experiments with different strategies is conducted. The different model configurations are listed below and described in Table 1. In all these experiments, all the RDCs are assumed to be of similar attitude, i.e., all are either safety or efficiency focused. No RDC is different from others.

1. Baseline – A central planning agent is incorporated with monthly system of reviewing the production plan is tested. The available days of production and maintenance are fixed in the centralised planning system. Replenishment of all RDCs takes place through pull based system. The central warehouse sends exactly ordered amounts to the system. And no materials are issued to the RDCs unless order is generated. The minimum run-lengths are fixed at the planning stage by fixing the planned production amount. If the amount planned to be produced for any product is found to be less than a day's production, it is planned to be produced for a full day. The safety stock amounts used by the RDCs depend on the historical standard deviation of demand. This is discussed in Chapter 4 (pp.112). Factory agents use local central warehouse stock information for ranking products to be produced. The factory agent is considered to be safety focused as it always aims at keeping production cycle time worth of stock at the central warehouse. The factory agent adopts selfish policy because it only considers local information and disregards network level information of product sales, stock-levels in various RDCs. Also it assumes the value of $k1=0$ (discussed before in section 6.1.1). The RDCs are similarly safety focused and self-centred. First of all, they raise orders more frequently whenever the stock-levels drop below the sum of cycle and safety stocks (set a higher reorder point, section 6.1.1). Secondly, they are selfish since they just place orders mechanically as soon as the stock level drops below the reorder point without considering any other information.

2. Baseline with weekly review of production plans –

This model is developed with more frequent adjustment of production of the baseline model. Each week the factory agent reviews the inventory levels of the different products at the central warehouse and checks the amount produced. If the product has already been produced to the planned amount but the central warehouse inventory drops to zero, the factory decides to produce another week's forecasted demand to cater to the excess. This excess production amount will be deducted from other products' (which are not yet produced in full) planned amounts.

3. Decentralised Daily Planning with efficiency focused factory –

Each member of the supply chain is given full autonomy in making decisions. The factory agent now monitors the central warehouse inventory at daily intervals and makes decisions on the production amount and duration for each product. The factory considers the central warehouse stock cover for ranking the products as the amount of stock required to fulfil forecasted demand during the average production run-length (which is much lower compared to the approximate production cycle times). In this case, both the factory and the central warehouse tend to be efficiency focused as they want to retain low stock-levels by considering only average production run-length worth of stock in ranking the different products. All other factors, the attitudes of the agents remain the same as the earlier two configurations.

4. Decentralised information structure with adjustable safety stock policy –

The RDCs in the decentralised structure can use improvisation instead of strictly following the standard deviation based safety stock estimation for ordering replenishments of their stocks. First step towards this improvisation is to use adjustable safety stock policy for replenishment order generation. The pros and cons of this method are described in Chapter 4 before. All other factors remain same as in the previous model configuration (3). The ordering functions of the RDCs are programmed in the way shown in eq. 10, Chapter 4.

5. Decentralised information structure with collaborative RDCs –

This models the distribution centres to order in a coordinated way to each other's benefits. First each distribution centre estimates the orders to be placed on the factory after receiving the incoming orders from their respective orderbanks and the forecast figures. Then they communicate with other distribution centres and the central warehouse to know their order quantities and the direct sales figures at the central warehouse. If for any product the total stock amount after dispatching the direct sales quantities at the central warehouse falls below the replenishment orders from the distribution centres, the distribution centres scale down their respective orders according to their order magnitude ratios. This is done after keeping aside the average production time worth of stock in that product. This assumes that the agents order materials from the factory just that amount which is specified by the replenishment policy adopted. They can order less or none in case of non-availability but they never order more. But the only difference in this model configuration compared to others before is that the distribution centres now communicate with each other to get the knowledge of how much each of the other distribution centres are ordering of that product from the central warehouse. To avoid any stockout at the central warehouse and in RDCs, the distribution centres at each time pulse at least receive something which is better than nothing had they ordered the materials solely based on the localised information.

6. Decentralised information structure with collaborative RDCs, partial information based push by central warehouse and local information based decision making by the factory –

The model is constructed using push by the central warehouse. In this configuration, the central warehouse retains bare minimum stock only to just meet the direct demand. Excess material is pushed based on relative order volumes to the different distribution centres, whenever there is a replenishment order generated from the respective RDCs. So it is not full push system, but a combination of pull and push system as the excess material pushing occurs only when a replenishment order is generated. Here the distribution centres place orders in the same manner, only the central warehouse pushes excess materials depending on availability. So this actually is focused on increasing the inventory near to the customer demand thus avoiding any chance of stockout due to large unprecedented demand spikes. However, the RDCs still order based on traditional pull based safety stock method and the factory uses local knowledge of central warehouse inventory covers to make decisions on the production sequence. The term partial information based push implies the central warehouse does not use information on the actual sales, stock levels etc for each RDC for pushing the materials (pp.124, Chapter 4).

7. Decentralised information structure with collaborative RDCs, full information based push by central warehouse and partial use of global information in decision making by the factory –

In this case, the central warehouse pushes excess materials based on the absorptive capacity of each ordering RDC. This is expressed as the ratio of cumulative sales to average inventory in the RDC (pp.128, Chapter 4). The factory does not use the full knowledge of the network available to it, for making decisions on production sequencing and planning. Instead it uses the global information based ranking of the products carried out by the central warehouse. It does not use the information on new products, their forecasts two months in advance, whether the products are sourced directly from the central warehouse or not. The factory acts without considering the Part II of the decision making process of the factory to stop or change production if the stock levels of any product in any of the RDCs falls below the safety level (discussed in details in Chapter 4, pp. 142). So the factory still acts to be self-centred, although partially uses global information.

This model uses push based replenishment for products, which are not directly demanded from the central warehouse, which means whenever there is stock available in these products at the central warehouse, the entire stock is ordered and accumulated in the respective country RDC where it is demanded. All other RDCs order based on pull-based replenishment strategy and if excess stock is available in any product, the central warehouse pushes that product as per the absorptive capacity of the RDCs (ability to absorb excess materials given by the ratio of cumulative demand to average inventory).

8. Decentralised information structure with learning RDCs, pull-push by central warehouse and full use of global information in decision making by the factory –

This model case would examine the effect of introducing learning (Flowchart 3, Chapter 4) in the different RDCs. Since the model is developed to examine the effect of introducing different strategies, so this model is constructed with the same set of parameters used while applying the model to the case example. The RDCs are considerate by sharing the inventory level information of the central warehouse alone and do not order if they find the central warehouse inventory level is falling short of the forecasted sales of products directly sold from the central warehouse during the average production run-length period. However, they do not share each other’s order information and do not scale down the orders.

Table 1, Experimentation Formulation

Model	Strategy / Disturbance	Information Structure: Centralised Information Structure	Information Structure: Decentralised Information Structure	Planning Horizon: Monthly Planning	Planning Horizon: Weekly Review	Planning Horizon: Daily Planning	Maintenance: Planned	Maintenance: Decided	Replenishment: Pull	Replenishment: Push	Run-Length: Fixed min	Run-Length: Learned Min	Replenishment Strategy: Fixed Safety Stock	Replenishment Strategy: Adjustable Safety Stock	Replenishment Strategy: Learned Target Cover	Production: Local Info	Production: Global Info	Production: Global Local Info	Factory Agent: Safe	Factory Agent: Efficient	Factory Agent: Selfish	Factory Agent: Considerate	RDCs: Safe	RDCs: Efficient	RDCs: Selfish	RDCs: Considerate
Baseline	Uncertain Demand	X		X			X		X		X		X			X			X		X		X		X	
Baseline with weekly production plan review	Uncertain Demand	X			X		X		X		X		X			X			X		X		X		X	
Decentralised information structure	Uncertain Demand		X			X	X		X		X		X			X				X	X		X		X	
Decentralised information structure with adjustable safety stock policy	Uncertain Demand		X			X	X		X		X			X		X				X	X		X		X	
Decentralised information structure with collaborative RDCs	Uncerrtain Demand		X			X	X		X		X			X		X				X	X		X			X
Decentralised information structure with collaborating RDCs, partial use of information by central warehouse & local information use by factory	Uncertain Demand		X			X	X		X	X	X			X		X				X	X		X			X
Decentralised information structure with collaborating RDCs, full use of information by central warehouse & partial use of global information by factory	Uncertain Demand		X			X	X		X	X	X			X			X			X	X		X			X
Decentralised information structure with learning RDCs, full use of information by central warehouse & full use of global & local information by factory	Uncertain Demand		X			X	X		X	X		X			X			X	X	X		X	X	X		X
Decentralised information structure with safe & efficient RDCs, full use of information by central warehouse & full use of global & local information by factory	Uncertain Demand		X			X	X		X	X		X		X	X			X	X	X		X	X	X		X
Decentralised information structure with safe & efficient RDCs, full use of information by central warehouse & full use of global & local information by factory & flexible manpower resource	Uncertain Demand		X			X		X	X	X		X		X	X			X	X	X		X	X	X		X

Instead, the central warehouse with full access to global information prudently decides which RDC to send based on the relative order volumes when the central warehouse has insufficient stock in comparison to the orders.

The factory agent is considerate because it uses all the available information to make decisions and does not neglect production of single country products. Here all the thresholds for *c, c1* and *k1* are taken as 0,0 and 4 respectively similar to the case example provided in Chapter 5. Also the factory agent learns the minimum run-length of production. Thus the factory agent is modelled as both safety (setting *c, c1* to 0) and efficiency focused (augmenting the counters *y, y1* based on the central warehouse stock levels falling below average production run-length of stock, learning minimum production run-length based on the frequency of production). Also by setting *k1* to 4, the factory is more considerate.

9. Decentralised information structure with safe and efficient RDCs, pull-push by central warehouse and full use of global information in decision making by the factory

This model uses both the adjustable safety stock based approach for generating replenishment orders. By this they assume a safe attitude. However, in order to balance the efficiency, they adopt the inverse relationship discussed in the learning agents in the previous model (Chapter 4). If the replenishment orders are found to be more than the adjusted target days' cover given by the sum of the days' cover expressed as a function of total annual demand and the standard deviation of sales, the RDCs order the amount by which the stock falls short of the target days' worth of forecasted demand. The single country products are immediately pushed to their respective country markets as soon as they are produced. The factory agent makes full use of global and local information available to it as outlined in Chapter 4. The maintenance function is carried out at pre-planned intervals during the year and is not flexible depending upon the nature of demand. All other factors remain the same as in configuration 8.

10. Decentralised information structure with safe and efficient RDCs, pull-push by central warehouse, full use of global information in decision making by the factory, flexible maintenance time –

This model will test the effectiveness of incorporating flexibility in the maintenance function in configuration 9. The system will intelligently decide when to stop the machine for maintenance rather than carrying out pre-planned maintenance based on available labour (Flowchart 4, Chapter 4).

6.2.1 Linking the model configurations to the conceptual model (Chapter 2)

Here the different model configurations (Table 1) along with the different trade-off judgements (stated in the conceptual model) taken care of in the model is discussed. The baseline model (described in Section 5.4.1) focuses more on centralised planning and activities, routinisation (depicted by pre-planned maintenance periods at fixed times around the year, fixed minimum time for production, traditional safety stock policy fixed centrally) rather than flexibility, leanness and efficiency (depicted by pull-based replenishment policy, local information based production) rather than thoroughness or agility (depicted by monthly production planning, lack of information sharing between the members). The effects of incorporating more awareness into the system, configuration 2 incorporates weekly production planning by more frequent monitoring and awareness of inventory levels. Configuration 3 helps evaluate another trade-off between centralisation and decentralisation, mentioned in the conceptual model, by introducing a decentralised structure to understand its benefits with respect to centralised structure. Also it introduces increased monitoring by building more awareness in the form of daily planning of production. The factory is assumed to take more efficiency focus with the aim to maintain lower stock levels at the central warehouse. Configuration 4 introduces improvisation and flexibility into the ordering mechanism of the RDCs by incorporating adjustable safety stock policy. Configuration 5 introduces collaborative RDCs to improve resilience. This is guided by the conceptual model, which implies the incorporation of integration, sharing information and collaboration among different members for improved resilience under uncertainty. Configuration 6 and 7 introduce excess material push by central warehouse to the different ordering RDCs. These configuration tests the importance of redundancy in improving resilience. Also these configurations test the combination of redundancy (induced by pushing materials close to markets) and information sharing. In both the configurations, the central warehouse controls the replenishment volumes but configuration 7 is based on full information usage by the central warehouse. The factory makes partial use of global information of stock levels (in configuration 7). Configurations 8, 9, 10 attempts at balancing flexibility (through incorporating learned minimum production run-length or flexible maintenance period in configuration 10), redundancy (push of materials not directly demanded from central warehouse) and efficiency (by either learning target covers or introducing a combination of adjustable safety stock and real time learning of target covers). So all these configurations are derived from the conceptual model developed in Chapter 2.

6.3 Results of Application of Different Strategies & Discussion

5 independent replications with different independent demand values (obtained from the demand distributions fitted to the actual demand in Chapter 5) are used to explore the application of the different strategies on the performance and risk management abilities of the entire system. The network inventory performance measure is considered for estimation of number of replications for each scenario. The absolute error is the half length of the confidence interval (95%) and from the pilot of 5 runs it is found to be 7752, with mean 144519 and the standard deviation of 6236. The ratio of half length of confidence interval to the mean, after 5 runs, is found to be less than the allowable percentage error (Díaz-Emparanza I, 2002). Thus 5 replications are conducted for statistical reliability of the results. The calculations and justifications for taking 5 runs are shown in Appendix – D.1. The total average network inventory, the average inventory at different RDCs, the average network CSL, CSL in individual RDCs, the total number of stockouts, average and maximum response times to any disturbances in individual RDCs and central warehouse, the bull-whip effects in major RDCs (UK, France, Italy) and the production figures (run-lengths, change-overs and idle times) are all shown below for all

the models over the 5 replications. The detailed results of the 5 replications across different countries are shown in Appendix – E.

1. Baseline – The total network inventory averaged over the five replications is found to be 144520 units. The over-all average CSL is 95.7%. The total changeover time, average production run-length and the total number of changeovers averaged over the 5 replications are 12.3 days, 3.36 days and 103 respectively. The vulnerability of the baseline system is exposed in the following: firstly, the total number of stockouts averaged over 5 replications is 148 (in the first replication, the total number of stockouts reaches 180), secondly, the average response time to any deterioration to stock level (either a huge drop in inventory or a stockout) is 5.62 days and finally, when the major RDCs react to any stockout or drop in inventory levels, the replenishment orders generated result in average bullwhip effects of 5.2 in UK, 3.83 in Italy and 4.2 in France across all the products sold in those RDCs. The aggregate results are shown in Table 2 below. Tables with more details are described in Appendix E.

In the RDC average inventory levels (AVI) (appendix-E) and the network inventory levels (Table 2a), although there is enough stock available at the central warehouse in the single country products (*X3, X4, X8, X9)* but all these products suffer tremendous service level issues (Table 2b) and stock-outs (Table 2c). RDCs are sluggish in responding to unexpected large changes in inventory levels (given by large response times in Table 2e). Another problem is the large number of stockouts and prolonged response time to disturbances in *X12*. Surprisingly the bull-whip effect in UK is very high for the product though on average 10 stockouts occur in each replication (Appendix E). Sluggish response of the factory in making *X6* at the right time is observed in long periods of stockout at the central warehouse. This is because the central planning drives the production based on historical forecasts and during that time there was no forecast of *X6*. On the other hand, since the factory adopts a safe procedure while deciding on the priority for production using a higher number of days' cover the highly demanded products get top priority for production though *X6* or *X12* is getting backlogged.

Table 2a: Average Network Inventory - Baseline

Products / Replication	*X1*	*X2*	*X3*	*X4*	*X5*	*X6*	*X7*	*X8*	*X9*	*X10*	*X11*	*X12*	*Total*
1	14784	11105	2572	2608	23897	10576	18750	6780	4640	25761	13113	7147	141735
2	11840	11055	2138	766	47355	17711	18799	2620	3307	10956	11589	5871	144007
3	16954	6961	3332	753	19422	6492	20663	4154	3733	18763	19294	15421	135943
4	19588	7170	3561	765	21474	14940	22202	3810	4199	20845	17265	15956	151775
5	20737	7432	2879	761	19556	13384	23567	4345	3902	19573	17223	15778	149137
Average	16780	8745	2897	1131	26341	12621	20796	4342	3956	19180	15697	12035	144519

Table 2b: Average Network CSL - Baseline

Products / Replication	*X1*	*X2*	*X3*	*X4*	*X5*	*X6*	*X7*	*X8*	*X9*	*X10*	*X11*	*X12*	*Average*
1	0.989299	0.975508	0.976482	0.767877	0.969287	0.95915	0.972735	0.96016	0.924183	0.980856	0.977009	0.943314	0.949655
2	0.994043	0.980876	0.807763	1	0.974022	0.940408	0.982351	0.943766	0.967427	0.996291	0.966337	0.980683	0.961164
3	0.988161	0.983074	0.85054	1	0.976958	0.946293	0.982852	0.932781	0.85403	0.993672	0.981642	0.930002	0.951667
4	0.980921	0.980884	0.919302	1	0.969955	0.944651	0.983781	0.973794	0.863504	0.994327	0.975077	0.957333	0.961961
5	0.989907	0.974532	0.970311	1	0.976375	0.950873	0.986267	0.965505	0.81061	0.992577	0.979532	0.920276	0.959731
Average	0.988466	0.978975	0.90488	0.953575	0.973319	0.948275	0.981597	0.955201	0.883951	0.991545	0.975919	0.946322	0.956835

Table 2c: Total Stock Outs - Baseline

Products / Replication	*X1*	*X2*	*X3*	*X4*	*X5*	*X6*	*X7*	*X8*	*X9*	*X10*	*X11*	*X12*	*Total*
1	15	2	3	10	28	9	21	2	4	20	27	39	180
2	13	3	4	0	21	9	15	2	3	11	19	26	126
3	20	4	5	0	27	11	15	2	5	11	16	30	146
4	24	2	4	0	24	13	13	2	4	8	21	40	155
5	18	4	3	0	21	14	11	2	3	7	20	29	132
Average	18	3	3.8	2	24.2	11.2	15	2	3.8	11.4	20.6	32.8	147.8

Table 2d: Average Bull-whip Effect - Baseline

Products	*X1*	*X2*	*X3*	*X4*	*X5*	*X6*	*X7*	*X8*	*X9*	*X10*	*X11*	*X12*	***Average***
Replication													
	UK RDC												
1	2.265291				2.432451	19.13948	4.049866			3.15714	1.655799	9.882566	6.083227
2	3.094751				3.351394	9.812908	2.714242			2.840933	2.103518	3.531208	3.921279
3	2.791087				3.098625	7.558503	2.852417			2.605807	2.468176	8.115475	4.21287
4	2.199968				2.211365	5.08905	2.733405			2.649182	2.695472	15.37538	4.707689
5	2.469693				2.805199	5.518125	2.8			2.963588	2.492064	31.3	7.192667
Average	**2.564158**				**2.779807**	**9.423613**	**3.029986**			**2.84333**	**2.283006**	**13.64093**	**5.223547**
	Italy RDC												
1	3.031856				4.861055		4.538739				3.740692		4.043086
2	3.294413				4.110111		2.521119				5.034778		3.740105
3	3.356654				3.217117		3.026116				2.462267		3.015539
4	2.985001				2.950483		5.147836				4.655761		3.93477
5	4.010712				4.762008		4.582546				4.344338		4.424901
	3.335727				**3.980155**		**3.963271**				**4.047567**		**3.83168**
	France RDC												
1	3.624453	1.634329			4.34322	2.413764	2.263776			2.316849	2.983324	11.24469	3.853051
2	2.246536	1.486023			3.57431	2.975355	2.03997			3.549493	2.591217	8.764754	3.403457
3	2.597462	1.347943			3.122152	3.36632	1.8074			3.115043	2.208065	21.23652	4.849988
4	2.627619	1.595596			2.709889	4.678691	2.204087			2.444279	1.913476	6.291607	3.058155
5	3.249769	1.978328			3.153294	3.094696	3.045741			3.077172	2.881284	26.74606	5.903293
	2.869168	**1.608444**			**3.380573**	**3.305565**	**2.272195**			**2.900567**	**2.515473**	**14.85673**	**4.213589**

Table 2e: Average Response Period- Baseline

Products	*X1*	*X2*	*X3*	*X4*	*X5*	*X6*	*X7*	*X8*	*X9*	*X10*	*X11*	*X12*	***Average***
Replication													
1	4.33875	1.805	6.2	3.98	4.6625	6.206	3.245	4.55	6.2	3.032857	4.6875	6.825714	4.644443
2	4.18	1.82	9.3	13.6	5.3825	6.596	3.75625	4.1	4.61	5.754286	4.6	7.685714	5.948729
3	4.2825	1.82	7.7	13.4	5.34	6.97	3.235	4.1	5.5	4.581429	5.23125	10.05571	6.017991
4	4.25875	1.75	5.6	12.5	5.2825	4.796	3.38	3.7	5.4	5.508571	5.0425	7.86	5.423193
5	4.13875	1.66	7.3	14.13	5.6775	6.392	3.455	5.4	3.5	5.05	5.22125	11.14286	6.088946
Average	4.23975	1.771	7.22	11.522	5.269	6.192	3.41425	4.37	5.042	4.785429	4.9565	8.714	5.624661

Table 2f - Baseline - Production Details

Replication Number	Products	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	Total	Average Run-Length	Total Change Over time
1	Production	123448	25136	10584	12255	90770	38422	167307	30260	21696	120891	110832	64668			
	Days	57.2	9.9	7.0	5.3	44.5	15.4	72.6	12.4	8.0	46.6	39.1	25.4	343.4	3.37	12.5
	Runs	11	2	7	5	5	7	18	7	8	8	12	12	102.0		
2	Production	118330	26116	6493	0	137386	54375	168954	14688	18984	115893	102491	48417			
	Days	54.8	10.3	4.3	0.0	67.3	21.8	73.3	6.0	7.0	44.7	36.2	19.0	344.7	3.83	11.13
	Runs	13	3	4	0	5	6	14	6	7	12	10	10	90.0		
3	Production	131315	22896	12096	0	106484	29952	160511	19584	21696	120642	125454	63852			
	Days	60.8	9.0	8.0	0.0	52.2	12.0	69.7	8.0	8.0	46.5	44.3	25.1	343.6	2.96	12.3
	Runs	11	9	8		10	12	18	8	8	11	14	7	116.0		
4	Production	128289	22896	12096	0	102662	45178	160040	19584	21696	124334	101535	72390			
	Days	59.4	9.0	8.0	0.0	50.3	18.1	69.5	8.0	8.0	48.0	35.9	28.5	342.6	3.26	13.3
	Runs	13	9	8		10	6	14	8	8	10	10	9	105.0		
5	Production	136507	22896	10584	0	97236	53427	158737	19584	21696	133757	112607	59172			
	Days	63.2	9.0	7.0	0.0	47.7	21.4	68.9	8.0	8.0	51.6	39.8	23.3	347.8	3.38	12.1
	Runs	12	9	7		8	8	14	8	8	10	12	7	103.0		
Average														103	3.36	12.3

By looking at the production figures for the baseline case, it can be inferred that since the factory is guided by forecast-led centrally planned amounts, it produces excess products in low demand products *X2, X6, X12.* This can be risky if the demand of these products dies down, the entire production amount will be wasted in the form of unsold stock. If the same production time had been invested in the production of high demand products such as *X1, X7, X5, X11 or X10,* the factory's vulnerability would have been reduced. Also producing the low demand products in large quantities guided by central planning creates another problem in the operation of the factory. Since more time is spent in producing these products, the stock-levels of the high demand products reduce more frequently during this time thus forcing the factory to make changeover more frequently between high and low demand products. This is reflected in the increased number of changeovers (a maximum of 116 in the 3rd replication) resulting in huge reduction in the production run-lengths (2.96 days in the 3rd replication). Due to such reactive planning of production, the factory is unable to control the changeover of products. Though the factory adopts a self-centred attitude to reduce changeover time and tend to prefer products in the same category as the produced product while carrying out a changeover, yet due to above situation this attitude acts against the factory agent. This is due to two reasons – firstly, when low demand products are produced in larger quantities due to plan frequent changeovers limit the self-centred attitude of the factory and factory conforms to the plan before trying to satisfy its own interest and secondly, when high demand products are planned to be produced in large quantities, the factory carries out several changeovers within the same category to take care of safety as well as own interest of changeover time minimisation. In order to maintain safe stock levels in each product, the factory does not produce any product for more time and while making changeovers it selects products within the same category more often than others. And if more products in the same category are planned to be produced more, more changeovers take place thereby lowering productivity. That is why, the total changeover time is 12.3 days when there are 116 changeovers, whereas with 105 changeovers the total changeover time is 13.3 days (changeover between products not in the same category occurs more frequently).

2. Baseline with weekly review – Introduction of weekly review of production plans does not seem to improve the performance of the system under uncertain demand. This is evident in the inventory, service level and production performance. The total average network inventory actually rises to 145422 compared to baseline system, the network service level on the average remains the same at 95.7%. Since the ordering policy remains the same, the bullwhip effects, the response to disturbances remains the same as the baseline case. However, the total number of stockouts when averaged over the five replications turns out to be more than the baseline system (150). A look at the production performance (Table 3e) of this system speaks of the flexibility of the production system in producing products in different amounts in comparison to the baseline case. This actually results in lower number of changeovers on the average (102) compared to the baseline case. But since the factory responds to real demand and the stock level fluctuations more frequently, the average changeover time increases to 12.5 days in comparison to 12.3 days. Though the average production run-length shows no signs of increase and remains the same as the baseline case at 3.36 days. The improvement however is in the average response time, average total number of stockouts over the five replications in the central warehouse. The average response time drops down from 7.7 days to 7.1 days for product *X5* and 11.8 days to 9.7 days for product *X12*. However, the average number of total stockouts in the central warehouse reduces for product *X12* from 2.2 to 1.6, while for other products this remains the same. So this signifies that due to more frequent review of production plan and local knowledge of central warehouse, the system is able to improve (though not significantly) the performance of central warehouse under uncertain demand. But the weekly review system fails to improve the entire network's resilience in terms of response time, number of stock outs, maintaining inventory and service level performance. This is due to the fact that, the RDCs adopt the same traditional inventory control procedure and do not share information or coordinate while placing orders. They act in a safe and self-centred manner without any information or care for other RDCs or the central warehouse.

Table 3a: Average Network Inventory - Baseline with weekly review

Products	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	Total
Replication													
1	17384	5709	2571	3257	15135	19019	18793	8870	3506	25729	16143	6421	142538
2	12562	5516	2764	766	18980	15606	20986	2931	3379	38940	18006	7747	148184
3	16752	6617	3358	753	17375	6847	21552	4559	5246	20366	15506	15718	134647
4	20470	7170	3564	765	16108	16241	23023	3930	4392	20340	20905	17841	154751
5	13425	7111	2761	761	21582	13294	22850	4244	4205	20047	19809	16901	146989
Average	16119	6425	3004	1261	17836	14201	21441	4907	4146	25084	18074	12926	145422

Table 3b: Average Network CSL - Baseline with weekly review

Products	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	Total
Replication													
1	0.989195	0.975508	0.976482	0.782781	0.969287	0.95906	0.972735	0.870856	0.92127	0.980856	0.976908	0.950432	0.943781
2	0.994043	0.980876	0.807763	1	0.974022	0.934981	0.982351	0.943766	0.967427	0.996291	0.965739	0.980116	0.960615
3	0.988161	0.983074	0.867621	1	0.976958	0.952537	0.982852	0.932781	0.913489	0.993672	0.981501	0.953489	0.960511
4	0.980921	0.980884	0.917442	1	0.969955	0.944651	0.983781	0.988413	0.852701	0.994327	0.975077	0.935367	0.960293
5	0.989907	0.974532	0.970311	1	0.976375	0.944068	0.986267	0.965505	0.807324	0.992577	0.979504	0.91884	0.958767
Average	0.988445	0.978975	0.907924	0.956556	0.973319	0.947059	0.981597	0.940264	0.892442	0.991545	0.975746	0.947649	0.956793

Table 3c: Total Stockouts - Baseline with weekly review

Products	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	Total
Replication													
1	16	2	3	9	28	9	21	2	4	20	28	36	178
2	13	3	4	0	21	10	15	2	3	11	27	26	135
3	20	4	6	0	27	11	15	2	4	11	17	26	143
4	24	2	6	0	24	13	14	1	4	5	25	42	160
5	18	4	3	0	21	14	11	2	4	7	22	27	133
Average	18.2	3	4.4	1.8	24.2	11.4	15.2	1.8	3.8	10.8	23.8	31.4	149.8

Table 3d: Average Response Period- Baseline with weekly review

Products	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	Average
1	4.30875	1.8	6.4	4.05	4.6075	5.346	3.434286	4.7	6.5	3.035714	4.6475	6.610714	4.620039
2	4.18	1.82	9.3	13.6	5.3825	6.486	3.75625	4	4.6	5.754286	4.80375	7.521429	5.933685
3	4.2825	1.82	7.7	13.4	5.34	6.97	3.235	4.1	5.5	4.581429	5.19	10.18714	6.025506
4	4.25875	1.75	5.6	12.5	5.2825	4.796	3.38	3.7	5.4	5.508571	5.13	8.06	5.447152
5	4.13875	1.66	7.3	14.13	5.6775	6.392	3.455	5.4	3.5	5.05	5.2275	9.892857	5.985301
Average	4.23375	1.77	7.26	11.536	5.258	5.998	3.452107	4.38	5.1	4.786	4.99975	8.454429	5.602336

Table 3e - Baseline with weekly review - Production Details

Replication Number	Products	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	Total	Average Run-Length	Total Change Over time
1	Production	112218	17808	10584	14229	85536	56674	167669	38885	18984	118758	111167	64470			
	Days	51.95	7	7	6.11	41.93	22.71	72.77	15.88	7	45.82	39.25	25.34	342.8	3.30	13.09
	Runs	12	7	7	7	8	6	15	7	7	7	11	11	104.0		
2	Production	121152	17734	10584		95895	58827	167692	17136	18984	146188	109727	45663			
	Days	56.1	6.97	7		47.1	23.57	72.8	7	7	56.4	38.8	17.95	340.7	3.62	11.38
	Runs	14	7	7	0	7	7	12	7	7	6	9	11	94.0		
3	Production	130162	20352	12096		98112	29929	165142	20809	21671	126712	128268	63363			
	Days	60.3	8	8		47.11	11.99	71.7	8.5	8	48.9	45.3	24.91	342.7	3.17	13.08
	Runs	13	8	8		9	11	13	10	8	10	11	7	108.0		
4	Production	134657	22896	12096		99446	46223	170461	19584	21696	118868	101747	63968			
	Days	62.3412	9	8		48.748	18.52	73.99	8	8	45.9	35.9276	25.1447	343.6	3.47	12.33
	Runs	11	9	8		9	6	14	8	8	10	10	6	99.0		
5	Production	116022	22896	10584		100508	47311	167233	19584	21696	125980	124395	61010			
	Days	53.71	9	7		49.3	18.96	72.6	8	8	48.6	43.9248	23.9819	343.1	3.24	12.83
	Runs	15	9	7		8	9	14	8	8	10	11	7	106.0		
Average														102.2	3.36	12.542

3.Decentralised Information Structure – This case also fails to improve on the performance and risk management ability of the entire supply chain. The average network inventory level rises compared to the previous two cases to 146872 units, the production changeover time increases to 14.5 days over the five replications, the number of stock outs is 148, the bullwhip effects stay the same as the replenishment policies are unaltered. The average network CSL improves to 96.5% and the response time averaged over all the products and five replications improves marginally to 5.4 days. Although the factory uses efficiency improving measure by using ranking based on the average production run-length worth of stock cover, but this results in more changeover times overall. This is because, the factory, not using global information for making decisions and following the ranking procedure based on local information, produces huge amounts of low demand products (Table 4e) such as *X8, X9, X4.* Also since the factory has the autonomy to produce any product for any amount of time, so basing its decision on central warehouse ranking results in producing *X4, X8, X9* for considerable amount of time. Since the ranking is based on inventory covering less number of days (average production run-length rather than production cycle time), other products do not get prioritised and hence their production gets stopped. This results in huge inventory of low demand products at the central warehouse and increased changeover time. The average production run-length remains the same at 3.35 days. This is also harmful under uncertain large demand spikes in high demand products as the factory may not be able to respond fast enough. Although the bullwhip effect remains the same due to same replenishment policies in different RDCs, the service level performance improves substantially for single country products. This is due to increased production of these products and the ability to produce these products at right time. The number of stockouts in *X12* reduces substantially across the network; in fact the central warehouse suffers no stockouts in this product. However, still the production is sluggish in responding to stockouts in product *X6*, registering almost same response time and lower over-all service level across all the RDCs. In fact, the decentralised information structure results in far worse service level performance in this product at the central warehouse and entire network compared to the earlier two cases. So it is clear that even day-to-day decentralised production planning by the factory with local information and efficiency focus cannot improve the performance level in all fronts (production, inventory and service levels).

Table 4a: Average Network Inventory - Decentralised Information Structure

Products / Replication	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	Total
1	15207	11243	3999	4857	15925	9816	27348	8820	7030	16341	13507	10813	144905
2	16087	11091	5392	5005	15823	10557	27422	6055	10622	16368	13456	11474	149351
3	14885	11101	3702	3470	15409	9629	22826	8328	10883	15550	12891	9882	138555
4	16292	11998	5172	5327	15401	10459	24633	13773	10826	17371	13227	10111	154590
5	15538	11657	4914	4293	16888	10503	24634	10398	8483	15806	14816	9030	146958
Average	15601	11418	4636	4590	15889	10193	25373	9475	9569	16287	13579	10262	146872

Table 4b: Average Network CSL - Decentralised Information Structure

Products / Replication	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	Total
1	0.989299	0.975508	0.976482	0.91993	0.969287	0.959335	0.972735	1	0.86	0.980856	0.976908	0.966937	0.962273
2	0.994043	0.980876	0.832409	1	0.974022	0.93497	0.982351	0.939934	0.964142	0.996291	0.950738	0.9798	0.960798
3	0.988161	0.983074	0.925396	1	0.976958	0.944955	0.982852	0.932781	0.932275	0.993672	0.981642	0.969156	0.967577
4	0.980921	0.980884	0.935581	1	0.969955	0.929944	0.983781	0.988413	0.887083	0.994327	0.975077	0.972489	0.966538
5	0.989907	0.974532	0.970311	1	0.976375	0.955496	0.986267	0.965505	0.820751	0.992577	0.979532	0.969279	0.965044
Average	0.988466	0.978975	0.928036	0.983986	0.973319	0.94494	0.981597	0.965326	0.89285	0.991545	0.972779	0.971532	0.964446

Table 4c: Total Stockouts - Decentralised Information Structure

Products / Replication	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	Total
1	15	2	3	13	28	9	21	0	4	20	27	35	177
2	13	3	3	0	21	10	15	3	2	11	37	26	144
3	20	4	5	0	27	11	15	2	3	11	17	25	140
4	24	2	3	0	24	12	13	1	3	8	21	36	147
5	18	4	4	0	21	12	13	2	3	7	20	30	134
Average	18	3	3.6	2.6	24.2	10.8	15.4	1.6	3	11.4	24.4	30.4	148.4

Table 4d: Average Response Period- Decentralised Informational Structure

Products / Replication	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	Average
1	4.27625	1.805	6.2	2.95	4.6625	6.566	3.245	4.5	6.3	3.032857	4.615	5.068571	4.435098
2	4.18	1.82	9.3	13.6	5.3825	6.486	3.75625	3.3	4.6	5.754286	4.80375	6.845714	5.819042
3	4.2825	1.82	7.7	13.4	5.34	6.97	3.235	3.8	5.1	4.581429	5.19	7.531429	5.745863
4	4.25875	1.75	5.6	12.5	5.2825	4.796	3.38	4.2	5.7	5.508571	5.13	6.135714	5.353461
5	4.13875	1.66	7.3	14.13	5.6775	6.392	3.455	5.1	2.95	5.05	5.2275	8.307143	5.782324
Average	4.22725	1.771	7.22	11.316	5.269	6.242	3.41425	4.18	4.93	4.785429	4.99325	6.777714	5.427158

Table 4e - Decentralised Information Structure - Production Details

Replication Number	Products	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	Total	Average Run-Length	Total Change Over time
1	Production	116646	16830	14975	16296	95852	28620	177420	38708	24850	117552	104484	56811			
	Days	54.0028	6.61557	9.9041	7	46.9863	11.4663	77.0052	15.8121	9.16298	45.3519	36.8941	22.3314	342.5	3.53	13.5
	Runs	14	1	8	7	10	4	9	5	2	11	14	12	97.0		
2	Production	117920	16830	14462	11640	92382	34371	180808	24408	38115	116159	99149	59040			
	Days	54.5926	6.61557	9.56481	5	45.2853	13.7704	78.4757	9.97059	14.0542	44.8144	35.0102	23.2075	340.4	3.30	15.65
	Runs	15	1	7	4	13	6	9	5	5	11	16	11	103.0		
3	Production	118493	16830	13861	9312	90196	30311	184201	38161	37450	114555	101513	56970			
	Days	54.8579	6.61557	9.16733	4	44.2137	12.1438	79.9484	15.5886	13.809	44.1956	35.845	22.3939	342.8	3.73	13.23
	Runs	13	1	7	4	11	3	10	4	5	11	12	11	92.0		
4	Production	124229	19374	17482.2	13968	90029.5	36255.3	167439	36526.8	26762.7	114888	99207.4	55769.8			
	Days	57.5134	7.61557	11.5623	6	44.1321	14.5254	72.673	14.9211	9.86827	44.324	35.0308	21.9221	340.1	2.96	15.92
	Runs	19	2	9	6	14	5	9	4	3	16	16	12	115.0		
5	Production	124853	16830	15823	11640	90723.8	32243.9	174888	37957.1	29202.7	116460	105211	51532.6			
	Days	57.8023	6.61557	10.465	5	44.4725	12.9182	75.9061	15.5053	10.768	44.9306	37.151	20.2565	341.8	3.26	14.22
	Runs	15	1	6	5	11	5	11	6	4	14	16	11	105.0		
Average														102.0	3.35	14.50

4. Decentralised information structure with adjustable safety stock – This case uses adjustable safety stocks based on daily forecast error and bias. The RDCs in this case order in a self-centred manner to take care of their own inventory position without any knowledge of other members. So if the central warehouse does not have enough stock available to supply to the respective RDCs, no materials are supplied. This is reflected in same total number of stockouts (148) as in the baseline case (Table 5c), longer response time to any disturbances in the form of huge inventory drop or stockouts (Table 5e). Although the reaction is slow but every time there is a drop, due to the safe attitude of the RDCs, over-reaction takes place and results in generating high bullwhip effects (7.6 for UK RDC, 6.04 for Italy RDC and 6.34 for France RDC) in comparison to the earlier two cases (Table 5d). Table 5a shows the average network inventory level which are less compared to earlier cases. When the average inventory levels in each of the RDCs in each product are explored, it can be observed that the average stock level at the RDCs in this case is higher than that in earlier cases. The average stock level at the central warehouse is low in this case. Another reason for this is the lowering of unsold stock of low-demand products. For example, in earlier three cases *X2, X3, X4, X8, X*9 register high average inventory levels at the central warehouse, which altogether increase the average network inventory level. But in this case, due to introduction of the procedure of adjusting the safety stock levels based on the mismatch between real demand and forecast, the high demand products are ordered in larger quantities by the country RDCs resulting in increased production of these products (*X7, X5, X1, X10, X11).* This is evident in Table 5f showing the production amounts of different products. The total changeover time and number of changeovers averaged over five replications reduce to 10.38 days and 78 respectively. The average production run-length also increases to 4.45 days. Still the factory is not able to balance the production of products properly as is evident in the production of single country product *X9* in large quantity. Although the production performance improves, but on looking at the risk management ability of the system it can be concluded that, the system is vulnerable to fluctuations in demand. The number of stockouts in the first replication stands at 219. This also causes the low inventory levels at the different RDCs. In spite of huge production and stock levels of high demand products at the central warehouse, these products suffer huge stockouts across the network (Table 5c and Appendix E).

Table 5a: Average Network Inventory - Adjustable Safety Stock

Products	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	Total
Replication													
1	14482	4966	3640	2417	14186	5853	21548	5934	8481	15583	11105	8805	117000
2	16226	5728	3614	1944	14803	10145	21380	6993	12145	16160	11216	8291	128644
3	13380	4583	2934	2257	12900	7746	20021	6667	9187	15097	11563	7562	113896
4	15225	4244	4013	2602	16443	9236	23104	7932	9689	17124	12337	8516	130465
5	14731	4401	3917	1974	15158	10901	21786	6344	11613	16090	12226	8207	127349
Average	14809	4784	3624	2239	14698	8776	21568	6774	10223	16011	11689	8276	123471

Table 5b: Average Network CSL - Adjustable Safety Stock

Products	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	Total
Replication													
1	0.995842	0.992433	0.925037	0.920882	0.988584	0.968368	0.959484	1	0.943724	0.985295	0.982671	0.989971	0.971024
2	0.986486	0.968725	0.887554	1	0.983883	0.973957	0.983911	0.985652	0.931193	0.991656	0.973936	0.95149	0.968204
3	0.989355	0.989646	0.914343	1	0.983257	0.976126	0.9825	0.970313	0.855063	0.990408	0.988389	0.978007	0.968117
4	0.989416	0.972516	0.950465	1	0.987257	0.971525	0.979858	0.998217	0.95209	0.990645	0.981451	0.99158	0.980418
5	0.988208	0.985873	0.915786	1	0.986415	0.971038	0.980449	0.985049	0.861315	0.989166	0.984011	0.989475	0.969732
Average	0.989861	0.981839	0.918637	0.984176	0.985879	0.972203	0.97724	0.987846	0.908677	0.989434	0.982092	0.980105	0.971499

Table 5c: Total Stockouts - Decentralised Information Structure with adjustable safety stock

Products	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	Total
Replication													
1	11	3	13	32	18	8	41	0	1	39	32	21	219
2	22	7	13	0	17	9	18	2	2	14	25	11	140
3	14	5	13	0	19	9	19	2	3	12	21	13	130
4	21	4	11	0	14	7	22	1	2	16	22	11	131
5	24	5	10	0	9	7	20	1	3	12	18	10	119
Average	18.4	4.8	12	6.4	15.4	8	24	1.2	2.2	18.6	23.6	13.2	147.8

Table 5d: Average Bull-whip Effect - Adjustable Safety Stock

Products	*X1*	*X2*	*X3*	*X4*	*X5*	*X6*	*X7*	*X8*	*X9*	*X10*	*X11*	*X12*	***Average***
Replication													
	UK RDC												
1	6.966698				5.6519	5.683631	9.266229			13.21498	5.581619	3.324989	7.098578
2	14.25194				9.542614	2.129251	6.982649			13.06504	4.72805	7.938596	8.376877
3	10.72493				7.80923	2.114477	7.113735			13.44876	4.231545	5.954269	7.342421
	9.39365				8.319519	2.287934	7.529611			14.08248	6.76479	5.597271	7.710751
	9.12169				6.71818	2.419627	5.678317			16.96853	5.720073	4.802809	7.347032
	10.09178				**7.608289**	**2.926984**	**7.314108**			**14.15596**	**5.405215**	**5.523587**	**7.575132**
	Italy RDC												
1	4.714288				6.422748		4.479846				5.233404		5.212572
2	6.484356				6.205249		2.691454				5.398974		5.195008
3	6.722279				6.497684		3.934626				4.925933		5.520131
4	8.633359				6.633168		3.960842				8.862309		7.02242
5	9.652083				11.75377		2.993505				4.744533		7.285973
	7.241273				**7.502524**		**3.612055**				**5.833031**		**6.047221**
	France RDC												
1	7.083637	2.707087			5.402608	6.269289	13.11321			2.248289	5.881535	4.523084	5.903593
2	7.503791	2.47544			6.269453	5.186016	7.781967			3.019243	7.37563	8.764754	6.047037
3	7.302942	2.270139			6.285719	7.728131	14.5448			2.712602	6.098	4.529173	6.433938
4	10.35585	1.969169			6.240272	4.541993	11.76587			2.97319	5.134327	6.521623	6.187786
5	9.196652	2.132614			5.959306	5.90006	19.50964			2.936694	5.449454	5.985662	7.13376
	8.288574	**2.31089**			**6.031472**	**5.925098**	**13.3431**			**2.778004**	**5.987789**	**6.064859**	**6.341223**

Table 5e: Average Response Period- Adjustable Safety Stock

Products	*X1*	*X2*	*X3*	*X4*	*X5*	*X6*	*X7*	*X8*	*X9*	*X10*	*X11*	*X12*	***Average***
Replication													
1	5.235	3.2	7.3	6.1	6.35	10.006	5.44	5.9	8	4.692857	5.4225	4.871429	6.043149
2	5.7425	2.85	6.9	13.5	9.185714	7.44	5.96875	5.6	6.8	5.585714	6.225	11.14714	7.245402
3	5.7125	4.7	8.6	15.5	7.7625	8.3	5.90375	7.3	6.5	5.185714	6.1	6.857143	7.368467
4	5.95875	2.3	4.8	13.2	7.49	7.404	5.7275	5.5	8.1	6.292857	5.5375	7.21	6.626717
5	5.6625	3	7.96	14.12	6.76	10.4	5.96625	5.6	10.5	5.942857	6.21875	6.834286	7.41372
Average	5.66225	3.21	7.112	12.484	7.509643	8.71	5.80125	5.98	7.98	5.54	5.90075	7.384	6.939491

Table 5f - Adjustable Safety Stock - Production Details

Replication Number	Products	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	Total	Average Run-Length	Total Change Over time
1	Production	122926	13981.2	11917.9	9758.77	121165	28908.8	182911	15397.2	19353.8	129789	104074	53183.4			
	Days	56.9104	5.49575	7.88218	4.19191	59.3944	11.5821	79.3885	6.2897	7.13636	50.0731	36.7492	20.9054	346.0	4.44	10.01
	Runs	12	2	3	4	10	5	11	2	2	9	10	8	78.0		
2	Production	126767	16110.3	11153.7	2328	105020	31374.2	179056	21649.5	40775.4	126079	104894	52511			
	Days	58.6886	6.33266	7.37679	1	51.4806	12.5698	77.7154	8.84376	15.0352	48.6414	37.0387	20.6411	345.4	4.43	10.65
	Runs	9	3	3	1	10	4	11	4	4	10	11	8	78.0		
3	Production	120209	14194.3	6461.18	4656	104576	32564.8	188623	36818	27902.8	131111	106713	48669.3			
	Days	55.6525	5.57952	4.27327	2	51.2628	13.0468	81.8676	15.04	10.2886	50.5828	37.681	19.131	346.4	4.81	9.6
	Runs	12	2	2	2	9	3	11	3	2	9	11	6	72.0		
4	Production	128906	16105.6	13576.8	11640	104817	31432	173640	24812.7	28118.9	122811	102086	54090.8			
	Days	59.6785	6.33082	8.97936	5	51.381	12.5929	75.3647	10.1359	10.3683	47.3809	36.0474	21.2621	344.5	4.20	11.5
	Runs	13	3	3	5	9	4	9	3	3	10	11	9	82.0		
5	Production	129568	15250.6	8857.25	6984	107326	31553.2	179870	18087.9	38916.1	128241	103287	51171.7			
	Days	59.9852	5.99474	5.85797	3	52.6109	12.6415	78.0686	7.38887	14.3496	49.4756	36.4714	20.1147	346.0	4.38	10.05
	Runs	11	3	2	3	9	3	12	3	3	10	11	9	79.0		
Average														77.8	4.45	10.36

The customer service level averaged over the different products in different RDCs for this case is 97.1%, a substantial improvement with respect to the baseline case. Even though the frequency of stockouts in *X6, X12* reduces but the response time increases considerably in this case. This signifies the over-confident but reactive nature of this inventory policy. Although the policy tracks the forecast error and generates replenishment orders at any variation of order from forecast but it generates large orders in cases of huge deviations. The situation in fact worsens for single country products. So application of adjustable safety stock policies in isolation without any information sharing and collaboration between different RDCs could not improve the resilience of the system to large deviations of demand from forecast.

5. Decentralised Information Structure with collaborative RDCs – The average network inventory is almost the same as the average network inventory in the previous case (123560 cases). The CSL on average improves for all the products in comparison to all scenarios and is found to be 98.5% (Table 6b). The problem is with the single country products and *X2.* It can be seen from Table 6a, that although the stock levels at the central warehouse are quite high in these products but the stock levels in the RDCs are not high enough and this raises the service level issues in these products. Specially *X2* in the 2nd replication is not produced on time resulting in poor customer service at both France RDC and central warehouse. However, on average the total number of stockouts (Table 6c) gets reduced drastically in all the products in this case (29 stockouts on average per replication). So collaborating to order sensibly with the knowledge of each other's and the central warehouse stock level results in better performance. But the bullwhip effect (Table 6d) increases substantially in this case in major RDCs (9.4 for UK, 9.7 for Italy and 11.2 for France RDC). Though the number of stockouts reduces but the response time to disturbances (Table 6e) in the form of drop in inventory due to spiky demand actually is longer than that in the baseline system (6 days). The response time for *X2, X3, X6, X1, X7, X9, X10, X11, X5* increases substantially in comparison to the baseline system. So even though the system performance improves but it is still not responsive enough to manage the disturbances. The production figures (Table 6f) are similar to the previous case (10.01 days average changeover time, 4.43 average run length and 79 changeovers).

Table 6a: Average Network Inventory - Collaborative RDCs

Products	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	Total
Replication													
1	13617	3693	3972	1757	11512	8943	22326	5634	8199	14311	13437	8071	115473
2	17164	6610	3901	1632	14691	7411	28650	6085	11784	18953	15958	8147	140987
3	13461	3256	4541	1081	11519	6868	19037	6106	7068	14945	12921	8379	109183
4	14731	4841	4104	1075	15416	9760	21625	5394	13765	15657	15255	8026	129650
5	14653	5273	3457	2368	12429	9462	19415	5679	10671	16308	15086	7704	122505
Average	14725	4735	3995	1583	13114	8489	22211	5780	10297	16035	14532	8065	123560

Table 6b: Average Network CSL - Collaborative RDCs

Products	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	Average
Replication													
1	0.994522	0.994624	0.994855	0.955446	0.994789	0.994716	0.989441	0.92148	1	0.998652	0.995464	0.995563	0.985796
2	0.999136	0.898811	0.958718	1	0.991397	0.988417	0.993773	0.955262	0.962452	0.999388	0.983488	0.989917	0.97673
3	0.998417	0.998009	0.993971	1	0.995943	0.992232	0.996281	0.940269	0.865114	0.998364	0.996921	0.986963	0.980207
4	0.998975	0.995022	0.993721	1	0.993276	0.989248	0.994685	0.997059	0.947769	0.999123	0.99432	0.994768	0.991497
5	0.997888	1	0.985727	1	0.991283	0.982959	0.993892	1	0.926479	0.997421	0.992596	0.993806	0.988504
Average	0.997787	0.977293	0.985399	0.991089	0.993338	0.989515	0.993615	0.962814	0.940363	0.99859	0.992558	0.992204	0.984547

Table 6c: Total Stockouts - Collaborative RDCs

Products	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	Total
Replication													
1	7	2	1	2	2	3	4	1	0	2	2	3	29
2	1	3	1	0	3	3	4	1	1	2	9	5	33
3	4	1	2	0	3	2	3	2	2	3	1	4	27
4	2	1	1	0	1	3	2	1	3	2	2	2	20
5	5	0	1	0	6	3	5	0	4	4	5	4	37
Average	3.8	1.4	1.2	0.4	3	2.8	3.6	1	2	2.6	3.8	3.6	29.2

Table 6d: Average Bull-whip Effect - Collaborative RDCs

Products	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	Average
Replication													
	UK RDC												
1	7.304027				7.745988	12.46391	11.5553			8.650026	8.455613	6.890491	9.009337
2	10.41104				8.488144	7.019849	6.828184			7.102518	11.34216	13.00834	9.171462
3	13.1769				12.00985	4.698961	9.355644			10.30733	7.499438	11.9037	9.85026
4	9				7.8	4.4	11.5			14.4	9.8	9.9	9.542857
5	11.60972				9.920809	4.330078	6.633269			10.29792	12.28399	10.26464	9.334345
	10.30034				**9.192958**	**6.58256**	**9.17448**			**10.15156**	**9.87624**	**10.39343**	**9.381652**
	Italy RDC												
1	6.238365				12.59001		8.661722				7.46129		8.737848
2	9.195687				10.26776		9.476983				11.30688		10.06183
3	8.547333				9.096325		9.346737				7.276215		8.566653
4	6.73996				8.449155		11.19414				9.869477		9.063184
5	13.11895				12.91903		12.92655				10.03568		12.25005
	8.768058				**10.66446**		**10.32123**				**9.189908**		**9.735913**
1	9.111942	4.565169			11.30248	17.00879	7.533611			8.526112	9.595616	11.09066	9.841797
2	8.966939	5.797477			6.952088	16.73143	8.642749			18.28453	4.196962	11.83283	10.17563
3	9.162357	3.952975			9.108781	36.26314	13.00495			16.55179	8.240659	16.5628	14.10593
4	9.127824	3.976696			7.164402	19.59428	6.764588			10.31235	6.411963	9.998919	9.168877
5	10.54869	3.461993			10.0524	18.72326	17.27365			15.62845	9.6751	15.91125	12.65935
	9.38355	**4.350862**			**8.91603**	**21.66418**	**10.64391**			**13.86064**	**7.62406**	**13.07929**	**11.19032**

Table 6e: Average Response Period- Collaborative RDCs

Products	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	Average
Replication													
1	5.22875	8.1	10.7	6.92	5.3475	5.52	3.98625	4.9	2.33	4.084286	4.9525	4.594286	5.555298
2	4.71375	2.47	13	10.1	6.36625	7.05	3.91875	2.5	5	5.267143	6.29375	5.33	6.000804
3	5.40125	9.205	8.9	10.9	6.455	5.908	4.55	4.1	6.4	4.634286	4.6	6.161429	6.43458
4	4.5	3.275	5.3	8.5	6.4	7.94	3.945	4.3	5.8	5.742857	5.1875	5.592857	5.540268
5	5.05	5.3	10.93	12.8	6.60625	5.88	4.3625	3.9	8.5	5.615714	5.75	6.005714	6.725015
Average	4.97875	5.67	9.766	9.844	6.235	6.4596	4.1525	3.94	5.606	5.068857	5.35675	5.536857	6.051193

Table 6f - Collaborative RDCs - Production Details

Replication Number	Products	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	Total	Average Run-Length	Total Change Over time
1	Production	118047	14168.7	9418.16	9622.86	114343	30743.6	185661	16453.1	22226.1	130309	109039	56033			
	Days	54.6516	5.56944	6.22894	4.13353	56.0506	12.3172	80.5818	6.72103	8.19546	50.2735	38.5024	22.0255	345.3	4.11	10.76
	Runs	14	2	2	4	11	4	13	2	2	10	11	9	84.0		
2	Production	121063	15653.8	12859.7	2262.77	103002	31988.9	192719	30465.6	38411.7	130477	97787.8	43661.3			
	Days	56.0475	6.15323	8.50511	0.97198	50.4914	12.8161	83.6454	12.4451	14.1636	50.3385	34.5296	17.1624	347.3	5.03	8.73
	Runs	10	1	3	1	8	6	11	2	3	8	9	7	69.0		
3	Production	123616	13964.7	9614.18	3838.53	107327	30777.4	183447	24049.6	18044.9	136818	108381	56310.6			
	Days	57.2296	5.48927	6.35858	1.64885	52.6115	12.3307	79.6213	9.82417	6.65373	52.7847	38.27	22.1347	345.0	4.06	11.05
	Runs	12	3	2	1	13	4	15	3	1	10	12	9	85.0		
4	Production	122760	14254.5	7026.98	3838.53	113516	34625.3	193183	16453.1	43224.1	129354	93710.4	49413.9			
	Days	56.8333	5.60317	4.64747	1.64885	55.6453	13.8723	83.847	6.72103	15.9381	49.9051	33.0898	19.4237	347.2	4.69	8.83
	Runs	11	2	2	1	9	4	15	2	3	9	8	8	74.0		
5	Production	135201	15269.2	15184.1	2328	103834	32745.3	173883	15560.7	27391.5	129451	117150	47230			
	Days	62.5929	6.00203	10.0424	1	50.8992	13.1191	75.47	6.35648	10.1001	49.9424	41.3664	18.5653	345.5	4.26	10.72
	Runs	14	2	3	1	10	4	16	2	3	9	11	6	81.0		
Average														78.6	4.43	10.02

6. Decentralised Information Structure with Collaborative RDCs, implementing push based replenishment – The total network average inventory reduces further in this case to 113861 units (Table 7a). All the products (specially those which are demanded in large volumes) are pushed to their respective ordering RDCs. This results in higher average inventory at the country RDCs and lower average inventory level at the central warehouse in these products. The customer service level drops to 97.8% (Table 7b) compared to the previous case. The main reason for this drop is huge backlogs at the central warehouse in product *X2,* at Ede RDC in product *X9* and at Niederbipp RDC in product *X3* (Appendix E). Actually on examining the stock out results, it is seen that more number of stockouts occur at central warehouse in almost all products compared to the previous case. Though the total number of stockouts on the average remains same at 30 (Table 7c). But the response time to stockouts (Table 7d) is the longest among all the cases described so far. This is because of the very long response time for products *X2* and *X3.* In fact, if seen in further details, at the central warehouse, in one of the replications the average response time for *X2* is 66 days, and the maximum response time for *X3* in Niederbipp RDC is 154 days. This is the result of the integration of the system. Since the production is coupled to the inventory and distribution, so as more and more materials are pushed to the respective RDCs, the production factory senses the drop in inventory and starts producing those products in large quantities. This is the cause of low production of *X2,* in replication 2 and 5 in comparison to other cases (Table 7e). This actually causes the high response time for the central warehouse to cope with the stockouts. Since the central warehouse constantly pushes materials based on order volumes, and since all RDCs order high demand products in large volumes, their stock levels reduce faster at central warehouse compared to the low demand products and this results in increased frequent production of these products since the factory does not base its decisions on global information and uses only central warehouse stock information to decide the priority of production. This actually aggravates the performance of the system for products *X2* or *X6* for which most of sales start to peak in the middle of the year. So the factory being busy in coping with falling stock-levels in high demand products due to increased push of materials, is unable to produce these products at the right time. The effect of order-volume based push of materials also affects the production performance adversely.

Table 7a: Average Network Inventory - Partial Information Based Push

Products	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	Total
Replication													
1	10659	2262	2662	3635	8784	9558	12794	5726	6641	13412	17241	16304	109677
2	17052	2491	3236	2973	7678	13690	16519	8992	11332	11321	11830	13263	120377
3	11161	2382	2736	3096	8053	5136	13257	8851	15236	11323	9911	11129	102270
4	19064	1849	4859	2844	10719	6572	15955	6758	10696	15201	12780	12226	119524
5	14385	2650	2883	2952	9607	5673	17901	10792	9096	18733	11828	10957	117457
Average	14464	2327	3275	3100	8968	8126	15285	8224	10600	13998	12718	12776	113861

Table 7b: Average Network CSL - Partial Information based push

Products	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	Average
Replication													
1	0.995881	0.903267	1	0.98906	0.991845	0.994716	0.988878	0.934314	0.892428	0.998847	0.995464	0.996678	0.973448
2	0.997424	0.925214	0.978435	1	0.99023	0.987633	0.993773	0.998129	1	0.995207	0.98948	0.989222	0.987062
3	0.997577	0.959669	0.733484	1	0.993758	0.985462	0.994835	0.987876	0.839752	0.998364	0.996921	0.986057	0.956146
4	0.99902	0.897089	1	1	0.994117	0.989248	0.994685	1	0.992579	0.998296	0.994201	0.994768	0.987834
5	0.998509	1	0.985727	1	0.993357	0.982959	0.993161	1	0.917371	0.998469	0.990924	0.992289	0.98773
Average	0.997682	0.937048	0.939529	0.997812	0.992661	0.988004	0.993067	0.984064	0.928426	0.997836	0.993398	0.991803	0.978444

Table 7c: Total Stockouts - Partial Information based Push

Products	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	Total
Replication													
1	5	2	0	1	7	3	4	1	1	1	2	2	29
2	5	1	1	0	5	5	4	1	0	5	6	6	39
3	4	1	2	0	4	3	5	1	1	3	1	5	30
4	1	2	0	0	1	2	3	0	1	4	2	2	18
5	3	0	1	0	6	3	7	0	1	3	6	4	34
Average	3.6	1.2	0.8	0.2	4.6	3.2	4.6	0.6	0.8	3.2	3.4	3.8	30

Table 7d: Average Response Period- Partial information based push

Products	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	Average
Replication													
1	5.2	14.9	5.3	5.33	5.59375	7.24	3.8925	2.33	0	4.1	5.2	3.971429	5.254807
2	5.335	13.35	16.5	5	6.625	6.7	4.25375	3.3	6	4.964286	5.9	4.861429	6.899122
3	5.2825	24.35	77	7	6.75	7.148	4.4	2	0.5	5.06	4.97125	5.414286	12.48967
4	4.85875	9.25	19.3	5	6.51875	10.5	4.065	2	0	5.734286	5.57375	4	6.400045
5	4.1775	34.75	2.5	0	6.57875	6	4.45875	0	5	4.584286	7.2375	4.542857	6.65247
Average	4.97075	19.32	24.12	4.466	6.41325	7.5176	4.214	1.926	2.3	4.888571	5.7765	4.558	7.539223

Table 7e - Partial information based push - Production Details

Replication Number	Products	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	Total	Average Run-Length	Total Change Over time
1	Production	114692	12246.5	5335.67	9601.24	110812	25849.5	166318	17938.4	30922.8	119417	116616	76146			
	Days	53.0981	4.81389	3.52888	4.12425	54.3194	10.3564	72.1865	7.32777	11.4022	46.0712	41.1779	29.9316	338.3	2.60	17.7
	Runs	22	2	3	4	18	5	26	4	4	17	14	11	130.0		
2	Production	128073	7412.57	5957.46	2472.62	96940.9	43273.9	175047	40073.1	23468.9	115981	105908	65419.3			
	Days	59.293	2.91375	3.94012	1.06212	47.52	17.3373	75.9754	16.3697	8.65373	44.7459	37.3968	25.7151	340.9	2.96	15.1
	Runs	18	2	3	1	17	4	21	5	3	16	13	12	115.0		
3	Production	123862	15018.9	7439.27	2472.62	99673.7	24684.6	167794	29330.9	36269.9	124530	114530	60205.1			
	Days	57.3434	5.90367	4.92015	1.06212	48.8597	9.88966	72.8273	11.9816	13.3739	48.0438	40.4413	23.6655	338.3	2.45	17.7
	Runs	23	3	1	1	19	5	28	4	2	19	21	12	138.0		
4	Production	140396	14749	16104.9	2472.62	96674.6	31181.1	164733	18176.5	42446.4	117537	107722	55857.1			
	Days	64.9983	5.79755	10.6514	1.06212	47.3895	12.4924	71.4987	7.42504	15.6513	45.346	38.0373	21.9564	342.3	3.08	13.7
	Runs	19	2	3	1	15	4	24	3	2	14	14	10	111.0		
5	Production	129862	9337.02	5335.67	2472.62	98163.6	29319.1	175849	43903.8	24973.5	123265	107583	62869.9			
	Days	60.1214	3.67021	3.52888	1.06212	48.1194	11.7464	76.3233	17.9346	9.20851	47.5558	37.9884	24.713	342.0	3.08	14.03
	Runs	18	2	3	1	14	6	19	4	3	15	15	11	111.0		
Average														121.0	2.84	15.65

The total number of changeovers increases to 121 when averaged over the five replications. In order to cope with the frequently falling inventory levels in high demand products without the use of global information on inventory levels at different RDCs, the factory produces these products for very small run-lengths. This increases the total changeover time (15.7 days on average) and reduces the run-length drastically to 2.84 days. So lack of information in planning production and distribution by the central warehouse actually deteriorates performance in the face of uncertainty. Increased response time to stockouts actually makes the system vulnerable to other unknown forms of disturbance. The bullwhip effects are not considered here since this system works on push based replenishment and the orders are generated in the same manner as the decentralised case with adjustable safety stock and collaborative RDCs. So the bullwhip effects are bound to be high.

7. Decentralised Information Structure with Collaborative RDCs, implementing push based replenishment for all products and partial use of global information by the production factory – The central warehouse now pushes materials to RDCs based on their actual sales and stock in each product. The average network service level increases substantially to 99.7% in comparison to all other cases discussed before (Table 8b). Though the average network stock level rises to 140100 units (Table 8a) compared to earlier two cases but it is still less than the inventory level in the baseline case. One of the main reasons of this increased inventory is the comparatively huge amount of production of high demand products (Table 8e). Also the production is more responsive to the changes in the inventory levels of low demand (*X8, X9)* or new products (*X2).* This results in zero production of *X4* but still achieving 100% CSL in this product at Niederbipp RDC. The system is now better capable of improving performance of almost all the products in the face of uncertainty. The total number of stockouts reduced to only 19 when averaged over the five replications. The response time on average reduced to 5.6 days compared to the previous two cases. Although the service levels improved for all products, but the average response time for low demand products actually increased many-fold (14.35 days). This is due to the introduction of the push-based system for single country products, which is actually a pull-based production system (discussed in section 6.1.2). So although it is tabulated under the Niederbipp RDC's response period, it actually measures the response time of the production to react to any abnormalities in the network stock-levels of this product.

Table 8a: Average Network Inventory - Partial Global Information Based Production

Products	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	Total
Replication													
1	16163	8239	1611	1210	17536	11792	19895	4609	6289	17331	15438	14304	134417
2	17467	9037	1381	765	15862	15137	22966	4959	8751	19105	15921	15106	146460
3	15194	7266	1230	754	15015	10498	19051	5801	8714	18932	14877	14157	131487
4	19625	9180	1037	761	17294	14501	20035	7230	5061	20426	19169	16053	150374
5	18632	8934	1099	760	17375	12807	21284	2250	2158	18462	18101	15901	137764
Average	17416	8531	1272	850	16616	12947	20646	4970	6195	18851	16701	15104	140100

Table 8b: Average Network CSL - Partial Global Information based Production

Products	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	Average
Replication													
1	0.99907	1	1	1	0.99544	0.9955	0.990329	1	1	1	0.995221	0.996678	0.997687
2	0.998318	1	0.988293	1	0.99299	0.996419	0.994259	1	1	0.999971	0.99355	0.997744	0.996795
3	0.997837	0.995221	0.995981	1	0.996861	0.996574	0.996257	1	1	0.999565	0.996921	0.994186	0.99745
4	0.99883	0.995022	0.990698	1	0.994117	0.991737	0.994202	1	1	0.999045	0.9928	0.991846	0.995691
5	0.997873	1	0.985727	1	0.994946	0.990671	0.991751	1	0.998873	0.998233	0.99247	0.993632	0.995348
Average	0.998386	0.998049	0.99214	1	0.994871	0.99418	0.99336	1	0.999775	0.999363	0.994193	0.994817	0.996594

Table 8c: Total Stockouts - Partial Global Information based Production

Products	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	Total
Replication													
1	3	0	0	0	1	3	3	0	0	0	3	2	15
2	2	0	1	0	2	3	2	0	0	1	1	2	14
3	3	1	1	0	2	2	4	0	0	1	1	3	18
4	2	1	1	0	0	2	3	0	0	1	3	5	18
5	5	0	1	0	1	3	5	0	1	2	7	3	28
Average	3	0.4	0.8	0	1.2	2.6	3.4	0	0.2	1	3	3	18.6

Table 8d: Average Response Period- Partial Information use by the production factory

Products	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	Average
Replication													
1	5.04125	1.35	15.3	7.2	4.79625	4.466	4.09375	5.135	7.67	5.254286	5.52	4.247143	5.839473
2	5.5875	1	11.8	3	6.8975	3.66	3.96125	3	7.5	5.86	5.8725	5.104286	5.270253
3	5.6375	1.15	23.75	5	6.29875	5.72	4.9375	5.3	7	4.837143	5.15875	5.2	6.665804
4	5.25875	5.85	5	3	7.2875	4.126	4.0575	3.15	2	6.304286	5.605	6.14	4.81492
5	5.1075	0.625	15.9	0	6.89375	6.646	4.29875	4.865	3.67	6.295714	6.0325	4.152857	5.373923
Average	5.3265	1.995	14.35	3.64	6.43475	4.9236	4.26975	4.29	5.568	5.710286	5.63775	4.968857	5.592874

Table 8e - Partial global information based production - Production Details

Replication Number	Products	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	Total	Average Run-Length	Total Change Over time
1	Production	126431	20352	4625	7129	100044	34418	172381	20882	23469	120332	108492	59466			
	Days	58.53	8	3.06	3.06	49.04	13.8	74.8	8.53	8.65	46.42	38.31	23.4	335.6	1.91	20.42
	Runs	30	6	2	3	19	11	32	4	3	28	23	15	176.0		
2	Production	127568	23635	3735	0	92120	43123	183155	41514	20811	120499	97840	56579			
	Days	59.06	9.29	2.47		45.16	17.28	79.49	16.96	7.67	46.49	34.55	22.24	340.7	2.56	15.35
	Runs	20	6	2	0	16	9	27	4	2	16	18	13	133.0		
3	Production	119642	20352	3734.73	0	93577.3	36859.1	180371	39886	20756.9	125135	105329	62595.7			
	Days	55.3896	8	1.46805	0	45.8712	14.76	78.2859	16.2933	7.65373	48.2774	37.1923	24.6052	337.8	2.56	17.2
	Runs	25	6	2	0	18	9	24	5	2	17	13	11	132.0		
4	Production	125960	25360.8	10195.2	0	102037	42802	181201	29741	14014.1	117367	102516	63418.7			
	Days	58.3146	9.96885	6.74282	0	50.0182	17.1482	78.6464	12.1491	5.16746	45.2803	36.1993	24.9287	344.6	3.38	11.45
	Runs	16	5	2	0	11	9	18	2	2	11	14	12	102.0		
5	Production	125533	27984	3112.94	0	96961.6	38233.6	168919	14737	16272	124840	115610	64718.8			
	Days	58.1173	11	2.05882		47.5302	15.3179	73.3155	6.02	6	48.1637	40.8227	25.4398	333.8	1.75	22.22
	Runs	29	8	2	0	22	13	35	7	5	26	26	18	191.0		
Average														146.8	2.43	17.33

Partial use of global information by the production factory actually limits the ability to produce the right product at the right time. Unfortunately, in spite of the above improvements in all fronts of performance and risk indicators, the production performance is very poor. The average run-length is low (2.43 days on average), the number of changeovers on average increases many-fold to 147 and the total changeover time on average increases to 17.33 days. This reduces the production efficiency although the system network inventory, individual RDC inventory and CSL's improve. So the lack of use of full information of network inventory levels result in chaotic production performance. Although the RDCs collaborate, the central warehouse uses real demand based absorptive capacity of the RDCs to send materials, the production factory uses full local and partly global inventory information but still the system fails to achieve over-all balance in performance levels as well as risk reduction measures. Use of fixed minimum time for production (1 day) and just basing the decision on global and local inventory based ranking of products together with push-based replenishment are found to be lacking in delivering the right resilience capabilities.

8. Decentralised information structure with safe and efficient RDCs, pull-push by central warehouse and full use of global information in decision making by the factory

This case achieves further improvement in customer service level (99.8% averaged over five replications) with higher average network inventory level (147017). The total number of stockouts on the average comes down to 13.2. The average response time improves to 3.4. The bull-whip effect averaged over the different products in UK and Italy RDC reduces compared to the baseline case. Though it increases in case of France RDC but the larger orders account for higher average CSL. Looking at Table 10, it can be seen that the average production run-length has increased compared to the previous cases and the baseline case to 4.41 days, the total changeover time has reduced to 9.4 days when averaged over the five replications. The reason for higher average network inventory is the long production spells in high demand products. This actually increases the average inventory at the central warehouse in these products. But since these products are highly demanded, the excess inventory is bound to be well utilised. The factory does not produce low demand products for long runs thus avoiding the possibility of unutilised stocks. All the low demand products are produced for smaller run-lengths to produce high demand products for longer time. This also reduces the total changeover time.

Table 9a: Average Network Inventory - Full Global Information Based Production

Products	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	Total
Replication													
1	17451	5523	1536	1377	23660	10169	21023	2957	3121	28331	19122	8136	142406
2	19378	5895	1218	765	21621	10298	35447	2498	2695	22195	19432	8824	150265
3	17074	3937	1696	752	15756	8235	25555	2450	2458	24562	30482	7393	140349
4	18641	5003	1380	761	19914	10962	38325	3329	2283	23391	20857	9514	154361
5	21785	4831	1199	758	17430	10827	31904	2369	3184	25510	19029	8879	147706
Average	18866	5038	1406	883	19676	10098	30451	2721	2748	24798	21784	8549	147017

Table 9b: Average Network CSL - Full Global Information based Production

Products	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	Average
Replication													
1	0.999481	1	1	0.993816	0.996778	0.997505	0.990995	1	1	0.996101	0.995505	0.997088	0.997272
2	0.999013	1	1	1	0.993281	0.998424	0.995469	1	1	0.999884	0.99355	0.995528	0.997929
3	0.997446	0.995221	0.995981	1	0.997685	0.996744	0.996377	1	1	1	0.997229	0.996249	0.997744
4	0.99902	0.995022	1	1	0.994117	0.997092	0.995481	1	1	0.999123	0.994499	0.996484	0.99757
5	0.999422	1	1	1	0.995771	0.996686	0.995266	1	1	1	0.994591	0.995035	0.998064
Average	0.998876	0.998049	0.999196	0.998763	0.995526	0.99729	0.994717	1	1	0.999021	0.995075	0.996077	0.997716

Table 9c: Total Stockouts - Full Global Information based Production

Products	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	Total
Replication													
1	1	0	0	1	1	2	5	0	0	3	2	2	17
2	2	0	0	0	1	2	2	0	0	1	1	2	11
3	2	1	1	0	1	2	2	0	0	0	1	4	14
4	1	1	0	0	1	3	2	0	0	2	1	2	13
5	1	0	0	0	1	2	3	0	0	0	2	2	11
Average	1.4	0.4	0.2	0.2	1	2.2	2.8	0	0	1.2	1.4	2.4	13.2

Table 9d: Average Bull-whip Effect - Full Information based Production

Products	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	Average
Replication													
	UK RDC												
1	1.822602				2.064269	5.839504	2.710267			2.535192	19.96578	1.731308	5.238417
2	3.303052				2.635603	2.073174	3.029417			2.889767	5.227173	2.181133	3.048474
3	1.610517				1.627899	2.534686	1.734802			2.506855	7.185591	1.672616	2.696138
4	1.75618				1.70848	2.115048	2.012328			2.9694	9.932136	1.440354	3.133418
5	1.489523				2.142414	2.383177	2.141993			2.245355	11.54321	1.656506	3.37174
	1.996375				**2.035733**	**2.989118**	**2.325762**			**2.629314**	**10.77078**	**1.736383**	**3.497637**
	Italy RDC												
1	1.836165				2.744519		2.312604				1.919134		2.203106
2	2.729909				4.253101		1.32536				1.918966		2.556834
3	2.121805				2.430722		1.910284				4.260349		2.68079
4	2.465119				2.034603		1.676248				2.165556		2.085382
5	2.166144				3.518306		1.613296				1.60183		2.224894
	2.263829				**2.99625**		**1.767558**				**2.373167**		**2.350201**
	France RDC												
1	2.888662	6.936014			2.596577	3.999419	4.573443			2.094287	1.857898	14.95558	4.987735
2	1.94916	6.094916			2.770567	3.920224	3.986486			3.043356	3.25055	13.15532	4.771323
3	3.750251	5.321539			2.388829	4.473412	4.592408			4.894627	1.82034	12.86478	5.013273
4	3.020202	4.505174			2.20649	4.930469	5.20824			1.598814	1.707513	9.430645	4.075943
5	2.940865	5.940068			2.045812	3.73713	5.807587			2.050091	1.922208	12.14812	4.573985
	2.909828	**5.759542**			**2.401655**	**4.330881**	**4.590144**			**2.736235**	**2.111702**	**12.60158**	**4.680196**

Table 9e: Average Response Period- Full information use by factory

Products	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	Average
Replication													
1	2.83875	5.7	7	3	3.1	3.74	2.7875	0	2	2.212857	2.24375	2.391429	3.084524
2	3.315625	8.65	7	13.5	3.65	2.92	2.86375	4	3.5	2.371429	3.9	2.071429	4.811853
3	3.92625	1.375	3.5	4	3.38	1.96	2.51875	4	4.33	4.185714	3.07125	2.15	3.199747
4	2.97	1.425	9	3	3.96625	2.38	2.4175	3.5	0	1.95	2.7375	2.058571	2.950402
5	2.94875	7.3	5.7	0	3.775	3.86	2.128125	2	1	2.35	1.9	1.162857	2.843728
Average	3.199875	4.89	6.44	4.7	3.57425	2.972	2.543125	2.7	2.166	2.614	2.7705	1.966857	3.378051

Table 10 - Full global information based production - Production Details

Replication Number	Products	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	Total	Average Run-Length	Total Change Over time
1	Production	141021	12821.8	5171.04	7309.92	116890	28801.5	171936	17552.2	14888.9	132410	117469	50983.2			
	Days	65.2875	5.04	3.42	3.14	57.2991	11.5391	74.6248	7.17	5.49	51.084	41.479	20.0445	345.6	4.11	10.6
	Runs	12	3	3	3	6	7	13	5	4	6	10	12	84.0		
2	Production	137727	16129	3008.88	0	109478	31178.6	208945	15618.2	13641.4	125556	118281	42810.8			
	Days	63.7626	6.34	1.99	0	53.6659	12.4914	90.6881	6.38	5.03	48.4398	41.766	16.8282	347.4	4.51	8.83
	Runs	11	4	2		5	8	9	5	4	8	9	12	77.0		
3	Production	134691	9845.28	4112.64	0	85995.1	29252.4	221002	14394.2	12773.5	144001	127122	45298.1			
	Days	62.357	3.87	2.72	0	42.1545	11.7197	95.9212	5.88	4.71	55.556	44.8878	17.8059	347.6	4.70	8.76
	Runs	12	3	2	0	6	7	12	4	4	7	7	10	74.0		
4	Production	121909	12720	4596.48	0	99839.1	32678.9	220703	14663.5	13831.2	137612	119894	45827.4			
	Days	56.4392	5	3.04	0	48.9407	13.0925	95.7911	5.99	5.1	53.0911	42.3354	18.0139	346.8	4.45	9.3
	Runs	10	4	3	0	6	7	12	4	5	7	8	12	78.0		
5	Production	139587	12541.9	4626.72	0	104592	31576.6	193255	14859.4	12258.2	133433	131115	45830.9			
	Days	64.6234	4.93	3.06	0	51.2704	12.6509	83.8778	6.07	4.52	51.4787	46.2975	18.0153	346.8	4.28	9.6
	Runs	12	4	3		9	7	9	5	3	6	12	11	81.0		
Average														78.8	4.41	9.42

9. Decentralised information structure with learning RDCs, pull-push by central warehouse and full use of global information in decision making by the factory – Introducing learning mechanism with fixed set of learning parameters and periods across all RDCs reduces the CSL from 99.8% in the previous case where a combination of both safety and efficiency focused agent is used to 99.7%. Though the inventory level on average at the network stage reduces in comparison to the previous case but the total number of stockouts on average increases substantially. Although it is assumed that the RDCs carry out isolated learning mechanism based on their own stock and CSL but from the stockout results (Table 12c) it is found that this actually adversely affect the performance in Russia, UK, Italy, Ede, Czech and Koblenz. The response time to stock outs or reduction in inventory due to demand spikes increases to 4 days as opposed to 3.4 days in the previous case. Production figures also deteriorate in the form of increased numbers of changeovers (82), reduced average production run-length (4.3 days) and increased changeover time (9.62 days).

10. Decentralised information structure with safe and efficient RDCs, pull-push by central warehouse, full use of global information in decision making by the factory, flexible maintenance time – In all the above cases, a fixed maintenance period of 10 days over the entire year is assumed at fixed intervals. However, this case relaxes that constraint and allows the factory to design maintenance based on the actual stock-positions of the different products in the central warehouse. All other results remain the same as in the configuration described in configuration 8 above, except the total average network inventory. It goes down due to low production amounts. The factory now has the flexibility to have more or less maintenance time for the converting machine based on the situation. This although requires huge flexibility from the labour supply but this configuration also shows the amount of redundant capacity present in the converting machine. With current production rates the amount of time the converting machine can stay idle even after achieving a CSL of 99.8% (same as in configuration 8) is 34.6 days on average (Table 11b). So with fixed maintenance period of 10 days a year the system in configuration 8 produces 25 days worth of production extra, which actually adds to the total network inventory. The positive thing of making the maintenance flexible is that, the production operation can be made more responsive to changes in the product demand patterns.

Table 11a: Average Network Inventory - Flexible Maintenance

Products	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	Total
Replication													
1	22278	4748	1500	1470	17303	9222	26103	2468	2128	19100	16035	7769	130124
2	15963	4639	1178	763	20374	8382	19439	2414	1984	20614	29371	7666	132787
3	15916	4002	1333	752	21504	8429	23307	3156	2134	19721	16870	7666	124790
4	21059	4490	1872	761	17919	9193	24095	2518	2823	16631	17027	7865	126254
5	15417	3703	1312	758	16676	8567	32050	2450	2338	23053	14672	32836	153832
Average	18126	4316	1439	901	18755	8759	24999	2601	2281	19824	18795	12761	133557

Table 11b - Flexible Maintenance - Production Details

Replication Number	Products	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	Total	Average Run-Length	Total Change Over time	Maintenance Time
1	Production	127738	10862.9	4823.28	7659.12	87408.2	27626.2	179046	16548.5	12642.1	145737	105633	45912.9				
	Days	59.1381	4.27	3.19	3.29	42.8471	11.0682	77.7108	6.76	4.66156	56.2258	37.2999	18.0475	324.5	4.27	8.71	**33**
	Runs	8	3	2	3	5	7	10	6	5	8	9	10	76.0			
2	Production	125420	12338.4	4626.72	0	85838.6	27925.5	181469	14541.1	13153.2	107209	151555	45360.4				
	Days	58.0648	4.85	3.06	0	42.0777	11.1881	78.7624	5.94	4.85	41.3613	53.5153	17.8303	321.5	3.97	9.55	**35**
	Runs	13	3	3	0	5	6	13	5	5	7	9	12	81.0			
3	Production	118817	10659.4	4672.08	0	85105.5	29753.5	202031	15789.6	14102.4	117700	111640	45679.9				
	Days	55.0081	4.19	3.09	0	41.7184	11.9205	87.6872	6.45	5.2	45.409	39.4209	17.9559	318.1	4.36	8.33	**40**
	Runs	10	3	3	0	4	7	10	5	5	7	10	9	73.0			
4	Production	137537	12949	4354.56	0	83141.1	31470.9	179694	14737	16244.9	116006	100749	43475.9				
	Days	63.6745	5.09	2.88	0	40.7555	12.6086	77.9924	6.02	5.99	44.7554	35.5751	17.0896	312.4	4.22	7.75	**46**
	Runs	9	3	2		5	7	12	5	4	9	8	10	74.0			
5	Production	116242	10252.3	4974.48	0	99832.5	27964.7	208344	15593.8	13071.8	125480	100152	80615.9				
	Days	53.816	4.03	3.29	0	48.9375	11.2038	90.427	6.37	4.82	48.4104	35.3643	31.6887	338.4	4.57	9.52	**19**
	Runs	12	4	3		6	7	10	6	4	5	10	7	74.0			
Average														75.6	4.28	8.77	34.60

Table 12a: Average Network Inventory - Learning RDCs

Products	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	Total
Replication													
1	18227	4594	1552	1472	18888	9325	26460	2437	2677	21626	21599	10229	139086
2	22837	5574	1217	763	22497	9179	30021	2215	2397	20042	20777	9184	146703
3	18088	5041	1652	752	20837	9186	27701	2119	1968	18693	21535	10751	138323
4	22434	4916	1746	761	21323	9519	29198	2295	2275	20574	20992	10006	146040
5	17970	4952	1132	758	19760	9298	30152	2499	2956	26235	20286	10637	146634
Average	19911	5015	1460	901	20661	9302	28707	2313	2455	21434	21038	10162	143357

Table 12b: Average Network CSL - Learning RDCs

Products	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	Total
Replication													
1	0.999481	1	1	1	0.996486	0.9955	0.993009	1	1	0.99841	0.995998	0.996473	0.997946
2	0.998515	1	1	1	0.991158	0.995404	0.991791	1	1	0.999884	0.99209	0.995441	0.997024
3	0.994497	1	0.995981	1	0.997685	0.984675	0.995681	1	1	0.997085	0.996807	0.995992	0.996534
4	0.990089	0.99542	1	1	0.994117	0.995591	0.994878	1	0.996712	0.999123	0.994129	0.996356	0.996368
5	0.998485	1	1	1	0.995411	0.993009	0.992673	1	1	1	0.992639	0.992962	0.997098
Average	0.999481	1	1	1	0.996486	0.9955	0.993009	1	1	0.99841	0.995998	0.996473	0.996994

Table 12c: Total Stockouts - Learning RDCs

Products	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	Total
Replication													
1	1	0	0	0	2	3	3	0	0	2	1	3	15
2	3	0	0	0	2	3	5	0	0	1	3	3	20
3	3	0	1	0	1	3	4	0	0	5	2	3	22
4	5	1	0	0	1	3	4	0	1	2	2	3	22
5	3	0	0	0	2	3	5	0	0	0	3	4	20
Average	3	0.2	0.2	0	1.6	3	4.2	0	0.2	2	2.2	3.2	19.8

Table 12d: Average Response Period- Learning RDCs

Products	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	Average
Replication													
1	3.75375	2.615	7	17.33	3.92875	5.3	3.65375	6.33	3.33	2.728571	3.7375	2.357143	5.172039
2	2.85625	1.7	15.5	3	4.4125	5.128	4.3375	1	1.33	2.055714	2.525	1.785714	3.802557
3	3.27875	1.5	15.7	4	3.5875	5.4	3.62125	0	0	2.11	3.5025	2.185714	3.740476
4	2.83	1.15	4	3	5.39	5.8	3.50375	0	4	1.818571	2.73125	1.828571	3.004345
5	3.96125	1.35	21.7	0	4.08125	5.18	3.2225	1.5	3.7	1.942857	2.005	2.228571	4.239286
Average	3.336	1.663	12.78	5.466	4.28	5.3616	3.66775	1.766	2.472	2.131143	2.90025	2.077143	3.99174

Table 12e- Learning RDCs, Production Details

Replication Number	Products	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	Total	Average Run-Length	Total Change Over time
1	Production	137432	11244.5	5322.24	7496.16	103413	29107.5	200081	16450.6	15051.6	118029	125736	51053.4			
	Days	63.6257	4.42	3.52	3.22	50.6926	11.6617	86.8408	6.72	5.55	45.5358	44.3982	20.0682	346.3	4.07	10.01
	Runs	13	3	3	3	6	7	10	6	5	6	11	12	85.0		
2	Production	139735	15365.8	4702.32	0	113922	28265.5	187940	15324.5	13749.8	132769	122628	44562.8			
	Days	64.692	6.04	3.11	0	55.8442	11.3243	81.5712	6.26	5.07	51.2226	43.3008	17.5168	346.0	4.17	10.2
	Runs	12	5	3		7	8	11	5	4	7	11	10	83.0		
3	Production	135270	12287.5	4067.28	0	105414	26587.6	204923	15349	12773.5	135281	120036	51705.7			
	Days	62.625	4.83	2.69	0	51.6738	10.6521	88.9421	6.27	4.71	52.1917	42.3857	20.3246	347.3	4.57	8.79
	Runs	10	3	2		6	6	12	6	4	9	10	8	76.0		
4	Production	141878	12669.1	5307.12	0	110716	31481.5	187663	14320.8	12963.4	133802	121668	46629.7			
	Days	65.6845	4.98	3.51	0	54.2726	12.6128	81.4511	5.85	4.78	51.621	42.9617	18.3293	346.1	3.85	10.3
	Runs	14	4	3	0	9	9	14	4	3	8	10	12	90.0		
5	Production	143756	12949	4883.76	0	103281	26535.6	198976	15642.7	12529.4	139100	120113	46115.4			
	Days	66.5535	5.09	3.23	0	50.628	10.6313	86.3613	6.39	4.62	53.6651	42.4127	18.1271	347.7	4.70	8.8
	Runs	9	4	3	0	7	7	12	5	3	6	10	8	74.0		
Average														81.6	4.27	9.62

6.3.1 Summary

A one-way Anova analysis is carried out between the results obtained from different cases utilising different resilience enhancement strategies or policies to manage disturbances in the face of gross mismatch between demand and forecast. Appendix D.2 lists the Anova results along with the different tests carried out to compare the multiple cases with one another. To gauge the significance of improvement achieved by adopting the different procedures or attitudes in the different cases, the average network inventory across all RDCs for the five replications, the average network CSL, average response time to any disturbances and average production run-lengths are compared between cases individually. The Anova result (F-test) shows that there exists significant difference in the above performance measures (both risk and operational). However, in order to understand which cases stand out of the rest in terms of these measures, Tukey's test (for equal population variance assumption, given by non-significant Levene's test) or Games-Howell procedure (for significant result in the Levene's test) is carried out. From the statistical tests, it can be observed that all three cases where the system uses a decentralised information structure in conjunction with a combination of pull and push replenishment, local and global information, safe and efficient attitudes of the agents, considerate nature of the different members towards others through collaboration and information sharing, flexibility in managing production run-length constraints result in significant rise in the average network CSL without significant increase in inventory levels compared to the baseline configuration(centralised planning based solely on forecasts, with or without weekly production review), decentralised information structure with self-centred factory using only local information of central warehouse stock-level and RDCs using both traditional or adjustable safety stock techniques without any information sharing or collaborative ordering. Only significant rise in inventory level occurs (apart from the one where maintenance is flexible) in comparison to the adjustable safety stock case, the reasons for which are discussed before when each case is analysed separately in details. Among the three cases, learning does not have any significant effect on reducing the response time in baseline case, whereas the other two configurations (8 and 10 above) achieve significant reduction in response time in comparison to all the cases except the configuration with partial information based push by the central warehouse (6). However, the average production run-length in the three cases is significantly higher than the baseline configuration, decentralised configuration with or without adjustable safety stock policy, and with or without both push based replenishment with partial or no global information usage by the factory.

By examining the statistical significance of the performance in various cases, the importance of decentralised information structure in conjunction with a combined pull-push replenishment (pull from individual RDCs rather than push from the central warehouse when materials are available while pushing materials which are not directly demanded from the central warehouse), local and global information, safe and efficient attitudes of the agents, considerate nature of the different members towards others through collaboration and information sharing, flexibility in managing production run-length and maintenance is realised.

6.4 Effects of changes in the agent attitudes, learning parameters

Experiments are conducted to understand the impact of changes in the key parameters based on the attitude of the different agents in the network. Only one set of demand data will be used to compare the performance for changes in these parameters. First, the effects of varying the learning period on the performance of the system will be described. And then, keeping the learning period unchanged, the learning rates are changed for high and low demand products across the RDCs

Effects of varying the learning period: Three different learning periods are considered: one with no experiential learning (that means the agents set the learning periods *period, satPeriod* to null), one with 15 days of learning period and another with 30 days of learning period. This means that, in the first case, the agents act to events as they occur and do not maintain a record of events for a certain period to act. So if one day the customer service level is 100%, the agent decreases the target cover by certain amount that very day rather than waiting for the *satPeriod.* This is the extreme case, where the RDC agents take an efficiency-focused orientation of managing inventory. This will be reflected in the results (Table 13).

The average customer service level and average response time across different products for different RDCs and central warehouse in Koblenz are shown. Since the effects of learning parameters on the system performance is analysed, the RDC level performance is judged. First of all, on the average, 30 days period of learning results in higher network CSL and lower average response time (though it is marginally higher than the average response time in the zero learning period case). However, the best production performance is obtained in the zero learning period case (evident in the increased average production run-length and reduced number of changeovers). This is because, the RDCs do not continuously increase their target days' cover neither do they wait for certain time period (when the CSL remains the same) to reduce the target days' cover. 30 days' period results in large inventory with insignificant rise in network CSL. This is specially observed in the large RDCs. In fact, for France and Germany (central warehouse at Koblenz) the service levels drop compared to the case with 15 days' learning period. Some of the smaller RDCs like Russia, Arceniega and Czech perform better with 15 days' learning compared to 30 days in terms of response time, inventory and CSL. Niederbipp is not affected by learning period variation in terms of CSL and in fact results in shorter response in the zero learning period case. The response time actually increases in the central warehouse in case of both the non-zero learning periods.

The results from the learning period experiment signify that, under uncertain demand situation, it is very difficult to learn, especially in an isolated manner and in order to increase one's own inventory level without having any knowledge of other members of the system. Since here, the entire system is tightly coupled from production to the individual RDCs, increasing the learning period can affect the performance of RDCs which do not use learning at all for replenishment order generation (like Ede and central warehouse at Koblenz). This is observed in decreasing inventory levels in Ede and central

Table 13: Effect of Different Learning Periods on the System Performance

Average Inventory

Learning Period	Koblenz	UK	Russia	Niederbipp	Italy	France	Ede	Czech	Arceniega	Average
0 days	9511	688	180	388	847	649	3310	320	419	1812.444
15 days	9120	995	527	757	905	734	2617	435	451	1837.889
30 days	7086	3256	946	695	1374	905	1839	707	455	1918.111

Average CSL

Learning Period	Koblenz	UK	Russia	Niederbipp	Italy	France	Ede	Czech	Arceniega	Average
0 days	99.99%	99.44%	97.98%	99.85%	98.94%	99.78%	100%	99.45%	99.67%	99.50%
15 days	99.95%	99.50%	98.29%	99.85%	99.28%	100%	100%	99.57%	99.67%	99.57%
30 days	99.83%	99.83%	98.29%	99.85%	99.80%	99.87%	100%	99.57%	99.65%	99.63%

Response Period

Learning Period	Koblenz	UK	Russia	Niederbipp	Italy	France	Ede	Czech	Arceniega	Average
0 days	1	3.234285714	6.885714	2.425	2.875	2.8375	0	4.016667	2.814285714	2.898717
15 days	1.51875	3.354285714	5.65	5.35375	2.8575	2.31125	2.6	2.871667	2.928571429	3.271753
30 days	1.7	4.3	5.2	2.74	2.7	2.1	1.4	3.5	2.96	2.955556

Production Run-Length & Number of ChangeOvers

Learning Period	Run-Length	ChangeOvers
0 days	5.13 days	67
15 days	4.7 days	74
30 days	3.68 days	90

warehouse in the case of 30 days' learning period. In fact, this affected the service level of central warehouse as well. So increasing the learning period is no solution to ward off risks in the form of supply demand mismatch and enhancing resilience to unwarranted incidents. Since in the face of other unwarranted incidents this could give rise to more risks and vulnerability by affecting other members in the supply chain directly or indirectly connected to the learning RDCs.

Effects of varying learning rates (incRate) – Two different experiments are conducted and these are compared with the learning RDCs case described in previous section. First, the learning rate of low demand products is reduced to 1 day and second, the learning rate of high demand products increased to 5 days. All other things (learning periods, learning parameters) are kept unchanged. This tests whether more safe and self-centred attitude of keeping customer service levels high in high demand products actually affects the performance level of the system on the whole. Table 14 shows that there is very insignificant difference between the three different cases for average network inventory and CSL. However, the response time and production performance of the system with RDCs employing higher learning rates for high demand products are much inferior compared to the two other cases. When the CSLs are investigated in more details at the RDC levels, the smaller RDCs Niederbipp, Russia, Czech and Arceniega show same CSL for all three cases. Inventory levels also increase by smaller percentage compared to the 2 day increment rates for all products. This is because, most of the products in all these RDCs are low demand products and so the third experiment is same as the second experiment. However for all these RDCs, reducing the increment rate for these products does not affect the service levels (because of very low demand) but reduces the average inventory levels. Main difference is observed in the CSL values of UK and Italy RDCs (though at the cost of inventory increase).

Koblenz RDC's service level drops insignificantly but this shows the vulnerability of the system in the face of higher learning rates for high demand product replenishment target covers in the RDCs. This also reduced the average inventory levels at Koblenz and Ede on one hand, and on the other increased the number of changeovers thus reducing the average production run-length reducing production efficiency.

Table 14: Effect of Different Learning Rates on the System Performance

Average Inventory

Increment Rate	Koblenz	UK	Russia	Niederbipp	Italy	France	Ede	Czech	Arceniega	Average
High Demand 2 days, Low demand 1 day	8974	991	484	750	905	730	2546	422	446	1805.333
High/Low Demand 2 days	9120	995	527	757	905	734	2617	435	451	1837.889
High Demand 5 days, Low demand 2 day	9049	1149	525	764	1013	785	2374	435	450	1838.222

Average CSL

Increment Rate	Koblenz	UK	Russia	Niederbipp	Italy	France	Ede	Czech	Arceniega	Average
High Demand 2 days, Low demand 1 day	99.95%	99.48%	98.29%	99.85%	99.28%	100.00%	100%	99.57%	99.65%	99.56%
High/Low Demand 2 days	99.95%	99.50%	98.29%	99.85%	99.28%	100%	100%	99.57%	99.67%	99.57%
High Demand 5 days, Low demand 2 day	99.94%	99.59%	98.29%	99.85%	99.56%	100.00%	100%	99.57%	99.65%	99.61%

Response Period

Increment Rate	Koblenz	UK	Russia	Niederbipp	Italy	France	Ede	Czech	Arceniega	Average
High Demand 2 days, Low demand 1 day	1.6	3.34	5.59	3.47	2.85	2.36	3.35	2.92	2.9	3.153333
High/Low Demand 2 days	1.51875	3.354286	5.65	5.35375	2.8575	2.31125	2.6	2.871667	2.92857143	3.271753
High Demand 5 days, Low demand 2 day	1.46	3.15	5.56	4.4	2.96	2.1	5.25	2.96	2.87	3.412222

Production Run-Length & Number of ChangeOvers

Increment Rate	Run-Length	ChangeOvers
High Demand 2 days, Low demand 1 day	4.74 days	75
High/Low Demand 2 days	4.7 days	74
High Demand 5 days, Low demand 2 day	4.23 days	84

***Effect of risk-averse and risk-loving nature of the production factory* –** The factory is modelled as risk-averse, risk-neutral or risk-loving. This is done by making the factory basing its decisions on varying amounts of inventory cover. A risk averse factory adds more contingency to the inventory and prefers products for production whose inventory falls below the average run-length and 30 days' worth of forecasted demand. The risk neutral agent uses 2 weeks on top of the average production run-length, while the risk-loving agent uses just the average production run-length worth of forecasted demand. The findings are tabulated in Table 15. Surprisingly, too much risk averseness can give rise to worse performance in terms of customer service levels, network inventory, production efficiency and response time compared to the case when risk neutral attitude is adopted by the factory. This is due to the fact that, as the risk-averse factory bases its decisions on increased number of days' cover in the risk-averse case, the high demand products get produced more often than other products thus making the factory unable to produce the right products at the right time. The entire service level performance deterioration is due to the reason that the system could not satisfy the demand at Ede RDC on time inspite of more number of changeovers and more inventories. So risk-averseness instead of improving the performance of the factory and the network, actually worsens the performance. However, considering no contingency at all while making crucial production decisions actually makes the situation far worse for smaller RDCs. Though it is not reflected in the CSL (except Ede) values, the reaction times to disturbances actually say it all. So a medium attitude is always better to deal with situations of uncertainty and managing disturbances. Factory which keeps one week over the production run-length worth of inventory cover, is found to perform the best in terms of all the performance measures.

Table 15: Effect of Different Factory Attitudes on the System Performance

Average Inventory

Factory Attitude	Koblenz	UK	Russia	Niederbipp	Italy	France	Ede	Czech	Arceniega	Average
Risk-averse	8670	1044	608	780	1092	855	3084	355	522	1890
Risk-neutral	9227	1044	608	399	873	855	2620	355	522	1833.667
Risk-loving	9356	1041	588	379	1090	854	2034	355	523	1802.222

Average CSL

Factory Attitude	Koblenz	UK	Russia	Niederbipp	Italy	France	Ede	Czech	Arceniega	Average
Risk-averse	99.98%	99.82%	98.62%	99.85%	99.89%	100.00%	98%	99.62%	99.70%	99.49%
Risk-neutral	99.98%	99.82%	98.62%	99.85%	99.82%	100%	100%	99.62%	99.70%	99.71%
Risk-loving	99.75%	99.81%	98.62%	99.85%	99.89%	100.00%	94%	99.62%	99.70%	99.05%

Response Period

Factory Attitude	Koblenz	UK	Russia	Niederbipp	Italy	France	Ede	Czech	Arceniega	Average
Risk-averse	1.25	3.23	5.49	1.41	2.17	1.85	6.5	2.74	2.1	2.971111
Risk-neutral	2.75	3.23	5.5	1.99	2.2	1.86	1.5	2.75	2.84	2.735556
Risk-loving	3.5	3.18	5.76	5.08	2.24	1.875	5.625	2.74	2.2	3.577778

Production Run-Length & Number of ChangeOvers

Factory Attitude	Run-Leng	ChangeOvers
Risk-averse	3.77 days	93
Risk-neutral	4.28 days	81
Risk-loving	4.81 days	74

Effects of varying factory focus – The factory is programmed to be extremely safety and global objective focused, when it considers the inventory levels of more number of products across the network in deciding the priority for production. This is done when the factory chooses the thresholds *c* and *c1 (*discussed in Chapter 4 in full details) to be zero. However, the factory can choose to be more and more local objective and efficiency focused by increasing the values of these thresholds. Two more situations are examined where the factory chooses to be in the middle of safety and efficiency focus by selecting *c=2, c1=1,* and another case where the factory totally becomes local objective of efficiency oriented by selecting *c=5, c1=2.* Increased efficiency focus actually makes the factory continue production of a single product until more products around the entire network falls below a safety stock level. Table 16 shows the results and it can be clearly seen that when the factory focuses on increasing efficiency without looking at the inventory levels of all the products, it results in chaos and the entire system suffers huge customer service issues. This is evident in the decreasing CSL as the values of the thresholds are increased. The worst case is when the factory tries to maximise the production efficiency by reducing the number of changeovers. Although the factory achieves its objective by increasing the average production run-length to 6.4 days with 52 changeovers over the year, but the CSL drops to 60% roughly. The network inventory rises massively due to long production runs. Particularly at the central warehouse in Koblenz the average inventory rises to 18640 because of long runs of few products. This however results in large backlogs and only 63.8% average CSL. The experiment with medium focus towards efficiency does not result in significant drops in CSLs in the country RDCs but significant drop (95.9%) is observed in the central warehouse compared to the first case (99.98%). This on the whole, reduces the CSL significantly and thus accounts for the lower inventory levels (more stockouts). Hence it can be said that, the factory cannot under any circumstances make decisions focusing solely on the objective of efficiency maximisation and ignore the inventory positions of all products in the entire network. This could prove to be dangerous for tightly coupled networks facing very uncertain demand and where the factory acts as the main source of supply.

Table 16: Effect of Different Factory Attitudes on the System Performance (Local and global objectives)

Average Inventory

Factory Focus	Koblenz	UK	Russia	Niederbipp	Italy	France	Ede	Czech	Arceniega	Average
Safe, c=0, c1=0	9227	1044	608	399	873	855	2620	355	522	1833.667
Safe+Efficient,c=2,c1=1	9087	1007	583	390	1141	829	1903	351	512	1755.889
Efficient,c=5,c1=2	18640	454	365	218	449	337	5056	180	258	2884.111

Average CSL

Factory Focus	Koblenz	UK	Russia	Niederbipp	Italy	France	Ede	Czech	Arceniega	Average
Safe, c=0, c1=0	99.98%	99.82%	98.62%	99.85%	99.82%	100.00%	100%	99.62%	99.70%	99.71%
Safe+Efficient,c=2,c1=1	95.90%	99.20%	98.60%	99.85%	98.50%	99.93%	99.59%	99.62%	99.58%	98.97%
Efficient,c=5,c1=2	63.77%	48.80%	66.50%	68.90%	54.60%	58.90%	61.66%	56.48%	57.33%	59.66%

Production Run-Length & Number of ChangeOvers

Factory Focus	Run-Leng	ChangeOvers
Safe, c=0, c1=0	4.28 days	81
Safe+Efficient,c=2,c1=1	4.6 days	77
Efficient,c=5,c1=2	6.41 days	52

6.5 Effects of different uncertain scenarios

From the above findings, it is seen that, the three cases (8,9 and 10 in section 6.2) are found to result in the best performance among all the different cases created by combining different strategies, policies, capabilities and attitudes of agents. In this section, several other uncertain events will be simulated for a single set of demand data and the performance of these systems will be tested to compare which of the above three cases result in the best performance in the face of different unwarranted events.

Demand Pattern changes of different products

The pattern of demand of different products can change due to several uncertain events and a resilient supply network should be able to cope with that. Sometimes, products forecasted to be high-demand experience low demand in some markets due to changed consumer behaviour pattern, demographic changes or some other unwarranted factors beyond the imagination of the organisation. Also sometimes products forecasted to be introduced in the later half of the year are launched at the beginning of the year due to some unprecedented competitor actions and sales are found to be rising immediately. In the current supply chain network, the demand data of the two products *X7* and *X2* are interchanged for France and Germany. This means that in these markets *X7* is not sold until the middle of the year though huge forecasts are made. This information is however not available beforehand and so the RDCs are expected to maintain stocks in *X7* to take care of the forecasted demand. But at the same time, the RDCs and the entire system need to fast respond to the increase in the demand of product *X2* right from the very beginning of the year. The increased demand would have impact on the production performance and the timing of production of different products. This will be reflected in the over-all performance of the systems. The system with the best service level performance under such situation is resilient to the unexpected changes in demand patterns of different products. Table 17 shows the performances of the three different systems with different strategies and capabilities of the agents. The configuration with flexible maintenance is found to be the best though it gives rise to lower production efficiency.

Table 17: Performance of different systems under change in demand pattern

Average Inventory

Configuration	Koblenz	UK	Russia	Niederbipp	Italy	France	Ede	Czech	Arceniega	Total
1. Learning RDCs	7821	525	1225	796	901	2575	2458	435	448	17184
2. Full information based combined system	9002	1043	607	442	1091	1351	2817	355	523	17231
3. Configuration 2 with flexible maintenance	7104	1043	607	413	1089	1351	2011	355	522	14495

Average CSL

Configuration	Koblenz	UK	Russia	Niederbipp	Italy	France	Ede	Czech	Arceniega	Average
1. Learning RDCs	99.34%	99.44%	98.29%	99.85%	99.28%	99.68%	100%	99.57%	99.65%	99.46%
2. Full information based combined system	99.44%	99.81%	98.62%	99.85%	99.67%	99.81%	95.92%	99.62%	99.65%	99.15%
3. Configuration 2 with flexible maintenance	99.44%	99.81%	98.62%	99.85%	99.67%	99.81%	100.00%	99.62%	99.65%	99.61%

Production Run-Length & Number of ChangeOvers

Configuration	Run-Length	ChangeOvers
1. Learning RDCs	4.1 days	88
2. Full information based combined system	4.2 days	85
3. Configuration 2 with flexible maintenance	3.52 days	99

The case with flexible maintenance produces exactly the same CSL except the Ede RDC. The case with fixed maintenance and the combination of safe and efficient replenishment order generation by the RDCs in a full information sharing environment, generates a backlog of 869 units at the Ede RDC in product *X9.* This is because when the factory manages the maintenance activity flexibly, it carries out maintenance based on real demand pattern and stock levels in the entire network rather than planning maintenance at the start of the year based on pre-determined labour availability (which is again based on forecasted sales). In the fixed maintenance case maintenance is carried out four times for total 10 days in the year (one day in the first month between 3rd and 4th week, one day in the third month again between 3rd and 4th week, four days in the fifth month between 2nd and 4th week and 4days in the last month of the year). So in the fixed maintenance case, the factory actually takes 6 days of maintenance before the stock levels of individual products reach a safe limit. So in the fixed maintenance case, because of the change in the demand patterns, all other products get produced after a gap in production near the 130th day (Figure 6.1) and the production of *X9* gets delayed resulting in the stockout near 180th day of the year. On the other hand, due to flexibility in carrying out maintenance, first maintenance is carried out after 185th day of the year and then based on the stock levels reaching safe levels, the factory carries out maintenance at regular intervals resulting in 60 days of maintenance in total (all carried out after the 180th day, as shown in the Figure 6.1).

Learning again fails to respond fast to the changes in demand patterns in different products. France RDC using the learning mechanisms actually reacts to any drastic fall in inventory in product *X2* in 3.8 days (on average) compared to the other two cases where the RDC reacts in 2.2 days (on average). As evident from Table 17, the average customer service levels are also lower in the case with learning RDCs (UK, Russia, Italy, Czech, France RDCs show drops in CSL). In fact, in product *X2,* with learning the total backlog was 857 units compared to 453 in the other two cases. But with learning the RDC over-reacts and the average stock level in *X2* rises to 13944 units compared to 3945 units in the other 2 cases. For product *X7* in France RDC, where in spite of low demand the RDC maximum stock level in this product reaches 8001 when the RDC uses learning.

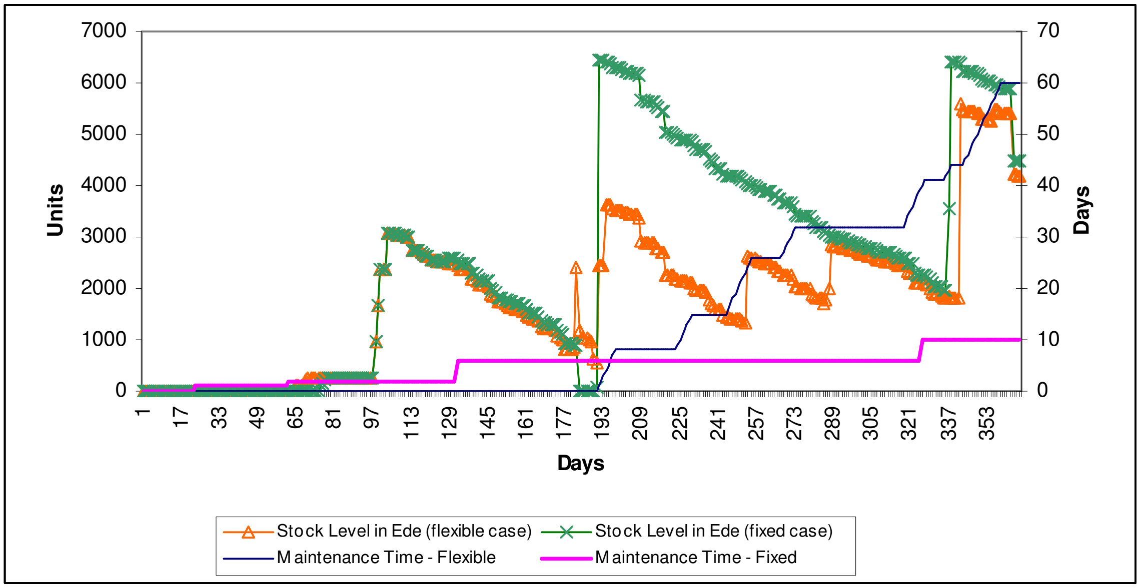


Figure 6.1. Stock Levels in Ede for product *X9* and Maintenance Periods in fixed maintenance (case 9, section 6.2) and flexible maintenance (case 10, section 6.2)

Production Breakdown –Random

Another uncertain event that can have disruption across the network is the breakdown of the converting machine in Koblenz. The factory breakdown is programmed to occur at two time intervals totally unknown to any member of the factory. Both the breakdowns are for 15 days, the first occurring between 90th and 150th day (within 3rd, 4th and 5th months) and the second occurring between 250th and 300th days (within 8th and 10th month). This is done just to examine which sets of strategies, either isolated or in combination, can be employed for better performance of the system when the breakdown occurs. Here the learning RDCs are not considered, and instead another configuration is considered where the push of materials from the central warehouse with full information of the sales and stocks is combined with the full information based production at the Koblenz factory. Since the uncertain event here is the breakdown of the factory, so it is worth investigating whether the push of materials to different RDCs can improve resilience by creating a buffer to meet customer demand during the factory breakdown

Table 18: Performance of different systems under uncertain factory break-down

Average Inventory

Configuration	Koblenz	UK	Russia	Niederbipp	Italy	France	Ede	Czech	Arceniega	Total
1. Full information based push-system	5145	2149	501	254	2168	909	4963	203	435	16727
2. Full information based combined system	6181	1043	607	408	1091	855	2265	355	523	13328
3. Configuration 2 with flexible maintenance	6622	1043	607	370	1089	854	1707	355	522	13169
4. Configuration 3 with risk averse factory	6500	1043	606	607	1092	855	2912	355	522	14492

Average CSL

Configuration	Koblenz	UK	Russia	Niederbipp	Italy	France	Ede	Czech	Arceniega	Average
1. Full information based push-system	99.64%	99.39%	97.98%	99.64%	99.87%	100.00%	98%	99.54%	99.37%	99.32%
2. Full information based combined system	99.95%	99.65%	98.62%	99.85%	99.89%	100.00%	100.00%	99.62%	99.70%	99.70%
3. Configuration 2 with flexible maintenance	99.95%	99.82%	98.62%	99.85%	99.89%	100.00%	97.40%	99.62%	99.70%	99.43%
4. Configuration 3 with risk averse factory	99.95%	99.82%	98.62%	99.85%	99.89%	100.00%	100%	99.62%	99.70%	99.72%

Production Run-Length & Number of ChangeOvers

Configuration	Run-Length	ChangeOvers	Maintenance Period
1. Full information based push-system	3.43 days	92	10
2. Full information based combined system	3.67 days	86	10
3. Configuration 2 with flexible maintenance	3.34 days	93	14
4. Configuration 3 with risk averse factory	3.42 days	93	7

period. In all these cases the factory is assumed to be of risk neutral nature (2 weeks' cover over the average run-length for considering the stock-levels of products). The fixed maintenance system worked the best and the push-system with full information based production resulted in the worst performance (Table 18). It can be observed that, although the average CSL improved in the UK RDC by making the maintenance flexible but over-all on the average the network CSL is less than the case with fixed maintenance period. Another system is examined with flexible maintenance and risk-averse factory.

In order to improve the performance of the system with flexibility in maintenance, the factory has to be risk averse in case of products that are not directly sold at the central warehouse and products that are sold only in single countries. Since these products need to be supplied from the central warehouse, so the factory must consider the lead-time, supply lead-time, production run-length (including set-up) and any contingency for breakdown. So a month's cover is added to the average production run-length by the factory before deciding on the priority for production of these products. So the single country products get priority for production in this factory if their stock drops below 30 days and average production run-length worth of estimated demand. From Table 18, it can be seen that though this has increased the total average inventory across the network to 14492 units (though less than the push-system, 16727 units), but the average network CSL is the highest. Also the production performance improved compared to the case where maintenance is not carried out at fixed predetermined time intervals. The maintenance time actually reduced to 7 days thus giving more effective production time and allowing the factory to produce products to take care of the breakdown period. Hence the factory needs to maintain some slack in its operation (specially for certain vulnerable operations susceptible to the risk of disruption in the form of breakdowns).

Demand Volume Increase in certain products by certain % - During Certain Periods in the large RDCs (Italy, UK, France and Germany)

This uncertain situation states that, the forecasted demands remaining the same, the major RDCs register higher increases than expected for certain months in certain high demand products. UK RDC faces twice the original demand in products *X1, X7* and *X10* during the entire 12th, 6th and 7th months respectively. Italy RDC faces five and 1.5 times the original demand in products *X7* and *X11* respectively during the entire 7th month. *X1* and *X*7's demand rose by 5 and 2 times respectively from original demand values in the 3rd and 9th months respectively in France RDC. Similarly Germany, catered by the central warehouse faces 5 times increases in product *X7* in month 3 and products *X10, X11* during the month 4. Hence over the entire network this resulted in a total demand increase by 44672 units compared to the normal case.

In order to see how the different cases cope with this sudden rise in demand in different country RDCs, the system with learning RDCs and the full information based combined system (described in case9, 10 section 6.2) with (case10) and without (case9) flexibly planned maintenance are compared. The findings are tabulated in Table 19. Total average inventory across the network does not vary much across the three cases. The factory is assumed to be risk-neutral and both the cases with fixed and flexible maintenance periods are equally efficient in achieving higher CSL compared to the learning case. Only noteworthy point is that, the case with flexible maintenance adjusted the number of maintenance days according to the rise in demand and the production became more flexible with more number of changeovers thus giving more buffers in case of large demand changes. So learning the target days' cover before ordering is not effective in dealing with uncertain spikes in demand. In the next situation described below, the two cases with and without flexibility in maintenance will be examined for their difference in dealing with huge increases in demand.

Table 19: Performance of different systems under uncertain demand spikes in large RDCs in high demand products

Average Inventory

Configuration	Koblenz	UK	Russia	Niederbipp	Italy	France	Ede	Czech	Arceniega	Total
1. Learning RDCs	7433	968	527	765	958	718	2059	435	448	14311
2. Full information based combined system	7437	1022	607	397	1077	856	2059	355	522	14332
3. Configuration 2 with flexible maintenance	7857	1022	606	397	1077	856	1554	355	522	14246

Average CSL

Configuration	Koblenz	UK	Russia	Niederbipp	Italy	France	Ede	Czech	Arceniega	Average
1. Learning RDCs	99.64%	98.70%	98.29%	99.85%	98.65%	99.96%	100%	99.57%	99.65%	99.37%
2. Full information based combined system	99.95%	99.82%	98.62%	99.85%	99.82%	100.00%	100.00%	99.62%	99.70%	99.71%
3. Configuration 2 with flexible maintenance	99.95%	99.82%	98.62%	99.85%	99.82%	100.00%	100.00%	99.62%	99.70%	99.71%

Production Run-Length & Number of ChangeOvers

Configuration	Run-Length	ChangeOvers	Maintenance Time
1. Learning RDCs	4.3 days	81	10
2. Full information based combined system	4.23 days	82	10
3. Configuration 2 with flexible maintenance	3.75 days	94	2

Two-fold increase in Demand in high-demand products during the entire year in large RDCs (Italy, UK, France and Germany)

The demands in UK increase two-fold over the entire year in products *X7* and *X12,* in Italy the demands rose to twice their value in product *X11,* in France products *X1* and *X7* experienced 100% increase in demand and in Germany products *X11 and X7* suffered similar increase in demand. Although the forecasts remain the same, the demands are modelled to increase to twice their normal values. As a result of this the total demand of all products increased by 31%. The maximum increases are seen in products *X7, X11* and *X12 (*around 60-65%). This is shown in the total demand in normal case and the current case (in Table 20). Since these are high demand products, this impacts the over-all demand scenario facing the entire network. The results are shown in Table 20. The performance of the system significantly improves in the case where the converting machine is maintained flexibly rather than at predetermined time intervals. So in the flexible maintenance case, the machine is run throughout the year without stopping for a single day.

This would require huge flexibility in labour, resources (supply materials, RDC operations). The production amounts in each individual product in both the cases shows that the factory while using the flexible maintenance produces products prudently and high demand products are produced for more number of days thus resulting in higher service level throughout the network. So flexibility in the regular operations and resources could serve as an essential capability for enhancing resilience in the face of huge deviations in demand and forecasts.

Table 20: Performance of different systems under double demand in large RDCs in high demand products

Average Inventory

Configuration	Koblenz	UK	Russia	Niederbipp	Italy	France	Ede	Czech	Arceniega	Total
1. Full information based combined system	1436	759	516	383	878	856	1773	312	474	7387
2. Configuration 2 with flexible maintenance	1905	878	575	380	996	643	1777	340	419	7913

Average CSL

Configuration	Koblenz	UK	Russia	Niederbipp	Italy	France	Ede	Czech	Arceniega	Average
1. Full information based combined system	63.75%	77.93%	97.26%	99.20%	88.28%	86.20%	97.24%	92.70%	91.04%	88.18%
2. Configuration 2 with flexible maintenance	86.29%	85.11%	98.62%	99.85%	95.60%	97.75%	94.65%	94.10%	95.90%	94.21%

Production Run-Length & Number of ChangeOvers

Configuration	Run-Length	ChangeOvers	Maintenance Time
1. Full information based combined system	2.76 days	124	10
2. Configuration 2 with flexible maintenance	2.72 days	129	0

Products	*X1*	*X2*	*X3*	*X4*	*X5*	*X6*	*X7*	*X8*	*X9*	*X10*	*X11*	*X12*
Total Demand in units (this case)	**128791**	4467	3503	530	96267	18678	**271182**	11103	10650	115902	**154350**	**64624**
Total Demand in units (normal case)	**112307**	4467	3503	530	96267	18678	**165655**	11103	10650	115902	**96328**	**39198**
Amounts Produced												
1. Full information based combined system	128027	2646	3175	0	70209	25025	258833	15202	12746	107361	152538	45016
2. Configuration 2 with flexible maintenance	128428	7123	3508	0	81926	24209	267817	12901	12150	108372	142166	49022
CSL, central warehouse												
1. Full information based combined system	63.52%	25.05%			66.25%	89.89%	61.71%			75.85%	63.36%	64.32%
2. Configuration 2 with flexible maintenance	88.91%	96.05%			86.31%	99.99%	69.15%			90.35%	85.27%	74.21%

6.6 Summary

From the above analysis of different configurations using different strategies either independently or in combination with different attitudes of the different agents in the network to manage uncertainties and then testing these cases under various hypothetical unwarranted events, it is found that, the resilience of a tightly coupled production/distribution system like the paper tissue company described here can be enhanced by a combination of several policies. These are,

a) Information sharing across different members of the supply chain, knowledge of the demand patterns of each and every product (both estimated and actual),
b) Decentralised structure providing autonomy to the different members to select actions in need,
c) Notice of latent pathogens (disasters waiting to happen) through regular monitoring, daily reviewing of plans as opposed to monthly review of production plans in the baseline case,
d) Full use of local and global information available to the factory before making decision on the priority for production,
e) Flexibility of the production factory to produce on demand, based on global and local information, not to fixed monthly plans,
f) Flexibility of the factory to carry out maintenance at times not planned beforehand,
g) Agility of the entire network to attend to any disturbances at any point of the network through collaborative activity of the different RDCs and improvising the replenishment order generation of the distribution centres to balance thoroughness and efficiency,
h) Taking a safe approach rather than efficiency focused approach by the factory is more beneficial in the face of totally unexpected events like production breakdown or unusual spikes in demand volumes.
i) A combination of push and pull type of replenishment

It is seen that decentralised information structure with daily monitoring of performance measures in the form of average inventory could not result in better performance under demand-forecast mismatch. In fact, the performance and risk measures deteriorate as the individual RDCs try to order more by using adjustable safety stocks rather than the traditional standard deviation based safety stock estimation technique. But this becomes highly effective when the individual RDCs start collaborating by sharing the ordering information and entire network inventory information and acting upon it in a collaborative manner rather than looking at their own interests and ordering as much as they can to increase their CSL.

When push type of replenishment is introduced into the system with central warehouse's access to both partial (based on order volume alone) and full information (both stock level and actual sales data), it is essential to ensure that the factory also gets full information visibility of the stock levels in the entire network. Or otherwise, due to the pushing of materials, the stock levels in the central warehouse will continually drop and the factory basing its decisions only on the local information will continually produce those products thus resulting in increased push to the RDCs. This will result in a vicious cycle where ultimately the RDCs will accumulate huge stocks even though demand might be very low. And most importantly the production efficiency will drop significantly because of large number of changeovers between products requiring frequent production in the different products. So the best result is obtained when push type of replenishment is adopted for single country products and pull type replenishment with collaborative ordering is adopted for other RDCs.

Learning was incorporated in the replenishment order generation system but it is not found to be good enough in cases where totally unpredicted events occur. Instead real time learning in the form of deciding target days' cover on the basis of total annual demand and the standard deviation in combination of adjustable safety stock policy to balance both efficiency and safety provides much better result in uncertainty.

Flexibility in the operation of the factory both in terms of using learned minimum days of production (in real time) and flexible maintenance time periods is extremely important in enhancing the resilience of the system.

Finally, a big part though not mentioned anywhere in supply chain resilience literature, is played by the internal attitudes of the different agents in the system in improving the resilience of the system. As can be seen, from the experiments with different attitudes and learning parameters of agents, continuing to learn over an increased period after disaster strikes actually results in over-reaction to disturbances and in a tightly couple production/distribution system this could create havoc by affecting the production efficiency adversely as has been seen in the experiments with a single set of demand but with varying learning period. And it is again found that zero learning period or real time learning results in better performance. Also adopting too safe procedure by the RDCs by increasing the increment rates for target days' covers of high demand products result in bad performance in terms of response time. It is also found that, under no circumstances can the factory act in its own interest of minimising changeover time by overlooking the interests of the RDCs. This is evident in the experiment, where the extreme efficiency focused factory though achieves very low changeover time over the year and high average production run-length but produces disastrous service level performance for all the RDCs and the central warehouse. Although under normal circumstance risk averseness of the factory might not be an effective option but when environment becomes very dynamic and uncertain (specially when the converting machine becomes unreliable and more prone to breakdowns), the factory should operate in a risk-averse mode, especially for critical products. This is observed in the experiments when the performances of the different configurations are examined under two factory breakdown situations.

Overall, this chapter provides a detailed summary of which procedures can serve as sources of disturbance, how to use different strategies and internal mechanisms (attitudes, interests of agents) in combination to improve resilience.

[page intentionally left blank]

Chapter 7

Conclusion

This chapter first summarises the interpretations obtained from the findings noted in Chapters 5 and 6. Then it will be shown how these address the research questions identified in Chapter 2. The contributions and managerial implications of this study will be discussed next. Finally, future scope for further research to extend this work will be explored.

7.1 Interpretation of findings – Addressing the Research Questions

7.1.1 Case Study

Chapter 5 describes the application of different strategies to improve the performance in the face of disturbances. These strategies when applied together do not have negative impact on the supply chain's risk management capability. The risk measures (bullwhip, maximum, minimum stock levels, quantity of large orders placed, average response time to any disruption either imminent or occurred) of the real system are compared with the model with all the strategies implemented together. However, the entire system reacts to a single set of demand data faced by the real system without any unexpected disruptions in the form of large spikes, unexpected shifts in demand patterns or production breakdowns, strikes etc. The resilience enhancement strategies adopted are successful in achieving the dual purpose of maintaining the performance of the system in the face of a single set of uncertain demand that are widely varying from the forecast. So even if the factory or the different RDCs adopt a low safety focus and adopt a high efficiency focus, the system performs well. Although the case study shows application of the improved model to one stand-alone case with a single set of demand data but it addresses the first research question – "How best to manage the disturbances and improve supply chain's resilience?" In the case study described in Chapter 5, disturbances mean unexpected deviations of sales from forecasts. The different techniques and capabilities required for improving resilience are discussed below. All these are applied together in the model to achieve the improvement in the performance of the system under uncertain demand widely differing from forecasts. The findings from the case study actually corroborate the different resilience enhancement strategies already discussed in supply chain literature. However the study by comparing the real world performance with the results from the model reveals how forecast-based monthly central production planning coupled with limited information sharing among the different members, inflexible production policies and solely pull-based replenishment order fulfilment can perform badly in the face of daily demand-forecast mismatch.

Decentralisation – Both organisational and supply chain resilience literature states that in an uncertain environment, decentralisation ensures flexibility of responses in the face of unexpected events (Weick, 1996, 1998; Anand & Mendelson, 1997; Samaddar et al, 2006). Normally in the literature the decentralised information structure in the supply chain implies individual members make decisions on the basis of local information available to them. But in the current case, each of the members are able to access global information as well as local information and use them together for making decisions. This results in better performance in managing uncertainty compared to the actual system, where the planning department with full access to global information makes monthly plans for the factories and guides the RDCs on how much to order when their stock levels dips below a certain level.

Information Sharing – Christopher and Lee (2004, p.391) stated that, in the case of supply chains "Information is power" when shared. Mason-Jones and Towill (1997, 1998b) corroborated this by stating that, "information-enriched" supply chains perform better than those that do not have access to information. When disturbances occur, visibility throughout the supply chain is the key to effective, timely efforts to intervene and minimise the adverse effects of such events (D'Antoni, 2003; Konicki, 2001a,b; Sheffi, 2001). In fact, Montgomery, et al. (2002, p3) state that:

"Visibility enables all supply chain members to easily see and manage the flow of products, services and information in real time or near real time, from end-to-end, as needed. True visibility is present when supply chain members can do this in concert, and they can do it across their existing technology platforms."

Visibility throughout the supply chain relies heavily on good information systems, connectivity throughout the supply chain, and collaboration between all supply chain partners. With timely information, supply chain members can respond quickly to disruptions or disturbances as they occur. Visibility cannot end at a factory gate or it cannot be solely limited to the central planner because products, supplies, components and all associated information must be shared globally. Christopher and Lee (2004) mention that, throughout the supply chain, key operational metrics status reports (inventory, demand, forecasts, production and shipment plans, yields, capacities and backlogs) should be accessible.

The agent based model designed to improve resilience of the case example assumes a decentralised information structure (Figure 4.2(b), Chapter 4) with each member of the supply chain having full visibility of the entire network unlike the real case where only the central planning has full visibility of the system while planning production is based on forecasts every month. The factory in the real system only decides the sequence of production based on local knowledge of central warehouse stock levels with no visibility of the network inventory status or forecasts in different countries. So naturally, such a system with clear barriers to full information sharing and usage is expected to perform badly under uncertainty. On the other hand, the modelled factory and RDCs have knowledge of all the products, their annual forecasts, product life cycle. This is one of the reasons why the actual system performs badly in comparison to the real system in terms of all measures.

Combination of Push & Pull – There has been vast supply chain literature that discusses the advantages of pull strategy in achieving better operations with simulation and analysis results (Ragatz and Mabert, 1988; Hoshino, 1996; Ou and Jiang, 1997; Dengiz and

Akbay, 2000). However Bonney et al, 1999 found out that push performed better with particular control information. In this research, the aim is to improve resilience by making the system more capable to manage uncertainty maintaining the same level of performance or improving the performance at the same time. The structure and operation of the real world supply network of the paper tissue manufacturer is such that, the factory after producing the products based on the centrally planned amounts pushes the products to the central warehouse where all the products are stored awaiting individual RDCs to drive the pull process by generating replenishment orders in the form of factory requests. No material movement occurs until the RDCs generate replenishment orders. This results in poor performance in product *X9,* where large inventory is available in central warehouse but Ede RDC suffers service issues (96.6%). This may be due to some other reasons such as transport problems but if the factory would have produced the products on time and the central warehouse pushed the products to the RDC immediately after production such a situation might have been avoided. Although the same situation does not occur for products *X3, X4* or *X8*, the average inventory in the central warehouse is higher than that in the RDC. This is prone to disruptions if the demand pattern changes suddenly. So a combination of push and pull replenishment is used in the model to improve the ability of the supply network to cope with totally uncertain demand spikes. So products demanded only in single markets are pushed to respective country RDCs as soon as they are produced while all other products are stored in central warehouse waiting to be pulled. This resulted in lower average inventory in the central warehouse for these products and 100% service levels in all of these products.

***Agility* –** Preparing for any disruption in supply chain is the key to achieving resilience. This is an ongoing process that should be revisited on a regular basis. The supply chain and organisational resilience literature (Weick and Sutcliffe, 2001; Berger, 1987; Weick, 1979, 1990, 1993, 1996; LaPorte and Consolini, 1991; Banbury and Tremblay, 2004; McDonald, 2006; Sheffi, 2005b; Christopher and Peck, 2004) suggest that the likelihood of disruptions can be reduced through monitoring, detecting and acting on the weakest signals for improving resilience. This implies that, when the likelihood of a disruptive event starts to spike, actions should be taken and reviews should be periodically undertaken. In the actual case, the production plan is made every month by the central planning department based on the forecasts. In the model, distributed decision system with local autonomy is introduced and each member is given autonomy to decide on the actions based on the situations they face. The factory based on the daily global and local knowledge of the inventory levels, sales and forecast in all the products across the network, decides on the production cycle time and sequence. Similarly, by monitoring the daily error and bias in forecasts, the RDCs adjust the safety stock amounts. This is not carried out in the actual case and is evident in the lower service levels in products *X10* and *X12* at central warehouse. The maximum time taken for the RDC inventory to return to stable state after coping with large mismatch between demands and forecasts is more than the time the RDCs in the real system takes (Figures 5.15 to 5.30). The results for the major RDCs are compared only because these contribute the most to the firm's revenues. More stockouts occur in the real case in these RDCs due to lack of monitoring at regular intervals and not having effective signalling system (discussed in Chapter 4 where the model formulation is described in details) that can trigger the appropriate actions (in the case of RDCs triggering the replenishment order for the right quantity and in the case of factory, the production of the right product at the right time). The factory in the actual case is totally guided by the central planning and produces exactly the amounts that are specified in the production plan. There is very little scope for the factory to react to any variations in the inventory levels across the network. Similarly, the RDCs in the real case base their orders on fixed safety stock covers determined by the standard deviation of demand and cycle stock determined by the fixed forecasts during lead time without any attempts to take into consideration the deviations of actual sales from the forecasts.

Flexibility – Many researchers (Rice and Caniato, 2003; Lee and Wolfe, 2003; Swamidass and Newell, 1987) have mentioned flexibility as one of the main enablers of supply chain resilience. In the real case, production of low-demand products is always planned to be for a day. Also in the real case the maintenance takes place at fixed time around the year that is taken care of by the central planning every month as available days of production. On the other hand in the model, the factory decides the maintenance period depending on stock status and total demand across the network. The factory is also highly flexible in deciding the production run-lengths for different products. Based on full visibility of network stock levels, the factory agent is modelled to identify and produce for longer periods products, which are high demand (from the forecast) or are selling in large quantities (from the cumulative sales data, the error in forecasts). Such flexibility results in very high run-lengths in these products (shown by the maximum run-lengths in Table 11 b in Chapter 5). However, the factory is made flexible enough to produce these products for very short run-lengths also when the need arises. This on the whole results in a highly flexible production system sensing the need for production in any product by closely monitoring the inventory levels, sales across the network and reacting to any changes as soon as they happen by switching production. Since the production is planned centrally in the real system, the real factory is inflexible to the actual fluctuations in demand as the review of plan takes place every month rather than every day. Since the factory has no autonomy to act apart from reacting to central warehouse stock levels for deciding the sequence of production. So every month the factory gets the planned amounts to produce but while deciding the sequence of production, if stock drops suddenly in the middle of production of one product, it reacts by producing products for very small production run-lengths.

***Redundancy* –** As emphasised in supply chain and organisational resilience literature (Sheffi, 2001 & 2005a; LaPorte, 1982; Weick, 1987,1993; LaPorte & Consolini, 1991) introducing redundancy can help mitigate risks against unwarranted events. More inventories are profitable when mistakes in production or planning occur or when customers demand high margin products at short notice, much different from the forecasts (Ocana and Zemel, 1996). Also supply chains running with fewer inventories in downstream RDCs may quickly run out of stock when none are holding enough inventory. However, too much redundant inventory might create problems since excess inventory might give rise to complacency. This happens for products *X5* in UK RDC and *X5, X11* in France RDC, where due to a cushion of huge stock the RDCs did not order on time resulting in stockouts when the demand suddenly overshot the forecast. In fact, in Italy there is an accumulation of huge redundant stock and the inventory level kept on increasing after every rise in demand. Redundancy without watchfulness and flexibility actually spelt disaster for central warehouse stock levels (Figures 5.31 to 5.42). The central warehouse went on accumulating large stocks in products *X7, X5* during the first 6 months when products *X1, X10, X11* actually suffered stockouts. In the modelled supply chain, the factory agent with the knowledge of network inventory levels of all the products prevents redundancy in any one product by producing it for a long time when other products suffer precarious inventory conditions. At the same time, the RDCs learn to adjust the target days' cover based on customer satisfaction level and demand-forecast mismatch. In the model, the RDCs take less redundancy focus and always order lower volumes when the CSL remains 100% for a small period of time. Similarly, the factory agent adopts a risk-neutral approach while deciding on priority for production. It decides to continue production in one product only if inventory of none of the products falls below average production run-length and a certain number of days' (a week for products directly sourced from central warehouse and 15 days for single-country products) worth of inventory cover. This avoids accumulating huge stocks in certain products since it can be cost-prohibitive and hamper the efficiency of the system.

***Collaboration* –** Improved communication and coordination is seen as one of the many ways to reduce organisational risks in numerous examples (Berger and Bradac, 1982; Berger, 1987; Weick, 1979, 1990, 1993, 1996; LaPorte and Consolini, 1991). Supply chain risk literature also stresses upon the same factor as a measure for reduction of risks (Hoyt & Huq, 2000; Handfield and Nichols, 1999; Peters and Hogensen, 1999; Chopra and Sodhi, 2004). The different RDCs and the central warehouse in the model act in a coordinated manner. Different RDCs after having full information of the inventories in different members of the supply chain decide on the replenishment orders if enough stock is not available at central warehouse. This gives rise to more careful and mutually beneficial distribution. On the other hand, in the actual case, each RDC places orders on the central warehouse without any knowledge of each other's stock levels and the amount sent to each RDC is centrally decided based on availability. Such uncoordinated behaviour gives rise to poor performance in terms of CSL and response to disturbances.

***Learning* –** An essential element of resilience is learning to maintain or regain dynamically stable state after a potentially destabilising disturbance and/or in the presence of continuous stress. Learning is introduced in the modelled agents. The factory agent learns the minimum time for production and the individual RDCs learn the target days' cover. This resulted in 100% CSL in almost all the RDCs in all products with lower average network inventory. The maximum time to restore the inventory levels in all the major RDCs in all products are found to improve by introducing the learning mechanism described in Chapter 4. Overall learning from past actually improved the risk management ability of the network in the real case. The ability to increase the target stock level at an increased rate and for a certain period (based on the frequency of disruptions) in the event of a disruption and the ability to adjust the target days' cover to original levels when the CSL remains same for a certain time interval controls the chance of over-reacting to sudden demand-forecast mismatches. At the same time, this also increases the ability of the system to react to any slightest signal of disturbance. On the other hand, the actual system places orders mechanically following the standard safety stock procedure thus over-reacting to any huge difference in the standard deviation of actual demand. This is the reason behind the higher bullwhip effect in the RDCs in the actual system compared to the model.

***Summary* –** From the detailed analysis and interpretation of findings from the case example, it can be concluded that, a decentralised informational structure with informed and intelligent combination of push-pull, flexibility, agility, redundancy and efficiency enhances the resilience of a supply network in the face of disturbances in the form of large deviations of demand from forecasts (up to 1000% deviation, shown in Table 5, Appendix C). This addresses the first research question and shows how the combination of different recommended capabilities mentioned in the supply chain resilience literature can improve the management of uncertain demand. However, the results are obtained for only one set of demand data for only one year. So it is very difficult to say whether the capabilities or their combinations would work in other cases when the situation might change dramatically. The case example although exploring the general capabilities and decision rules, control mechanisms required for improving resilience in terms of responding to uncertain demand at the right time without hampering the existing efficiency of the system, does not explore which rules or capabilities can be source of disturbance when applied in isolation or in combination. Also in the case, a single set of learning parameters, fixed attitudes of the agents are considered and there is no scope of testing the effects of varying these. The next section interprets the results from the experimentation described in Chapter 6 and addresses the two remaining research questions.

7.1.2 Experiments

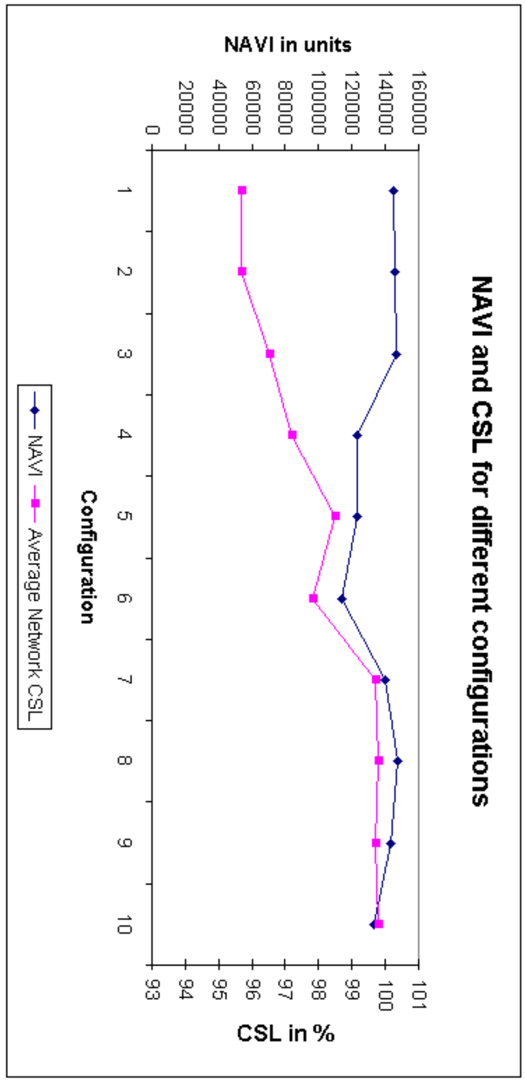
Several experiments are run with five different replications of the demand distribution derived from the actual sales data during the year 2004. The findings are used to explore whether the different strategies and capabilities used in the case example for improving resilience can sustain the same level of performance under various different uncertain scenarios either individually or in tandem.

Rules, decisions, control procedures that can be sources of disturbance –

The average values of different performance measures and the risk management ability of the entire network for five different replications of demand are shown in the following figures. Figure 7.1 shows the average over-all performance of the 10 configurations described below (also see Chapter 7 for the detailed description of each of the configurations). From the figure it can be concluded that the system performance was the worst in the first three configurations. Centralised planning with limited decision making authority and traditional safety stock method of replenishment without any coordination actually deteriorates the performance and even introducing weekly production plan reviews or decentralised informational structure with full autonomy to review production plans to make daily decisions on production does not improve the NAVI substantially.

However, introducing the decentralised informational structure along with changing the focus of the factory from safety focus to efficiency focus for selection of products for production actually improved the average CSL across the entire network, though marginally from 95.7% to 96.5%. There is no change however in the number of stockouts, average response time, total number of changeovers and average production run-lengths in all these three configurations (Figure 7.2). Introducing adjustable safety stock based replenishment improves the NAVI position, average CSL (97.2%), number of changeovers, average production run-length (Figures 7.1 and 7.2). But the number of stock outs rises and so does the average response time to disturbance. This is because, due to increased stock accumulation in the network, complacency sets in and the system becomes sluggish in responding to slight disruptions because it is resting on the huge inventory buffer. This results in the average response time rising to 7 days in comparison to 5.6 days in the baseline case. So although the performance apparently improves but the system is more vulnerable to even small amounts of demand-forecast mismatches highlighted by no change in the total number of stockouts averaged across the five replications. Configuration 5 drastically improves performance in terms of average network CSL (98.5%), total number of stockouts (29) compared to configuration 4. This shows that coordination between different members of the supply chain is absolutely essential to manage disturbances and improve resilience. The number of changeovers and average production run-lengths do not change but the average response period reduced to 6 days, though little more than the baseline case.

So far, among the 5 configurations, configuration 5 gives the best result and many supply chains might adopt this configuration and can perform well in the face of normal demand forecast variations. The bullwhip effect is the highest in this configuration (Figure 7.3). This shows that one of the main enablers of supply chain resilience is coordination and information sharing between different members. Also, in this configuration the RDC agents are considerate towards other RDCs and the central warehouse when there are not enough materials in the central warehouse to satisfy all replenishment requests.



Configuration	
1	Central Planning with monthly review of production plan, traditional safety stock and pull based replenishment, limited information accessibility and autonomy of factory, limited information flow across the network
2	1+ weekly review of production plan
3	Decentralised information structure, more autonomy to factory to plan production daily based on local stock information, fixed minimum production time (1 day), pull and traditional safety stock based limited information based replenishment
4	3 + adjustable safety stock use by RDCs
5	4 + coordinated pull based replenishment
6	4 + coordinated push based replenishment (push is made based on order size)
7	4 + informed and coordinated push based replenishment (push is now based on sales and stock information of RDCs), single country products are pushed as soon as produced
8	4 + use of local and global information by factory, learned minimum production time, introducing improvised pull-based coordinated replenishment for all products except single country products, which are pushed
9	4 + use of local and global information by factory, learned minimum production time, introducing learned pull-based coordinated replenishment for all products except single country products, which are pushed
10	8 + flexible maintenance time

Configurations 1,2 : Factory Agent considered safety-focused and self-centred
Configuratons 3,4,5,6,7: Factory Agent considered efficient and selfish
Configuratons 8.9.10: Factory Agent considered safety-focused, efficient and considerate
Configuratons 1,2,3,4: RDC Agent considered safety-focused and selfish
Configuratons 5,6,7: RDC Agent considered safety-focused and considerate
Configuratons 8,9,10: RDC Agent considered safety and efficiency-focused and considerate

Figure 7.1: NAVI and Average network CSL for different configurations

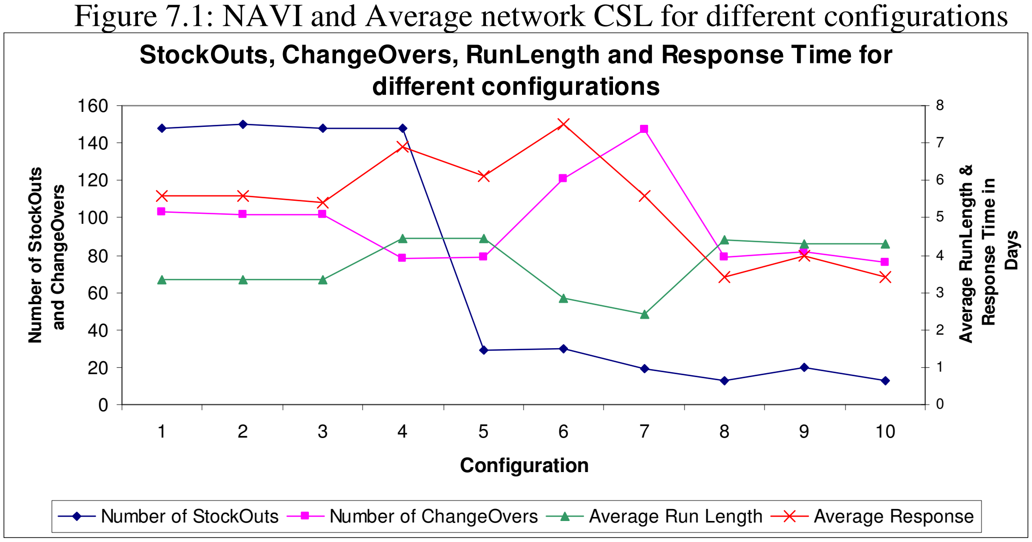


Figure 7.2: Production Performance and Risk Measures for different configurations

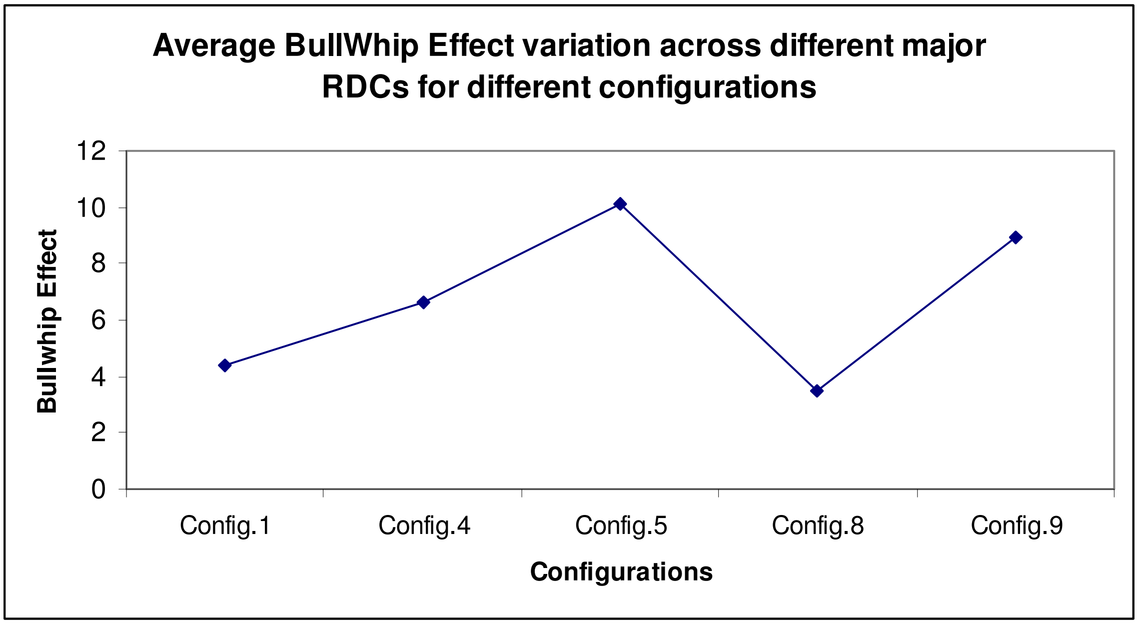


Figure 7.3: Bullwhip Effect averaged across major RDCs, all products and five replications for 5 configurations

However the factory is still considered to be efficiency focused and selfish because it bases all decisions on local information of central warehouse stock levels which does not give it enough visibility to track the slightest signals of disruption in the entire network which might result in disaster if not taken care of. The next two configurations (6 and 7) are modelled with the central warehouse pushing the materials whenever available and when there is a request from the individual RDCs. In both these cases the factory remains selfish and efficiency focused. However, in the first case the factory has access to only local information of stock levels, while in the second case it has access to global information but uses it partially. So in both the cases, production is mainly based on local information of stock levels in the different RDCs. The results show that configuration 6 actually worsens the performance of the system in every aspect of performance, while although configuration 7 improves the CSL to 99.7% but registers the least average production run-length with 148 changeovers in total. NAVI, average reaction time is almost the same as the baseline configuration. So although, configuration 7 improves upon one aspect of the performance (CSL) but due to excessive pushing of materials and due to lack of availability and usage of global information the production performance deteriorates. The difference in the performances of the next three configurations (8, 9, 10) is very difficult to understand. However, there is very little difference in NAVI, CSL, average run-length and number of changeovers. The average response time is higher in configuration 9 (4 days in comparison to 3.4 days in configurations 8 and 10), where learning is introduced in the RDCs. Also there are more stockouts on average in configuration 9 than 8 and 10 (20 in comparison to 13 in both the cases). Investigating the average bullwhip effects across all products in major RDCs (shown in Figure 7.3), the RDCs are found to over-react in case of disturbances in configurations 5 and 8 resulting in large bullwhip effects (10 and 8.9 respectively). The lowest bullwhip effect (3.4) is observed in configuration 8. Considering all performance measures, configurations 8 and 10 are found to be the best under different sets of demand data.

The findings from the experiments and the comparison of the performance in different fronts help in identifying the rules, decisions and control procedures that can be used to improve resilience but can become sources of potential disturbance. So, this addresses the second research question. These are discussed below,

– First, decentralisation is not found to be effective in managing different uncertain demand situations if implemented without coordination, communication or proper sharing and usage of information. Instead, it is found that in a supply chain with distributed decision making authorities, if different members try to act in achieving their own objectives without considering other member's interests or the interest of the entire network, the results are disastrous.
– Coordination and information sharing is necessary to improve the resilience of the supply chain to demand-forecast mismatch but it is not sufficient if different members of the supply chain do not wish to make full use of the available information. This is why in spite of improving the CSL, reducing the number of stockouts the response is sluggish in configurations 5,6 and 7.
– Too much safety focus taken by the different RDCs can result in overly sensitive system causing overnervous huge corrective reactions. This happens in

configurations 4 and 5, when the bullwhip increases many times compared to the baseline case for the pull based replenishment orders.

– Too much monitoring of changes for agility can also cause harm in uncertain and dynamic environments. This happens in configurations 2 and 4, when weekly review is introduced in centrally planned production and the adjustable safety stock based on daily forecast-demand mismatch is considered for making replenishment ordering decisions respectively. Configuration 2 gives rise to more stockouts on the average, while configuration 4 results in larger bullwhip and response time compared to baseline.
– Push type replenishment by the central warehouse based on relative order volumes or stock and actual sales volumes must be accompanied by full information availability and usage by the factory responsible for producing materials. If this is not done, the production performance suffers due to huge number of changeovers as the inventory at the central warehouse never stabilises due to continuous push of materials and since the factory makes its decisions based only on the central warehouse stock levels this sets in the vicious circle of production, push and more production. This becomes even more dangerous in a tightly coupled supply network where all the operations depend on each other.
– Too much redundancy created in the system by complete push based replenishment can harm the responsiveness of the system to disturbances measured by the response time. This is shown by the high response times in all the push based configurations (5,6 and 7).
– Fixed maintenance period or minimum production run-length (set at 1 in all configurations from 1 to 7) results in inferior performance under uncertainty. Flexibility of adjusting the minimum production run-length in response to real demand improves the performance of the factory and the entire network under uncertainty. The factory agent uses simple rules of adjusting the minimum run-lengths based on the frequency of production. So three different minimum run-lengths are used for three different groups (high, medium and low; the low

demand group actually combines both medium low and low demand groups of products).

– Strategy like learning which appear to be working perfectly in improving the actual system's performance with actual demand data, is found to be insufficient in the face of huge uncertain deviations from forecasts in totally different set of demand patterns. Thus learning although improves overall system performance in terms of all measures but increases the bullwhip, stockouts and response time to react to disturbances. This is partly because the learning is based on daily deviation of sales from forecasts. Since daily forecasts are often wrong, every day the situation is different and the agents cannot learn to cope with such uncertainty. So learning can work when the error level is within certain acceptable limits but fail to work in such tightly coupled system when the error level is uncertain as well.

All these rules, strategies, policies, control procedures are used to improve the resilience of the supply chain but if applied in the above manner, they can be source of disturbance themselves thus increasing the number of "latent pathogens" (disasters waiting to happen). Also this section demonstrates the dynamic characteristics of supply chain resilience. As it is seen, the learning techniques work fine under one set of demand data but when situation changes learning does not help and in fact harms the performance of the system by increasing the bullwhip effects. This also speaks of the importance of the attitudes of different agents, which will be discussed in the next section to address the final research question. Excessive stress on any single strategy (flexibility or redundancy or efficiency) can be disastrous for supply chain resilience and a balanced approach is essential for improving the resilience of the supply chain (shown in the conceptual framework described in Chapter 2, figure 2.9). So the next section shows the rules, strategies or control procedures that can improve resilience but do not become potential source of disturbance.

Adaptive Response to Disturbances

Experiments are carried out under different uncertain scenarios and with different attitudes of the different agents in the supply chain to understand how the supply network can adaptively respond to disturbances through interconnecting linkages. From the findings of these experiments and the ones discussed in previous section, the characteristics, which facilitated the adaptive response of the entire network, are listed below. This addresses the third research question quite well.

- In order to sense and respond to slightest signals of disruption to improve resilience of an interactively complex tightly coupled production/distribution system comprising the supply network, the RDCs which prefer extreme safety (by increasing the learning period or by increasing the learning rate for high demand products in the learning configuration) are found to be performing badly under the same set of demand. In fact, real-time learning with no memory of past (increasing the inventory cover continuously) is found to provide the best all-round performance improvement (Table 13, Chapter 6).
- Introducing collaboration among the RDCs with full information sharing helps in developing fast response to disturbances. The factory (the source of materials for the entire network) should always have full access to information and make full use of this information to decide on which product to produce and the duration of production in each product.
- Detailed information of different products and their demand patterns is used by the central warehouse to categorise different products into four different groups – high, medium, low medium and low sales. This actually helps the factory to pool products according to their demand and decide on the production duration.
- Flexibility of adjusting the minimum production run-length in response to real demand improves the performance of the factory and the entire network under uncertainty. The factory agent uses simple rules of adjusting the minimum run-lengths based on the frequency of production. So three different minimum run-lengths are used for three different groups (high, medium and low; the low

demand group actually combines both medium low and low demand groups of products).

- Flexibility of carrying out maintenance at time when the inventories of all products in the central warehouse are at safe level is found to improve the performance of the system under the situation where the demand patterns of different products change suddenly (Table 17, 19 Chapter 6). It is seen that the configuration with fixed maintenance period and without learning actually performs the worst in terms of CSL. The best example of the advantage of using flexible manpower resources is when there is unexpectedly huge increase in demand of certain high demand products (Table 20, Chapter 6). Drastic improvement in CSL is observed in the configuration where flexible maintenance timing is used (94.2% compared to 88.2% in the configuration where fixed maintenance timing is used). So it is essential that the resources (manpower) that carry out maintenance should be flexible enough to respond to such changes in environment.
- Risk-neutral factory though found to be performing well compared to risk averse or risk loving factories under normal variation of demand but under totally random breakdown of machines (which normally happens for machines with low production reliability) risk averse factories produce better results in the case where maintenance is made flexible (Table 18, Chapter 6). So flexibility in maintenance can cope with uncertain situations in the form of huge demand forecast mismatch but while facing low probability high impact events such as long factory breakdown or strikes in factory flexibility in maintenance alone cannot help and the factory needs to be prepared well by keeping a risk averse attitude all through, specially since the entire network's performance depends on the converting operation in the factory.
- The independent experiments with different factory attitudes reveal that the factory under no circumstances can act to be risk-loving (Table 15, Chapter 6) or self-centred with too much focus on self-objective of production efficiency

improvement (Table 16, Chapter 6). This can prove to be harmful in normal and uncertain circumstances as well.

- The RDCs and the factory are assumed to adopt a combined safety and efficiency focused attitude in configurations 8 and 10. Since real-time learning is found to be more suitable in situations of uncertainty (Table 16, Chapter 6), the RDCs in these configurations are assumed to order frequently for high demand products with low target days' cover in these products, while they are assumed to order at much longer intervals for low demand products. This is the efficiency focus of the individual RDCs and prevents the RDCs from over-reacting to any disturbances in the form of huge deviations of sales from forecasts. However, at the same time, the RDCs monitor the daily sales-forecast error and bias and estimates the safety stock based on that. This is the safety focussed attitude of the agent. In the above configurations, the agent uses both and it is found to be effective under uncertain situations. Instead of sticking to traditional safety stock estimation techniques, the RDCs use an improvised combination of safe and efficient replenishment strategy. Similarly, the factory can adopt a combination of safety and efficiency focus rather than using excessive safety focus or efficiency focus. It takes on a safety focus by considering the inventory levels of all products before making change in production sequences. At the same time, it considers a week over average run length worth of stock in each product before making the decision on the duration of production and thus adopts an efficient attitude. So a combination of both actually helps the entire network to adaptively respond to uncertain situations. This actually well supports the idea of improvisation in the face of uncertainty discussed in organisational resilience literature.

Through the application of the agent based model to the actual case example and carrying out the different experiments with different ranges of parameters depicting possible behaviour of the different agents, the aim to improve resilience of the complex supply chain is fulfilled. The different attitudes and behaviours of the multiple agents comprising the supply network actually hold the key in improving the resilience of supply chains.

The research findings suggest that, however flexible the resources are, however well-informed the different members are, however well-integrated the members are through coordination and communication, however well-equipped a supply chain is with mitigation and recovery capabilities the individual managerial judgements that can obtain a balance between various dimensions of performance (both global and local efficiency, quality and speed of responding to customer orders) and the resilience (speedy reaction, maintaining buffers, flexibility in resource management) play the most important role in improving the resilience of the entire network. Ability of the supply chain to effectively react to disturbances is in part a function of how much resilience is built into the supply chain, in part on how quickly it can spot disruptions and assess possible responses to events and in part how adept the supply chain is at preparing for events and in taking decisive actions in response to disruption. The experiments carried out actually show how the different behaviour and attitudes of the different agents and their interconnecting linkages can give rise to improved resilience under different uncertain situations. It can be seen that, different situations require different behavioural pattern from different agents. For example, the factory agent should be risk neutral in a stable production situation where the chance of machine breaking down is very little, but under situation when the machine can break down at any instance, the factory agent has to be risk averse and show more preference for safety rather than efficiency. This addresses the third research question effectively.

Summary

After exploring the literature on supply chain resilience before, it was concluded that it provides little help in understanding the dynamics of resilience, the behaviours, internal decision rules and control mechanisms responsible for enhancing or building resilience in a supply chain, the combinations of different recommended practices essential for building resilience. The agent based model, application of the model to the case example and the experiments help in understanding these issues, explores and evaluates combinations of different behaviours (safe or efficient, selfish or considerate), parameters (learning period and rate), capabilities (flexibility, agility, responsiveness) and strategies (information sharing – full/partial, collaboration, push/pull, safety stock policy, centralisation/decentralisation, redundancy) in improving the resilience of the network through interconnecting linkages.

7.2 Contribution & Managerial Implications

7.2.1 Contribution

The important contribution of this research is to study and provide methods for improving the management of uncertainty and thereby improving operational resilience in complex multi-product, multi-country real-life production/distribution system. A number of contributions to knowledge emerge from this research. The first contribution is to pin-point the strategies to be adopted and adjusted and the parameters/measures to be monitored for improving the resilience of a complex supply chain. The contemporary literature on supply chain resilience has recommended a plethora of possible ways of improving supply chain resilience, but none has analysed the effects of adopting all at once or balancing different strategies or different decision trade-offs. This research is quite different from other studies on supply chain resilience. This research considers the operational resilience to different untoward incidents with different strategies and behaviours of the agents. This research shows that even applying different practices recommended in supply chain resilience literature together can be of no benefit in different uncertain situations if the different agents do not behave intelligently by balancing both aspects of performance (efficiency, selfish focus on self-objective) and resilience (safety, consideration for others). Even if full information is shared, if the agents do not wish to use that fully can actually deteriorate the ability to handle disturbances in the form of normal demand-forecast mismatches. This research also shows that, several practices (decentralisation, push based replenishment, redundancy) when used in isolation can be source of potential disturbance themselves. This research analyses different strategies, their combined applications to understand the supply chain behaviour under uncertainty and identifying the dominant strategies responsible for improving the resilience of the supply chain. Different possible trade-offs between centralisation and decentralisation, planning and improvisation, full and partial information sharing are evaluated, which have not been studied in literature before. Overall this study addresses the dynamic aspect of supply chain resilience, which is missed out in contemporary literature in supply chain resilience. This research shows that, no practice is sufficient for addressing all types of uncertainties and one practice appearing to be doing well in one uncertain situation appears to be insufficient in another. So supply chain resilience is an ongoing process, which the agents have to continuously work on through intelligent judgements. Another important contribution of the thesis is the formulation of intelligent rules for making decision to produce the right product at the right time balancing the local objective of improving production efficiency and global objective of improving network customer service level and network inventory.

Bendoly et al (2006) in a recent review of literature on behavioural research in operations and supply chain management stressed on the disconnection between the theoretical concepts, tools and the actual rules-of-thumb followed in practice. In their study, they conclude that most theories of operations management or supply chain management ignore important characteristics of real systems and therefore are perceived to be hard to apply in practice by managers. Also, even if methods are known and do apply, they may be difficult to implement given lack of information or proper motivation. According to them (p.737), "*A common factor in this breakdown is people. When it comes to implementation, the success of operations management tools and techniques, and the accuracy of its theories, relies heavily on our understanding of human behaviour.*" They concluded that, study of behavioural issues in this field is relatively scarce. So another contribution of this research is to provide an understanding of the internal decision making mechanisms and behaviours; the variables, states and performance measures to base those decisions on; the dynamics of interconnecting informational linkages of the different agents through an agent-based computational framework for enhancement of resilience of complex production distribution systems. The case study is used as an illustration of the application of this framework to study and improve the resilience. However, the framework can be applied to any complex production/distribution system with any number of products with any demand profile, any forecast bias and errors and any number of distribution centres.

In the context of complexity, the role of models is described in following way (Khalil and Boulding, 1996, p148):

'Any kind of scientific statement, concept, law and any description of a phenomenon is a model construction which tries to reflect phenomena of the external world. Reality is extremely complex; it consists of strongly or more weakly related events….. Science seeks the simplest relationships by which examined phenomena can at least be described or demonstrated. It creates simplified models which only partly reflect reality, but which allow contemplation, and what is most important, pragmatic, even if sometimes modest, predictions.'

The underlying assumptions involved in the modelling of situations were systematically presented (Chapter 3, Figure 3.1). Allen and McGlade (1987) argued, 'since the natural systems forming the environment surrounding us, in reality maintain their complexity, mechanical equations used in such models do not capture the real interactions and adaptability of the natural system!' Emmeche (1996, p43) stated, a distinction is often made between 'descriptive' and 'ontological' complexity. The more this distinction, the more are the models away from representing reality as is evident from Figure 3.1. The situation is the following: there is on the one hand freedom in modelling and on the other hand constraints from reality, but two are not independent of each other. Ciliers (2001) argues that, models attempt to grasp the structure of complex systems, although he concluded, 'it is impossible to have a perfect model of a complex system'. Ultimately, he says, 'we cannot escape the use of models, we can also not escape the responsibility involved in using them'.

Another debate on relevance of models is highlighted by Chu, Strand and Fjelland (2003). They state, the real systems, embedded in an external world are much different than models that are not embedded anywhere. Allen (2001b) stated that, modelling approach is not that it should create true representations of reality. Instead it is seen as a method that leads to the provision of causal conjectures that can be compared with and tested against reality. This model is our ‘interpretive framework’ for sense making and knowledge building. It will almost certainly change over time as a result of our experiences. Allen says, it will change over time as a result of experiences. Models are developed in order to answer questions that are of interest to developer or potential user and both model and questions will change over time. Questions addressed influence the variables chosen for study, the mechanisms that are supposed to link them, the boundary of the system considered and the type of scenarios and events that are explored. In short, model is not reality but merely a creation of the modeler that is intended to help reflect on the questions that are of interest. So complex systems models are useful in understanding the dynamics involved in functioning of complex systems.

A complex systems representation of supply networks and the need to understand the behaviour under uncertainty in order to improve resilience, implies the use of modelling in addressing the research questions identified in the thesis. In general, almost all organisations function according to heuristically defined routines and rules. While this may be adequate for some simple tasks, in most real situations learning by different agents within the organisation is extremely difficult because of the feedbacks, time delays and multiple causations that are involved and which confuse attempts at “sense making” following some action. Because of this, it can be speculated that most organisations are good enough to exist and survive in the current “normal” range of disturbances, but nobody knows how much better they could perform, or how some abnormal disturbances might affect them. It is therefore not surprising that analyses of life-expectancy of firms (Foster and Kaplan, 2001), shows essentially that firms are failing increasingly rapidly, and indeed that nearly all firms fail (Ormerod, 2006). Clearly, whatever is said about excellence, and strategy etc. the fact is that they do not deal with the complexity and uncertainty of their environments. In other words, as Schumpeter first wrote in 1938, the creative destruction of evolutionary change, successive innovations and disturbances, drive the changing complexity of the world, and is therefore what drives markets and industries.

By using complex systems modelling methods, such as multi-agent models of the type described here, I can explore outcomes of the system under a significant range of possible agent behavioural rules and environmental events, and so find improved levels of functioning and of resilience. Building such models as a means to understand and improve resilience of supply networks is a significant contribution. In summary, I would suggest that this is an important practical way in which the performance and resilience of supply networks can be examined and improved.

Finally, my lasting contribution to supply chain management is a conceptual model of supply chain resilience based on broad, critical review of literature about the multi-faceted phenomenon of supply chain resilience. The thesis then tests theory by developing and analysing the performance of a complex system, agent based model representing a complex real world supply chain network under the influence of several resilience enhancement procedures under different uncertain scenarios. In addressing the research questions discussed before, this research confirmed the existing theory by showing that resilience is improved by decentralisation (Weick, 1996, 1998; Anand & Mendelson, 1998), information sharing (Christopher & Lee, 2004; Mason-Jones & Towill, 1997, 1998; Montgomery et al, 2002), agility (Christopher & Peck, 2004; Sheffi, 2005; Weick, 1979, 1990, 1993, 1996), flexibility (Rice & Caniato, 2003; Lee & Wolfe, 2003; Swamidass & Newell, 1987), redundancy (Sheffi, 2001, 2005; Weick, 1987, 1993; LaPorte, 1982), collaboration (Hoyt & Huq, 2000; Handfield and Nichols, 1999; Peters & Hogensen, 1999) and learning (Gunderson, 2000; Dovers & Handmer, 1992). The thesis contributes by adding to the supply chain resilience literature some of the essential counter-intuitive findings of this research. These are quite different from literature and are listed below,

- In spite of full information sharing, if the different supply chain entities do not make full use of information, the resilience in the face of uncertainty actually deteriorates. This runs counter to the common findings in most literature which emphasises that information sharing is the most important for reducing uncertainty (Christopher & Lee, 2004; Blackhurst et al, 2005; Chopra & Sodhi, 2004)

- Several practices (decentralisation, redundancy) cannot be effective when used individually [this actually has wider contribution in the field of complexity science by showing that independent self-organizing agents considering only local information for satisfying local goals are not the best solution (Holland, 1995)]. No mention has been made in literature on the importance of these two capabilities in improving supply chain resilience (Anand & Mendelson, 1997; Oliver & Delbridge, 2002; Samaddar et al, 2006)
- Learning is not effective under several uncertain scenarios other than deviations of sales from forecasts [e.g., uncertain demand spikes in large RDCs in high demand products (Table 19, Chapter 6)]. This refutes common belief that learning, planning, preparedness for disaster actually improves resilience (Mitroff & Alpasan, 2003; Gunderson, 2000; Dovers & Handmer, 1992). This also establishes that resilience capabilities are dynamic and one capability used to manage disturbances in one uncertain situation does not apply to all uncertain scenarios. So the thesis contributes by presenting a dynamic view of supply chain resilience.
- Evaluating the effects of different trade-offs between different levels of information sharing (full, partial, local, global), planning (daily, weekly, monthly) or centralisation (central planning or individual autonomy) is another significant contribution to theory.
- Applying different theory informed practices can be of no benefit in improving resilience if different agents do not behave intelligently by balancing both aspects of performance and resilience. The detailed decision making rules, procedures and behaviours, attitudes for improving resilience are not covered in extant supply chain resilience literature.

7.2.2 Managerial Implications

It can be argued that when unpredictability is a given the only strategy that makes sense is a strategy to become adaptive — to sense early and respond quickly to abrupt changes in individual customer needs. As a result, a firm's operations must be driven by current customer requests — implicit as well as articulated — rather than by plans to make and sell what customers are forecasted to want in the future. This research provides a methodology to understand the key issues essential for improving operational resilience in a complex production distribution system facing uncertain demand. Each member of the supply network needs to have a certain inherent ability to deal with the uncertainties, which is described by the functional stage of the agents. In order to improve operational resilience, they need to have an adaptive ability to change their decisions with respect to changes in environment.

Several managerial insights for building an operationally resilient supply network can be extracted from this research. They can be summarised as: 1) knowing earlier (sensing and interpreting – this involved incorporating true sensors at different parts of the supply chain and monitoring them regularly, e.g., forward cover at the central location and throughout the network, cumulative sales over average inventory ratio for each product aggregated over the network), 2) managing-by-wire (informed coordinated decision making that constitutes institutional memory and intelligence, e.g., evident in the assembly of the model where each element has the full visibility of the entire network), 3) designing a supply network as a complex system (*integrate* all elements and their functions — in order to create an efficient and well-coordinated system), 4) production and dispatching capabilities from the customer request back (assemblage of modular, functional capabilities and roles, which are dispatched and coordinated in response to current customer requests, e.g., evident in designing the production schedules based on real time customer requests, especially for single country products) and 5) decentralising informational structure and giving autonomy to each element of the supply chain to achieve local goals with learning and full knowledge of global impacts (this is achieved in the current agent based model through coordinated ordering of materials by the RDCs, by reducing inventory when service level is achieved over a certain time horizon, thus not demanding materials unnecessarily from the source and giving other more deserving RDCs the chance to order materials on time when they are needed). So, in summary, this study shows the need for flexibility in all the elements of the supply network, full information sharing across the entire network, demand-led adaptive production planning and sequencing, distributing materials based on a combination of push-pull strategy (push strategy for products which are demanded only in single markets, whereas using pull based strategy (focusing on real demand) for ordering products which are sold in multiple markets).

7.3 Limitations & Scope for Further Research

There are few limitations in the current agent based model. First of all, the model is aimed at improving the supply chain's management of uncertainty through different strategies adopted by the different agents. But the agents concerned here are mainly within the same supply chain and compete for resources among the members from the same company supply chain. No consideration is given to the market share in each country or the behaviour of competitor agents. This was due to the non-availability of competitor's data in similar type of product market. So this can be an area for further research.

Secondly, the model is based under the assumption that, infinite raw material inventory is available at the manufacturing facility. The model can be extended to include the raw material supply network in future research.

Thirdly, no cost data was available for any of the operations. Future research can incorporate the costs of different operations into the agents' decision making function. This would better help in understanding the trade-offs. For example, the supply network would be able to decide on many alternatives such as, ordering volumes (ordering all at once or in regular intervals), transportation (whether to send high demand materials every day is more cost effective than sending at regular intervals), inventory (holding cost is more than stockout costs) and production volumes (which is more cost efficient – stopping the machine or producing continuously to build stocks and doing more changeovers).

Fourthly, this network actually starts from a single converting machine producing the twelve different products, which are then distributed across 12 different countries. In the real case, Koblenz houses around twenty such machines that source the same raw materials from the paper mills and other accessories suppliers. So it would be an interesting piece of work to see how the interaction of different machine's supply networks affect each other by competing for maintenance resources, raw materials and distribution resources.

Fifthly, The model in this research assumes that all the different RDC agents are either safe or efficient or both. But it has not explored the case when any one of them might behave differently from others. Actually, an obvious extension of this work could be to see the effects of different behavioural rules followed by different agents and thus incorporating diversity into the network to see how it affects the resilience of the network.

Finally, the model could also be developed to explore the possible results of changing the structure of the supply network, and in this way offer strategic as well as operational advice. Clearly some structural choices may prove more resilient than others and so this too can be studied.

This research provides a theoretical template for evaluating different practices employed to manage uncertainty. The work carried out in this research can be extended further by studying the effects of the different model configurations (out of the ten described here) under different uncertain scenarios and finding out the best possible configuration and capabilities. Currently, the different configurations are tested under a single uncertain scenario in the form demand-forecast deviation. Future work can test them under different uncertain scenarios.

References

AT Kearney, 2003, *Supply chains in a vulnerable, volatile world,* Executive Agenda, 6(3)

Adams, T.J., Austin, S.P., Soprano. R.S. and Stiene, LM., 2002, Assessing the transition to production risk, *Program Manager,* September, 10-21.

Agrawal, N and Cohen, M, 2001, Optimal material control in an assembly system with component commonality, *Naval Research Logistics,* 48, 409–429.

Ahn, H.J., Lee, H. and Park, S.J., 2003, A Flexible agent system for change adaptation in supply chains, *Expert Systems With Applications*, 25, 4, 603-618.

Akkermans, H., 2001, *Emergent supply networks: Systems dynamics simulation of adaptive supply agents,* Proceedings of the 34th Hawaii International Conference on System Sciences.

Alber, K. and Walker, W., 1997, *Supply chain management: A practitioner's approach,* APICS Conference Proceedings.

Allen, P. M., 1976, Evolution, population dynamics and stability, *Proc Natl Acad Sci, USA,* 73, 3, 665 – 668.

Allen, P.M. and McGlade, J.M., 1987, Evolutionary drive: The effect of microscopic diversity, error making and noise, *Foundation of Physics* 17, 7, 723 – 728.

Allen, P.M., 1994, Coherence, chaos and evolution in the social context, *Futures, 2*6, 6, 583 – 597.

Allen, P.M., 2000, Knowledge, ignorance and learning, *Emergence*, 2, 4, 78-103.

Allen, P.M., 2001a, A complex systems approach to learning, adaptive networks, *International Journal of Innovation Management,* 5, 2, 149 – 180.

Allen, P.M., 2001b, What is complexity science? Knowledge of the limits to knowledge, *Emergence,* 3, 1, 24 – 42.

Allen, P.M, 2004, The complexity of structure, strategy and decision making, Chapter 5 in J. Foster and S.J. Metcalfe, eds., *Evolution and economic complexity,* Cheltenham, Edward Elgar , 85 – 107, ISBN: 1-84376-526-8 .

Allen, P and Strathern, M., 2004, Evolution, emergence and learning in complex systems, *Emergence,* 5, 4, 8 – 33.

Allen, P.M., Datta, P.P. and Christopher, M., 2006a, Improving the resilience and performance of organizations using multi-agent modelling of complex production-distribution system, *Risk Management,* 8, 294-309.

Allen, P. M., Strathern, M. and Baldwin, J. S., 2006b, Evolutionary drive: New understanding of change in socio-economic systems, in *Emergence complexity & organization,* 8, 2, ISSN: 1521-3250.

Allwood, J.M. and Lee, J.H., 2005, The design of an agent for modelling supply chain network dynamics, *International Journal of Production Research,* 43, 22, 4875-4898.

Altiok, T. and Raghav, R, 1995, Multi-stage, pull type production/inventory systems, *IEEE Transactions,* 27, 190-200.

Anand, K.S. and Mendelson, H., 1997, Information and organization for horizontal multimarket coordination, *Management Science*, 43, 12, 1609–1627.

Anderson, Jr. E.G., Fine, C.H. and Parker, G., 2000, Upstream volatility in the supply chain: the machine tool industry as a case study, *Production and Operations Management,* 9, 239-261.

Anderson, S., 2003, Business + IT = Resilience, *Contingency Planning & Management,* September/October

Armbruster D., Marthaler D. and Ringhofer C., 2002, *Efficient simulations of supply chains,* Proceedings of the 2002 Winter Simulation Conference, USA

Arns, M., Fischer, M., Kemper, P. and Tepper, C., 2002, Supply chain modelling and its analytical evaluation, *Journal of the Operational Research Society*, 53, 885-94.

Aviv, Y., 2002, Gaining benefits from joint forecasting and replenishment processes: The case of auto-correlated demand, *Manufacturing & Service Operations Management*, 4, 1, 55-74.

Axelrod, R., 1997, *The complexity of cooperation: Agent-based models of competition and collaboration*, Princeton (NJ): Princeton University Press.

Axsater, S. and Zhang, W.F., 1999, A joint replenishment policy for multi-echelon inventory control, *International Journal of Production Economics,* 59, 243–250.

Backx, T., Bosgra, O. and Marquardt, W., 1998, *Towards intentional dynamics in supply chain conscious process operations,* Contribution to FOCAPO1998, Snowbird, Utah.

Baita F, Ukovich W, Pensenti R, and Favaretto D, 1998, Dynamic routing-and-inventory problems: A review, *Transportation Research*, 32, 585–598.

Baldwin, J. S., Allen, P. M., Winder, B and Ridgway, K, 2003, Simulating the cladistic evolution of manufacturing, *Journal of Innovation Management, Policy and Practice,* 5, 2/3, 144 – 156.

Banbury, S. and Tremblay, S., 2004, *Situation awareness: A cognitive perspective,* Aldershot, Ashgate.

Banerjee, S., Banerjee, A., Burton, J. and Bistline, W., 2001,Controlled partial shipments in two-echelon supply chain networks: A simulation study, *International Journal of Production Research,* 71, 91-100.

Barad, M. and Sapir, D., 2003, Flexibility in logistic systems-modeling and performance evaluation, *International Journal of Production Economics*, 85, 3, 155-70.

Barbuceanu,M. and Fox, M.S.,1995, *The architecture of an agent based infrastructure for agile manufacturing,* IJCAI-95 Workshop on Intelligent Manufacturing, Montreal.

Barbuceanu, M and Fox, M., 1997, *Integrating communicative action, conversations and decision theory to coordinate agents,* Proceedings of Autonomous Agents, 47-58, Marina Del Rey.

Beamon, B.M., 1998, Supply chain design and analysis: Models and methods, *International Journal of Production Economics,* 55, 281-294.

Bendoly, E., Donohue, K. and Schultz, K.L., 2006, Behaviour in operations management: Assessing recent findings and revisiting old assumptions, *Journal of Operations Management,* 24, 737-752.

Berger, C.M. and Bradac, J.J., 1982, *Language and social knowledge: Uncertainty in interpersonal relations.* London, Edward Arnold

Berger, C.M., 1987, Communicating under uncertainty, in M.E.Roloff and G.R. Miller, eds., *Interpersonal processes: New dimensions in communications research,* Newbury Park, CA, Sage.

Berger, P.D., Gerstenfeld, A. and Zeng, A.Z., 2004, How many suppliers are best? A decision-analysis approach, *Omega-International Journal of Management Science*, 32, 1, 9-15.

Berning, G., Brandenburg, M., Gursoy, K., Mehta, V. and Tolle F.J., 2002, An integrated system solution for supply chain optimisation in the chemical process industry, *OR Spectrum*, 24, 4.

Bilgen, B. and Ozkarahan, I., 2004, Strategic, tactical and operational production-distribution models: A review, *International Journal of Technology Management,* 28, 2, 151-171.

Billington, C., Johnson, B. and Triantis, A., 2002, A real options perspective on supply chain management in high technology, *Journal of Applied Corporate Finance,* 15, 2, 32–43.

Blackhurst, J., Craighead, C.W., Elkins, D. and Handfield R.B., 2005, An empirically derived agenda of critical research issues for managing supply-chain disruptions, *International Journal of Production Research,* 43, 19, 4067-4081.

Boisot, M. and Child, J., 1999, Organizations as adaptive systems in complex environments: The case of China, *Organization Science*, 10, 237-252.

Bok J.K., Grossmann I.E. and Park S., 2000, Supply chain optimisation in continuous flexible process networks, *Industrial and Engineering Chemistry Research*, 39, 1279–1290.

Bonabeau, E. and Meyer, C., 2001, Swarm intelligence: A whole new way to think about business, *Harvard Business Review,* 80, 3, 109-116.

Bonney, M.C., Zhang, Z., Head, M.A., Tien, C.C. and Barson, R.J., 1999, Are push and pull systems really so different? *International Journal of Production Economics, 85, 127-140.*

Bose, S. and Peckny, J.F., 2000, A model predictive framework for planning and scheduling problems: A case study of consumer goods supply chain, *Computers and Chemical Engineering,* 24, 329-335.

Bradshaw, A. and Daintith,D, 1976, Synthesis of control policies for cascaded production-inventory systems, *International Journal of Systems Science,* 7, 9, 1053-1070.

Braithwaite, A. and Hall, D., 1999, Risky business? Critical decisions in supply chain management: Part 1, *Supply Chain Practice,* 1, 2, 40-55.

Buchanan, D., and Connor, M., 2001, Managing process risk: Planning for the booby traps ahead, *Strategy & Leadership*, 29, 3, 23-28.

Bunderson, J.S. and Sutcliffe, K.M., 2002, Comparing alternative conceptualizations of functional diversity in management teams: Process and performance effects, *Academy of Management Journal, 45, 875-893.*

Burbridge, J.L., 1961, The new approach to production, *Production Engineer,* 40, 769-784.

Burns, J.F. and Sivazlian, B.D., 1978, Dynamic Analysis of multi-echelon supply systems, *Computer & Industrial Engineering,* 2, 181-193.

Cachon G.P. and Zipkin, P.H., 1999, Competitive and cooperative inventory policies in a two-stage supply chain, *Management Science*, 45, 936–953.

Caridi, M. and Cavalieri, S., 2004, Multi-agent systems in production planning and control: An overview, *Production Planning & Control*, 15, 2, 106-118.

Carlson, J.M. and Doyle, J.C., 2000, Highly optimized tolerance: Robustness and design in complex systems, *Physical Review Letters,* 84, 11, 2529-2532.

Carlsson, D., D'Amours, S., Martel, A. and Ronnqvist, M., 2006, *Supply chain management in the pulp and paper industry,* FORAC working paper, DT-2006-AM-3, October.

Carpenter, S., Walker, B., Marty Anderies, J. and Abel, N., 2001, From metaphor to measurement: Resilience of what to what? *Ecosystems,* 4, 765 – 781.

Casti, J., 1994, *Complexification: Explaining a paradoxical world through the science of surprise,* New York, Harper Collins.

Cavalieri, S., Cesarotti, V. and Introna, V., 2003, A multiagent model for coordinated distribution chain planning, *Journal of Organizational Computing and Electronic Commerce*, 13, 3-4, 267-287.

Chaib-draa, B., 1995, Industrial applications of distributed AI, *Communication of ACM*, 38, 11, 49–53.

Chaib-draa, B., Moulin, B., Mandiau, R., and Millot, P., 1992, Trends in distributed artificial intelligence, *Artificial Intelligence Review*, 6, 35–66.

Chandra P and Fisher M.L., 1994, Co-ordination of production and distribution planning, *European Journal of Operational Research,* 72, 503–517.

Chang, M.H. and Harrington, J.E., 2000, Centralization vs. decentralization in a multi-unit organization: A computational model of a retail chain as a multi-agent adaptive system, *Management Science,* 46, 11, 1427 – 1440.

Chapman, P., Christopher, M., Juttner, H., Peck, U. and Wilding, R., 2002, *Identifying and managing supply chain vulnerability*, http://www.som.cranfield.ac.uk.

Chen,Y., Peng, Y., Finin, T., Labrou, Y., Cost, S., Chu, B., Yao, J., Sun, R. and Wilhelm, B., 1999, *A negotiation based multi-agent system for supply chain management*, Working notes of the Agents '99 Workshop on Agents for Electronic commerce and Managing the Internet-enabled Supply Chain, Seattle, WA.

Choi, T.Y., Dooley, K.J., and Rungtusanatham, M., 2001, Supply networks and complex adaptive systems: Control versus emergence, *Journal of Operations Management*, 19, 351-366.

Chopra S. and Sodhi M. S., 2004, Managing risk to avoid supply-chain breakdown, *Sloan Management Review,* 46, 1, 53-61.

Christopher, M., 1998, *Logistics and Supply Chain Management,* London, Financial Times.

Christopher, M., 2000, The agile supply chain: Competing in volatile markets, *Industrial Marketing Management*, 2000, 29, 1, 37 - 44.

Christopher, M. and Towill, D.R., 2000, Supply chain migration from lean and functional to agile and customised, *International Journal of Supply Chain Management*, 5, 4, 206-13.

Christopher, M. and Lee, H., 2001, *Supply chain confidence – The key to effective supply chains through improved visibility and reliability*, Vatera Inc. white paper, Global Trade Management.

Christopher, M., Peck, H., Rutherford, C. and Juttner, U., 2002, *Supply chain vulnerability*, Final report on behalf of DTLR, DTI and Home Office.

Christopher, M., Peck, H., Rutherford, C. and Juttner, U, 2003a, *Understanding supply chain risk: A self-assessment workbook,* Department for Transport-Cranfield University - Cranfield University.

Christopher, M., Peck, H., Rutherford, C. and Juttner, U, 2003b, Supply chain resilience, *Cranfield Centre for Logistics & Supply Chain Management,* November, appendix 1.

Christopher, M. and Lee, H., 2004, Mitigating supply chain risk through improved confidence, *International Journal of Physical Distribution & Logistics Management,* 34, 5, 388-396.

Christopher, M. and Peck, H., 2004, Building the resilient supply chain, *International Journal of Logistics Management*, 15, 2, 1-14.

Christopher, M., 2004, *Creating resilient supply chains'*, www.exel.com/advantage, 11, 18-19.

Chung, W.W.C., Yam, A.Y.K. and Chan, M.F.S., 2004, Networked enterprise: A new business model for global sourcing, International Journal of Production Economics, 87, 267–280.

Chu, D., Strand, R. and Fjelland, R., 2003, Theories of complexity, *Complexity,* 8, 3, 19-30.

Cilliers, P., 2001, Boundaries, hierarchies and networks in complex systems, *International Journal of Innovation Management,* 5, 2, 135-147.

Clark, N., Trejo, F. P. and Allen, P.M., 1995, *Evolutionary dynamics and sustainable development,* Aldershot, Edward Elgar.

Cloutier, L., Frayret, J.-M., D'Amours, S., Espinasse, B. and Montreuil, B., 2001, A commitment-oriented framework for networked manufacturing coordination, *International Journal of Computer Integrated Manufacturing*, 14, 6, 522–534.

Coutu, D.L., 2002, How resilience works, *Harvard Business Review,* May, 47-55.

Coyle, R.G., 1982, Assessing the controllability of a production and raw material systems, *IEEE Transactions on Systems Management And Cybernetics,* 12, 867-876.

Cranfield University, 2003, Creating resilient supply chains: A practical guide, Report produced by the Centre for Logistics and Supply Chain Management.

Csete, M.E. and Doyle, J.C., 2002, Reverse engineering of biological complexity. *Science,* 295, 1664-1669.

D'Antoni, H., 2003, Behind the numbers: Real-time information aids supply chains, *InformationWeek,* 936, 71.

Daft, R.L. and Lewin, A.Y., 1990, Can organization studies begin to break out of the normal science straitjacket: An editorial essay, *Organisation Science,* 1, 1, 1-9.

Das, S. and Patel, P., 2002, An audit tool for determining flexibility requirements in a manufacturing facility, *Journal of Integrated Manufacturing Systems*, 13, 4, 264-274.

Davidsson, P. and Wernstedt, F., 2002, A multi-agent system architecture for coordination of just-in-time production and distribution, *Knowledge Engineering Review,* 17, 4, 317-329.

Davis, T., 1993, Effective supply chain management, *Sloan Management Review, 34*, 4, 35-46.

Deevey, E., 1995, *Creating the resilient organization,* Englewood Cliffs, NJ, Prentice Hall.

Dejonckheere, J., Disney, S.M., Lambrecht, M.R. and Towill, D.R., 2004, The impact of information enrichment on the bullwhip effect in supply chains: A control engineering perspective, *European Journal of Operational Research,* 153, 727-750.

Deloitte, Touche, Tohmatsu, 2003, *Mastering complexity in global manufacturing,* A Deloitte Research Global Manufacturing Study.

Dengiz, B. and Akbay, K.S., 2000, Computer simulation of a PCB production line: Metamodeling approach, *International Journal of Production Economics, 63, 195-205.*

Díaz-Emparanza, I., 2002, Is a small Monte Carlo analysis a good analysis? Checking the size power and consistency of a simulation-based test, *Statistical Papers*, 43, 4, 567-577.

Diks, E.B., de Kok, A.G. and Lagodimos, A.G., 1996, Multi-echelon systems: A service measure perspective*, European Journal of Operational Research*, 95, 241–263.

Diks, E.B. and de Kok, A.G., 1998, Optimal control of a divergent multi-echelon inventory system, *European Journal of Operational Research*, 111, 75–97.

Diks, E.B. and de Kok, A.G, 1999, Computational results for the control of a divergent N-echelon inventory system, *European Journal of Operational Research,* 59, 327–336.

Dodd, C. and Kumara, S. R. T., 2001, *A distributed multi-agent model for value nets,* IEA/AIE, 718–727.

Dovers, S.R. and Handmer, J.W., 1992, Uncertainty, sustainability and change, *Global Environmental Change*, 2, 4, 262–276.

Duclos, L., Vokurka, R. and Lummus, R., 2003, A conceptual model of supply chain flexibility, *Industrial Management & Data Systems*, 103, 446–456.

Edmondson, A.C., 1999, Psychological safety and learning behaviour in work teams, *Administrative Science Quarterly*, 44, 350-383.

Elias, N., 1998, *On civilization, power and knowledge*, Chicago, University of Chicago Press.

Emmeche, C., 1997, Aspects of complexity in life and science, *Philosophica*, 59, 1, 47-68.

Erenguc, S.S., Simpson, N.C. and Vakharia, A.J., 1999, Integrated production/distribution planning in supply chains: An invited overview, *European Journal of Operational Research*, 115, 219-236.

Evans, G. N., Naim, M.M. and Towill, D.R., 1998, Application of a simulation methodology to the re-design of a logistical control system, *International Journal of Production Economics,* 56-57, 157-168.

Faisal, M. N., Banwet, D.K. and Shankar,R., 2006, Mapping supply chain on risk and customer sensitivity dimensions, *Industrial Management and Data Systems,* 106, 6, 878-895.

Finch, P., 2004, Supply chain risk management, *Supply Chain Management: An International Joumal,* 9, 2, 183-196.

Fine, C.H., 2000, Clockspeed-based strategies for supply chain design, *Production and Operations Management*, 9, 3, 213-221.

Fisher, M.L., 1997, What is the right supply chain for your product? *Harvard Business Review*, 75, 2, 105-116.

Flick, U., 1998, *An Introduction to Qualitative Research*, London, Sage.

Forrester, J.W., 1961, *Industrial Dynamics,* Cambridge, Massachusetts, MIT Press.

Foster, R and Kaplan, S., 2001, *Creative destruction: Why companies that are built to last underperform the market – and how to successfully transform them,* New York, Doubleday.

Fox, M. S., Chionglo, J. F., and Barbuceanu, M., 1993, *The integrated supply chain management*, Internal report of the Enterprise Integration Laboratory, Department of Industrial Engineering, University of Toronto (Ontario), Canada.

Fox, M. S., Barbuceanu, M., and Teigen, R., 2000, Agent-oriented supply-chain management, *International Journal of Flexible Manufacturing Systems*, 12, 165−188.

Frayret, J.M., D'amours, S., Montreuil, B. and Cloutier, L., 2001, A network approach to operate agile manufacturing systems, *International Journal of Production Economics*, 74, 1-3, 239-259.

Fu, Y. and Piplani, R., 2000, Multi-agent enabled modelling and simulation towards collaborative inventory management in supply chains, in J. A. Joines, R. R. Barton, K. Kang, and P. Fishwick, eds., *Proceedings of the 2000 Winter Simulation Conference*, Piscataway, NJ, IEEE, 1763−1772.

Ganeshan, R., Jack, E., Magazine, M.J. and Stephens, P., 1999, A taxonomic review of supply chain management research in S. Tayur, R. Ganeshan and M.Magazine, eds., *Quantitative models for supply chain management,* 840-879, Boston, MA, Kluwer Academic Publishers.

Garavelli, A.C., 2003, Flexibility configurations for the supply chain management, *International Journal of Production Economics*, 85, 2, 141-153.

Gasser, L. and Briot, J.P., 1992, Object-based concurrent programming and distributed artificial intelligence, in Avouris, N. and Gasser, L., eds., *Distributed artificial intelligence: Theory and practice,* Kluwer Academic Publishers.

Geary, S., Childerhouse, P., Towill, D., 2002, Uncertainty and the seamless supply chain, *Supply Chain Management Review*, July/August, 52-61.

Gehman, H. W., 2003, *Columbia Accident Investigation Board*, Report Volume 1, NASA - GAO, August.

Gerwin, D., 1984, Relationship between structure and technology, in, P.C., Nystrom and W.H., Starbuck, eds., *Handbook of organizational design,* Vol. 2, London, Oxford University Press.

Gibson, J.L., Ivancevich, J.M. and Donnelly Jr., J.H., 1997, *Organizations: Behaviour, structure, processes*, Chicago, Irwin.

Giunipero, C. L. and Eltantawy, R. A., 2004, Securing the upstream supply chain: A risk management approach. *International Journal of Physical Distribution & Logistics Management,* 34, 9, 698-713.

Giunipero,L.C., Denslow, D. and Eltantawy, R.A., 2005, Purchasing/supply chain management flexibility: moving to an entrepreneurial skill set, *Industrial Marketing Management*, 34, 602-613.

Gjerdrum, J., Shah, N. and Papageorgiou, L.G., 2001, Transfer prices for multienterprise supply chain optimisation, *Industrial and Engineering Chemistry Research,* 40, 1650–1660.

Gordon, J.E., 1978, *Structures,* Harmondsworth, UK, Penguin Books.

Guessoum, Z. and Briot, J.-P., 1999, From active objects to autonomous agents, *IEEE Concurrency*, 7(3).

Gunasekaran, A., Macbeth, D. K., and Lamming, R., 2000, Modeling and analysis of supply chain management systems, *Journal of the Operational Research Society*, 51, 1112−1115.

Gunderson, L., 2000, Ecological resilience – In theory and application, *Ann. Rev. Ecol. Syst.,* 31, 425-439.

Haapaniemi, P., 2003, The adaptive enterprise, *CEO Viewpoints*, May.

Haeckel, S.H., 1999, *Adaptive enterprise: Creating and leading sense-and respond organizations*, Boston, Harvard Business School Press.

Haehling von Lanzenauer, C. and Pilz-Glombik K, 2002, Coordinating supply chain decisions: An optimization model, *OR Spectrum,* 24, 59–78.

Hale, A. and Heijer, T., 2006, Defining resilience, in E. Hollnagel, D.Woods and N. Leveson, eds., *Resilience engineering: Concepts and precepts,* Aldershot, UK, Ashgate.

Hamel, G. and Valikangas, L., 2003, The quest for resilience, *Harvard Business Review,* 52-63.

Handfield, R. and Nichols, E., 1999, *Introduction to Supply Chain Management*, Englewood Cliffs, NJ., Prentice-Hall.

Handmer, J.W. and Dovers, S.R., 1996, A typology of resilience: Rethinking institutions for sustainable development, *Industrial and Environmental Crisis Quarterly,* 9, 4, 482–511.

Haq, A.N., Vrat, P. and Kanda, A., 1991, An integrated production-inventory-distribution model for manufacture of urea: A case, *International Journal of Production Economics*, 39, 39–49.

Harland, C. M., 1996, Supply chain management: Relationships, chains and networks, *British Journal of Management*, 7, Special Issue, S63 – S80.

Harland, C.M., Lamming, R.C. and Cousins, P.D., 1999, Developing the concept of supply strategy, *International Journal of Operations and Productions Management,* 19, 650 – 673.

Harland, C.M., Lamming, R.C., Zheng, J. and Johnsen, T.E., 2002, A taxonomy of supply networks, *IEEE Engineering Management Review,* 30, 4,

Harland, C., Brenchley, R., and Walker, H., 2003, Risk in supply networks, *Journal of Purchasing and Supply Management, 9,* 2, 51-62.

Haywood M. and Peck H., 2003, *Improving the management of supply chain vulnerability in UK aerospace manufacturing,* Proceedings of the 1st EUROMA/POMs Conference, Lake Como, June 16th – 18th, 2, 121 – 130.

Haywood, M. and Peck, H., 2004, *Supply chain vulnerability within UK aerospace manufacturing: Development of a vulnerability management toolkit,* Supply Chain Practice, 6, 1, February, 72-83.

Hendricks, K. B. and Singhal, V.R., 2003, The effect of supply chain glitches on shareholder value, *Journal of Operations Management,* 21, 5, 501–522.

Hendricks, K. B., and Singhal, V. R., 2005, An empirical analysis of the effect of supply chain disruptions on long-run stock price performance and risk of the firm, *Production and Operations Management*, 14, 35-52.

Holland, J.H., 1992, *Adaptation in natural and artificial systems*, Michigan, USA, University of Michigan Press.

Holland, J.H., 1995, *Hidden order: How adaptation builds complexity*, Reading, MA, Addison-Wesley.

Holland, J.H., 1998, *Emergence, from chaos to order*, Reading, MA, Addison-Wesley.

Holling, C.S., 1973, Resilience and stability of ecological systems, *Annual Review of Ecology and Systematics,* 4, 1–23.

Holling, C.S., 1986, The resilience of terrestrial ecosystems: local surprise and global change, in, W.C. Clark and R.E., Munn, eds., *Sustainable development of the biosphere,* Cambridge, UK, Cambridge University Press.

Hollnagel, Erik, 1993, *Human reliability analysis: Context and control,* London, Academic Press.

Hollnagel, E. and Sundström, G., 2006, States of resilience, in, E. Hollnagel, D.Woods and N., Leveson, eds., *Resilience engineering: Concepts and precepts,* Aldershot, UK, Ashgate.

Holmström, J., 1997, Product range management: A case study of supply chain operations in the European grocery industry, *International Journal of Supply Chain Management*, 2, 8,107-15.

Holweg, M., and Pil, F., 2001, Successful build-to-order strategies: Start with the customer, *Sloan Management Review*, 43, 1, 74–83.

Hong, Y. and Choi, T.Y., 2002, Unveiling the structure of supply networks: Case studies in Honda, Acura and Daimler Chrysler, *Journal of Operations Management*, 20, 469-493.

Horne, J., 1997, Coming age of organizational resilience, *Business Forum,* Spring to Fall, 24-28.

Hoshino, K., 1996, Criterion for choosing order policies between fixed-size and fixed-interval, push-type and pull-type, *International Journal of Production Economics,* 44, 91-95.

Hoyt, J. and Huq, F., 2000, From arms length to collaborative relationships in the supply chain: An evolutionary process, *International Journal of Physical Distribution and Logistics Management,* 30, 9, 750-764.

Hutchins, G., 2003, Risk management in the supply chain, Quality Congress, ASQ's Annual Quality Congress Proceedings, 57, 49-58.

Jennings, N., 2001, An agent-based approach for building complex software systems, Comms. of the ACM, 44, 4, 35-41.

Jennings, N. and Wooldridge, M., 1998, Applications of intelligent agents, in, N.R. Jennings and M. Wooldridge, eds., *Agent technology: Foundations, applications and markets*, 3–28, New York, Springer-Verlag.

Johnson, M.E., 2001, Learning from toys: Lessons in managing supply chain risk from the toy industry, *California Management Review*, 43, 3, 106-125.

Jung, H., Ahn, H. and Rhee, S., 1999, Impact of buyer's order batching on the suppliers demand correlations and capacity utilization, *Production Planning and Control*, 10, 5, 472-85.

Jung, Y.J., Blau, G., Pekny, J.F., Reklaitis, G.V. and Eversdyk, D., 2004, A simulation based optimization approach to supply chain management under demand uncertainty, *Computers and Chemical Engineering*, 28, 2087-2106.

Juttner, U., Peck, H. and Christopher. M., 2003, Supply chain risk management: Outlining an agenda for future research, *International Journal of Logistics: Research and Applications,* 6, 4, 197-210.

Jüttner, U., 2005, Supply chain risk management, *International Journal of Logistics Management,* 16, 1, 120-141.

Kafoglis, C., 1999, Maximize competitive advantage with a supply chain vision, *Hydrocarbon Processing,* February, 47-50.

Kahn, J.A, 1987, Inventories and the volatility of production, *The American Economic Review,* 77, 667–679

Kallrath J, 2002, Planning and scheduling in the process industry, *OR Spectrum*, 24, 219–250.

Karacel, S. C., and Mize, J. H., 1996, A formal structure for discrete event simulation, part I: Modeling multiple level systems, *IIE Transactions*, 28, 9, 753-760.

Kenis, P. and Knoke, D., 2002, How organizational field networks shape interorganizational tie-formation rates, *Academy of Management Review,* 27, 275-293.

Khalil, E.L. and Boulding, K.E., 1996, *Evolution, order and complexity,* London, Routledge.

Kilgore, M., 2003, *Mitigating supply chain risks,* White paper, Chainalytics LLC, Atlanta, Georgia.

Kleijnen, J.P.C., 1995, Verification and validation of simulation models, *European Journal of Operational research,* 82, 145-162.

Klein, R.J.T., Nicholls, R.J. and Thomalla, F., 2003, Resilience to natural hazards: How useful is this concept, *Environmental Hazards,* 5, 35-45.

Kleindorfer, P. R., Belke, J.C., Elliot, M. R., Lee, K., Lowe, R. A. and Feldman, H., 2003, Accident epidemiology and the U.S. chemical industry: Accident history and worst-case data from RMP*Info, *Risk Analysis,* 23, 5, 865–881.

Kleindorfer, P.R. and Saad, G.H., 2005, Managing disruption risks in supply chains, *Production and Operations Management*, 14, 1, 53-68.

Kobasa, S. C., Maddi, S. R., Puccetti, M. C. and Zola, M. A., 1985, Effectiveness of hardiness, exercise, and social support as resources against illness, *Journal of Psychosomatic Resources*, 29, 525-533.

Kohn, W, Brayman, V. and Ritchey, J. A., 2000, Enterprise dynamics via non-equilibrium membrane models, *Open Systems & Information Dynamics*, 7, 4, 327-348.

Konicki, S., 2000a, He's fixed on keeping the supply chain strong, *InformationWeek,* 869, 41.

Konicki, S., 2000b, Supply-chain adjustments key after attacks, *InformationWeek,* 866, 72.

Kornienko, S., Kornienko, O. and Priese, J., 2004, Application of multi-agent planning to the assignment problem, *Computers in Industry*, 54, 273-290.

Kouvelis, P. and Milner, J., 2002, Supply chain capacity and outsourcing decisions: The dynamic interplay of demand and supply uncertainty, *IIE Transactions*, 34, 717-728.

Krupp, J.A.G., 1982, Effective safety stock planning, *Production and Industrial Management Journal,* 23, 3, 35-47.

Lagodimos, A.G., 1992, Multi-echelon service models for inventory systems under different rationing policies, *International Journal of Production Research,* 30, 939-958.

Lambert, D.M., Cooper, M.C. and Pagh, J.D., 1998, Supply chain management: Implementation issues and research opportunities, *International Journal of Logistics Management,* 9, 2, 1 – 19.

La Porte, T.R., 1982, On the design of nearly error-free organizational control systems, in, D. L. Sills, C. P. Wolf and V. Shelanski, eds., *Accident at three mile island: The human dimension,* Boulder, CO, Westview Press.

La Porte, T R. and Consolini, P, 1991, Working in practice but not in theory: Theoretical challenges of high-reliability organizations, *Journal of Public Administration Research and Theory,* 1, 19-47.

Law, A.M. and Kelton, W.D., 2000, *Simulation modeling and Analysis,* Boston, McGraw-Hill.

Lawrie, G., 2003, *Preparing for adaptive supply networks,* TechStrategy Report, Forrester Inc.

Lee, H. and Billington, C., 1993, Material management in decentralized supply chains, *Operations Research,* 41, 5, 835-847.

Lee, H., Padmanabhan, V. and Whang, S., 1997, Information distortion in a supply chain: The bullwhip effect, *Management Science*, 43, 4, 546-558.

Lee, H. and Whang, S., 1998, *Information sharing in a supply chain,* research paper series, No. 1549, Graduate School of Business, Stanford University, Stanford, CA.

Lee, H., and Whang, S., 1999, Decentralized multi-echelon supply chains: Incentives and information, *Management Science, 45*, 5, 633-640.

Lee, H.L., 2002, Aligning supply chain strategies with product uncertainties, *California Management Review*, 44, 3, 105-119.

Lee, H. and Wolfe, M., 2003, Supply chain security without tears, *Supply Chain Management Review,* January/February, 12-20.

Lee, H., 2004, The triple:A supply chain, Harvard Business Review, 82, 10, 102-112.

Lengnick-Hall, C. A. and Beck, T. E., 2003, *Beyond bouncing back: The concept of organizational resilience*. Paper presented at the National Academy of Management meetings, Seattle, WA.

Lengnick-Hall, C.A. and Beck, T.E., 2005, Adaptive fit versus robust transformation: How organizations respond to environmental change? *Journal of Management*, 31, 5, 738-757.

Li, D. and O'brien, C., 2001, A quantitative analysis of relationships between product types and supply chain strategies, *International Journal of Production Economics*, 73, 1, 29-39.

Li, Z., Kumar, A. and Lim, Y. G., 2002, Supply chain modelling - A co-ordination approach, *Integrated Manufacturing Systems,* 13, 8, 551-561.

Lim, S.J., Jeong, S.J., Kim, K.S. and Park, M.W., 2006, A simulation approach for production-distribution planning with consideration given to replenishment policies, *International Journal of Advanced Manufacturing Technology,* 27, 593-603.

Lin, F., Tan, G.W. and Shaw, M.J., 1998, *Modelling supply networks by a multi-agent system,* Proceedings of 31st Annual Hawaii International Conference on Systems Science, IEEE.

Lin, F., Tan, G.W. and Shaw, M.J., 1999, Multiagent enterprise modelling, *Journal of Organizational Computing and Electronic Commerce,* 9, 1, 7-32.

Lin, F., and Pai, Y., 2000, Using multi-agent simulation and learning to design new business processes, *IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans*, 30, 3, 380–384.

Lorenz, E.N., 1963, Deterministic nonperiodic flow, *Journal of Atmospheric Science,* 20, 130 – 141.

Loughman, T.P., Fleck, R.A. and Snipes, R., 2000, A cross-disciplinary model for improved information systems analysis, *Industrial Management & Data Systems*, 100, 8, 359-369.

Macy, M. and Willer, R., 2002, From factors to actors: Computational sociology and agent-based modeling, *Annual Review of Sociology,* January, 28, 143-166.

Mallak, L., 1998, Putting organizational resilience to work, *Industrial Management,* Nov/Dec, 40, 6, 8-13.

Maloni M.J. and Benton, W.C., 1997, Supply chain partnerships: Opportunities for operations research, *European Journal of Operational Research,* 101, 419–429.

Martha, J. and Subbakrishna, S., 2002, Targeting a just-in-case supply chain for the inevitable next disaster, *Supply Chain Management Review,* September/October, 18-24.

Mason-Jones, R. and Towill, D.R., 1997, Information enrichment: Designing the supply chain for competitive advantage, *International Journal of Supply Chain Management,* 2, 4, 137-148.

Mason-Jones, R. and Towill, D.R., 1998a, Shrinking the supply chain uncertainty cycle, *Control*, 17-22.

Mason-Jones, R. and Towill, D.R., 1998b, Time compression in the supply chain: Information management is the vital ingredient, *Logistics Information Management,* 11, 2, 93-104.

Mason-Jones, R., Naim, M.M. and Towill, D.R., 1997, The impact of pipeline control on supply chain dynamics, *The International Journal of Logistics Management,* 8, 2, 47-61.

Mason-Jones, R, Naylor, B. and Towill, D., 2000, Lean, agile or leagile? Matching your supply chain to marketplace, *International Journal of Production Research,* 38, 17, 4061-4070.

Massachusetts Institute of Technology Research Project, 2003, *Supply chain response to terrorism,* Centre for Transportation and Logistics.

Maturana, F., Shen, W., and Norrie, D., 1999, Metamorph: An adaptive agent-based architecture for intelligent manufacturing, *International Journal of Production Research*, 37, 10, 2159–2173.

Mccarthy, I.P. and Tan, Y.K., 2000, Manufacturing competitiveness and fitness landscape theory, *Journal of Materials Processing Technology*, 107, 1-3, 347-352.

McCullen, P and Towill, D., 2002, Diagnosis and reduction of bull-whip in supply chains, *Supply Chain Management: An International Journal,* 7, 3, 164-179.

McDonald, N., 1999, *Human-centred management for aircraft maintenance,* Deliverable report to the European Commission no, ADAMS-WP4A-D2 ADAMS Project No BR95-1732, Trinity College, Dublin, Department of Psychology.

McDonald, N., 2006, Organisational resilience and industrial risk, in, E. Hollnagel, D.Woods and N., Leveson, eds., *Resilience engineering: Concepts and precepts,* Aldershot, UK, Ashgate.

McKelvey, B., 1997, Quasi-natural organization science, *Organization Science,* 8, 351 – 380.

Meyer, A.D., 1982, Adapting to environmental jolts, *Administrative Science Quarterly,* 27, 515-537.

Miles, R.H., 1980, Macro-organizational behaviour, Santa Monica, Goodyear.

Milner, J. M. and Kouvelis, P., 2002, On the complementary value of accurate demand information and production and supplier flexibility, *Manufacturing & Service Operations Management,* 4, 2, 99–113.

Min, H. and Zhou, G.G., 2002, Supply chain modelling: Past, present and future, *Computers & Industrial Engineering*, 43, 1-2, 231-249.

Mintzberg, H., 1979, *The Structuring of Organizations*, Englewood Cliffs, NJ, Prentice-Hall.

Mitroff, I.I. and Alpasan, M.C., 2003, Preparing for the evil, *Harvard Business Review,* 81, 4, 109-115.

Montgomery, A., Holcomb, M.C. and Manrodt, K.B., 2002, *Visibility: Tactical solutions, strategic implications*, Cap Gemini, Ernst & Young, Georgia Southern University and the University of Tennessee.

Morgan, G., 1986, *Images of organization,* Beverly Hills, CA, Sage Publications.

Naim,M.M. and Towill,D.R., 1994, Establishing a framework for effective materials logistics management, *International Journal of Logistics Management,* 5, 1, 81-88.

Naim, M.M., Holweg, M. and Towill, D.R., 2003, *On systems thinking, engineering and dynamics – Their influence on modern logistics management,* Logistics and Networked Organisations' Proceedings of the 8th International Symposium on Logistics, Sevilla.

Naish, H.F., 1994, Production smoothing in the linear quadratic inventory model, *The Economic Journal,* 104, 864–875.

Nassimbeni, G., 1998, Network structures and coordination mechanisms – A taxonomy, *International Journal of Operations and Production Management,* 18, 6, 538-554.

Naylor, B, Naim, M.M. and Berry, D., 1999, Leagility: Integrating the lean and agile manufacturing paradigms in the total supply chain, *International Journal of Production Economics*, 62, 107-118.

Nelson, R. R., and Winter, S. G., 1982, *An evolutionary theory of economic change*, Cambridge, MA, Belknap.

Nissen, M., 2001, Agent-based supply chain integration, *Information Technology and Management,* 2, 3, Special Issue on Electronic Commerce in Procurement and the Supply Chain, 289-312.

O'Donnell, T., Maguire, L., McIvor, R. and Humphreys, P., 2006, Minimizing the bullwhip effect in a supply chain using genetic algorithms, *International Journal of Production Research,* 44, 8, 1523-1543.

Ocana, C. and Zemel, E., 1996, Learning from mistakes: A note on just-in-time systems, *Operations Research*, 44, 1, 206-214.

Oliver, N. and Delbridge, R., 2002, The characteristics of high performing supply chains, *International Journal of Technology Management*, 23, 1-3, 60-73.

Ormerod, P., 2006, *Why most things fail: Evolution, extinction, economics,* New Mexico, Panthoen.

Ou, J. and Jiang, J., 1997, Yield comparisons of push and pull control methods on production systems with unreliable machine, *International Journal of Production Economics,* 50, 1-12.

Pagell, M., Newman, W.R., Hanna, M.D. and Krause, D.R., 2000, Uncertainty, flexibility and buffers: Three case studies, *Production and Inventory Management Journal,* 41, 1, 35-43.

Paolucci, M. and Sacile, R., 2005, Agent-based manufacturing and control systems, Boca Raton, Florida, CRC Press.

Parunak, H. V. D., 1996, Applications of distributed artificial intelligence in industry, in, G. M. P., O'Hare and N.R., Jennings, eds., *Foundations of distributed artificial intelligence*, John Wiley & Sons.

Parunak, H.V.D., 1998, Industrial and practical applications of distributed artificial intelligence, in, G., Weiss, ed., *Multi-agent systems*, Cambridge, MA ,The MIT Press.

Parunak, V., Savit, R. & Riolo, R., 1998, Agent based modelling vs. equation based modelling: A case study and user's guide, *Proceedings of Workshop on Modeling Agent Based Systems*, Paris.

Parunak, V. and Vanderbok, R., 1998, *The DASCh experience: How to model a supply chain?* http://www.erim.org/~vparunak/iccs98.pdf.

Pentland, B. T. and Reuter, H. H., 1994, Organizational routines as grammars for action, *Administrative Science Quarterly*, 39, 484-510.

Perea-Lopez, E., Grossmann, I.E., Ydstie, B.E. and Tahmassebi, T., 2001, Dynamic modelling and decentralized control of supply chains, *Industrial and Engineering Chemistry Research,* 40, 3369-3383.

Perrings, C., 1994, *Ecological resilience in the sustainability of economic development*, International Symposium on models of sustainable development, Paris, Vol II, 27-41.

Perrow, C., 1999, *Normal Accidents: Living with high-risk technologies,* New Jersey, Princeton University Press.

Peters, J.E. and Hogensen, A.J., 1999, New directions for the warehouse, *Supply Chain Management Review*, Global Supplement, 23-25.

Pfohl, H.C. and Buse, H.P., 2000, Inter-organisational logistics systems in flexible production networks – An organisational capabilities perspective, *International Journal of Physical Distribution & Logistics,* 30, 5, 388 – 408.

Pimm, S.L., 1984, The complexity and stability of ecosystems, Nature, 307, 321–326.

Porter, B. and Bradshaw, A., 1974, Modal control of production-inventory systems using piece-wise constant control policies, *International Journal of Systems Science,* 5, 8, 733-742.

Pratt, D. B., Farrington, P. A., Basnet, C. B., Bhuskute, H. C., Kanath, M., and Mize, J. H., 1994, The separation of physical, information, and control elements for facilitating reusability in simulation modelling, *International Journal of Computer Simulation*, 4, 3, 327–342.

Prietula, M., 2001, Advice, trust and gossip among artificial agents. A. Lomi, E.R. Larsen, eds., *Dynamics of organizations: Computational modelling and organization theories*, Menlo Park, CA, AAAI Press / MIT Press, 141-177.

Pyke, D.F. and Cohen, M.A., 1993, Performance characteristics of stochastic integrated production-distribution systems, *European Journal of Operations Research,* 68, 23 – 48.

Radjou, N., 2002, *Executive overview: Adaptive supply networks*, Techstrategy Report, Forrester Inc.

Ragatz, G.L. and Mabert, V.A., 1988, An evaluation of order release mechanism in a job-shop environment, *Decision Sciences,* 19, 1, 167-189.

Randall, T. and Ulrich, K., 2001, Product variety, supply chain structure, and firm performance: Analysis of the U.S. bicycle industry, *Management Science*, 47, 12, 1588-1604

Randall, T.R., Morgan, R.M. and Morton, A.R., 2003, Efficient versus responsive supply chain choice: An empirical examination of influential factors, *Journal of Product Innovation Management*, 20, 6, 430-443.

Rasmussen, J., 1997, Risk Management in a dynamic society, *Safety Science,* 27, 2, 183-213.

Reason, J.T., 1987, An interactionist's view of system pathology, in, J.A. Wise and Debons, A., eds, *Information systems: Failure analysis*, Berlin, Springer-Verlag, 211-220.

Reason, J.T., 1990a, *Human error*, Oxford, Oxford University Press.

Reason, J.T., 1990b, The contribution of latent human failures to the breakdown of complex systems, *Philosophical Transactions of the Royal Society of London, B*, 37, 475-484.

Reason, J.T., 1995, Understanding adverse events: Human factors, *Quality in Health Care*, 480-489.

Reason, J.T., 1997, *Managing the risks of organizational accidents,* Aldershot, UK, Ashgate Publishing Limited.

Rice, J.B. and Caniato, F., 2003, Building a secure and resilient supply network, *Supply Chain Management Review,* September/October, 22-30.

Riddalls, C.E., Bennet, S., and Tipi, N. S., 2000, Modelling the dynamics of supply chains, *International Journal of Systems Science*, 31, 8, 969-976.

Rigby, C., Day, M., Forrester, P. and Burnett, J., 2000, Agile supply: Rethinking systems thinking, systems practice, *International Journal of Agile Management Systems,* 2, 3, 178-186.

Robbins, S.R., 1990, *Organization theory: Structure, design, and application,* Englewood Cliffs, NJ, Prentice-Hall Inc.

Robbins, S.P., 1992, *Essentials of organizational behaviour,* Englewood Cliffs, N.J., Prentice Hall.

Roberts, K.H., 1990, Some characteristics of high reliability organizations, *Organization Science,* 1, 160-177.

Rochlin, G.I., La Porte, T.R., and Roberts, K.H., 1987, The self-designing high reliability organization, *Naval War College Review,* Autumn.

Russell, S. and Norvig, P., 2003, *Artificial intelligence - A modern approach*, Englewood Cliffs, NJ, Prentice-Hall.

Rowbottom, U., 2004, Managing risk in global supply chains, *Supply Chain Practice,* 6, 2*,* 16-23.

Rupp, T.M. and Ristic, M., 2000, Fine planning for supply chains in semiconductor manufacture, *Journal of materials processing technology*, 107, 390 - 397

Saad, N. and Kadirkamanathan, V., 2006, A DES approach for the contextual load modelling of supply chain system for instability analysis, *Simulation Modelling Practice and Theory,* 14, 541 –563.

Saad, S.M. and Gindy, N.N., 1998, Handling internal and external disturbances in responsive manufacturing environments, *Production Planning and Control,* 9, 8, 760-770.

Sadeh, N., Hildum, D., Kjenstad, D., and Tseng, A., 1999, *MASCOT: An agent-based architecture for coordinated mixed-initiative supply chain planning and scheduling,* Workshop notes, Agent-Based Decision Support for Managing the Internet-Enabled Supply Chain, 3rd International Conference on Autonomous Agents (Agents' 99).

Sagan, S. D., 1993, *The limits of safety: Organizations, accidents, and nuclear weapons,* Princeton, New Jersey, Princeton University Press.

Samaddar, S., Nargundkar, S. and Daley, M., 2006, Inter-organizational information sharing: The role of supply network configuration and partner goal congruence, *European Journal of Operational Research,* 174, 744-765.

Samuelson, P.A., 1939, Interaction between the multiplier analysis and the principle of acceleration, *Review of Economic Statistics, 21, May, 75-79.*

Sanchez, A.M. and Perez, M.P., 2005, Supply chain flexibility and firm performance: A conceptual model and empirical study in the automotive industry, *International Journal of Operations and Production Management,* 25, 7, 681-700.

Saporito, B., 1997, Behind the tumult at Procter & Gamble, *Fortune,* 129, 5, 74-82.

Sarimento, A.M. and Nagi, R., 1999, A review of integrated analysis of production-distribution systems, *IIE Transactions,* 31, 1061-1074.

Sauer, J., Freese, T., and Teschke, T., 2000, Towards agent-based multi-site scheduling, in, J. Sauer and J. Khler, eds., *Proceedings of the ECAI 2000 Workshop on New Results in Planning, Scheduling, and Design*, Berlin, Universitat Oldenburg, 123−130.

Scheiritz, N. and Grossler, A.V., 2003, *Emergent structures in supply chains – a study integrating agent based and systems dynamics modelling,* Proceedings of the 36th Annual Hawaii International Conference on System Sciences, January 6-9, Hawaii

Schulman, P R., 1993, The negotiated order of organizational reliability, *Administration and Society,* 25, 3, 353-372.

Sen, S. and Weiss, G., 1998, Learning in multiagent systems, in, G., Weiss, ed., *Multi-agent systems*, Cambridge, MA ,The MIT Press.

Seo, Y., Jung, S. and Hahm, J., 2002, Optimal reorder decision utilizing centralised stock information in a two-echelon distribution system, *Computers and Operations Research,* 29, 171–193.

Shamir, 2007, Forecast's wrong? Fix your safety stocks, *Consumer Goods Technology, Inside News,* 1-10.

Sheffi, Y., 2001, Supply chain management under the threat of international terrorism, *The International Journal of Logistics Management,* 12, 2, 1-11.

Sheffi, Y., Rice, J.M., Fleck, J.B. and Caniato, F., 2003, Supply chain response to global terrorism: A situation scan, *Proceedings of EUROMA/POMS Conference, Cernobbio, lake Como*, 2, 121 -130.

Sheffi, Y., 2005a, Preparing for the big one, *Manufacturing Engineer*, 84, 5, 12-15.

Sheffi, Y., 2005b, *Resilient enterprise overcoming vulnerability for competitive advantage*, Massachusetts, MIT Press.

Sheffi, Y. and Rice, J.B., 2005, A supply chain view of the resilient enterprise, *Sloan Management Review*, 47, 1, 41-48.

Shen, W., Norrie, D. H., and Barthès, J.-P. A., 2001, *Multi-agent systems for concurrent intelligent design and manufacturing*, London and New York, Taylor and Francis.

Sherbrooke, C.S., 1968, Metric: A multi-echelon technique for recoverable item control, *Operations Research,* 16, 122–141.

Shtub, A., Bard, J. and Globerson, S., 1994, *Project management,* Englewood Cliffs: New Jersey, Prentice Hall.

Simchi-Levi, D., Kaminsky, P. and Simchi-Levi, E., 2000, *Designing and managing the supply chain*, Maidenhead, McGraw-Hill.

Simon, H.A., 1996, *The sciences of the artificial,* 3rd Ed., Cambridge, MA, USA, MIT Press,.

Sinha. P.R., Whitman, L.E. and Malzahn, D., 2004, Methodology to mitigate supplier risk in an aerospace supply chain, *Supply chain management: An International Journal,* 9, 2, 154-168.

Smith, D., 1990, Corporate power and the politics of uncertainty: risk management at the Canvey Island complex, *Industrial Crisis Quarterly,* 4, 1, 1-26.

Smith, D., 1995, The dark side of excellence: Managing strategic failures, in, J. Thompson, ed., *Handbook of strategic management*, London, Butterworth-Heinemann, pp. 161-191.

Smith, D., 2005, Business (not) as usual: Crisis management, service recovery and the vulnerability of organisations, *Journal of Services Marketing,* 19, 5, 309-320.

Smith, R., 2004, Operational capabilities for the resilient supply chain, *Supply Chain Practice,* 6, 2, 24-35.

Sörensen, K. and Janssens, G.K., 2001, Buffer allocation and required availability in a transfer line with unreliable machines, *International Journal of Production Economics,* 74, 1-3, 163-173.

Starr, R., Newfrock, J. and Delurey, M., 2003, Enterprise resilience: Managing risk in the networked economy, Booz, Allen and Hamilton Inc., *Strategy and Business*, 0, 30.

Sterman, J.D., 2000, *Business dynamics: Systems thinking for a complex world,* Boston, McGraw-Hill.

Stoltz, P., 2004, Building resilience for uncertain times, *Leader to Leader*, Winter, 16 - 17.

Surana, A., Kumara, S., Greaves, M. and Raghavan, U.N., 2005, Supply chain networks: A complex systems perspective, *International Journal of Production Research,* 43, 20, 4235-4265.

Sutcliffe, K.M. and Vogus, T., 2003, Organizing for resilience, in, K.S. Cameron, J.E. Dutton and R.E. Quinn, eds., *Positive organizational scholarship: Foundations of a new discipline,* 94-110, San Francisco, Berrett-Koehler.

Svoronos A. and Zipkin P., 1988, Estimating the performance of multi-level inventory systems, *Operations Research*, 36, 57–72

Swamidass, P. M. and Newell, W. T., 1987, Manufacturing strategy, environmental uncertainty and performance: A path analytic model, *Management Science*, 33, 509 - 524.

Swaminathan, J.M., Smith, S.F. and Sadeh, N.M., 1998, Modelling supply chain dynamics: A multiagent approach, *Decision Sciences,* 27, 3, 607-632.

Tang, C.S., 2006, Robust strategies for mitigating supply chain disruptions, *International Journal of Logistics: Research and Applications,* 9, 1, 33-45.

Taylor, D. and Brunt, D., 2001, *Manufacturing Operations and Supply Chain Management*, London, Thomson Learning.

Teece, D.J., Pisano, G. and Shuen, A, 1997, Dynamic capabilities and strategic management, *Strategic Management Journal,* 18, 7, 509 – 533.

Tempelmeier, H., 2000, Inventory service-levels in the customer supply chain, *OR Spectrum*, 22, 361–380.

Thomas, J. B., Clark, S. M., and Gioia, D. A., 1993, Strategic sensemaking and organizational performance: Linkages among scanning, interpretation, action, and outcomes, *Academy of Management Journal*, 36, 239-271.

Thomas, D. J. and Griffin, P.M., 1996, Coordinated supply chain management, *European Journal of Operational Research*, 94, 1–15.

Thompson, D., 1967, *Organisations in action,* New York, McGraw Hill.

Timmerman, P., 1981, *Vulnerability, resilience and the collapse of society: A review of models and possible climatic applications,* Institute for Environmental Studies, University of Toronto, Canada.

Timmerman, P., 1986, Mythology and surprise in the sustainable development of the biosphere, in, W.C. Clarck and R.E. Munn, eds., *Sustainable Development of the Biosphere,* Cambridge, Cambridge University Press, 435-453.

Timpe, C.H. and Kallrath, J., 2000, Optimal planning in large multi-site production networks, *European Journal of Operational Research*, 126, 422–435

Towill, D.R., 1991, Supply chain dynamics, *International Journal of Computer Integrated Manufacturing,* 4, 4, 197-208.

Towill, D.R., 1992, Supply chain dynamics the change engineering challenge of the mid 1990s, *Proceedings of the Institute of Mechanical Engineering,* 206, 233-245.

Towill, D.R., 1996, Industrial dynamics modelling of supply chains, *International Journal of Physical Distribution and materials Management,* 26, 23-42.

Towill, D.R., 1997, Forridge – Principles of good practice in material flow, *Production Planning & Control*, 8, 7, 622-32.

Towill, D.R. and Naim, M.M., 1993, *System dynamic models for improving the design and operations of supply chain,* in the Proceedings of the 30th International Matador Conference, 389-412.

Tucker, A.L. and Edmondson, A.C., 2003, Why hospitals don't learn from failures: Organizational and psychological dynamics that inhibit system change, *California Management Review,* 45, 2, Winter, 55-72.

Turbide, D., 1997, The new world of procurement, *Midrange ERP*, July-August, 12-16.

Turing, A. M., 1950, Computing machinery and intelligence. *Mind*, 59, 236, 433–460.

Turner, B.A., 1976, The organizational and interorganizational development of disasters, *Administrative Science Quarterly*, 21, 378-397.

Turner, B.A., 1978, Man-made disasters, London, Wykeham.

Turner, B.A., 1994, The causes of disaster: Sloppy management, *British Journal of Management,* 5, 215-219.

Tzafestas, I. and Kapsiotis, G., 1994, Coordinated control of manufacturing/supply chains using multi-level techniques, *Computer-Integrated Manufacturing Systems,* 7, 206-212.

Vachon, S. and Klassen, R.D., 2002, An exploratory investigation of the effects of supply chain complexity on delivery performance, *IEEE Transactions on Engineering Management*, 49, 3, 218-230.

Van der Vorst, J., Beulens, A., De Wit, W. and Van Beek, P., 1998, Supply chain management in food chains: Improving performance by reducing uncertainty, *International Transactions in Operational Research*, 5, 6, 487-499.

Van der Vorst J. and Beulens, A., 2002, Identifying sources of uncertainty to generate supply chain redesign and strategies, *International Journal of Physical Distribution and Logistics Management*, 32, 6, 409-430.

Van Hoek. R, 2000, The thesis of leagility revisited, *International Journal of Agile Management Systems,* 2, 3, 196-201.

Van Hoek. R., 2003, *Are you ready? Risk readiness tactics for the supply chain*, Logistics Research Network, Institute of Logistics and Transport, London.

Van Valen , L , A new evolutionary Theory, *Evolutionary Theory* 1, 1 – 30 .

van Wezel W.M.C. and van Donk D.P., 1996, *Scheduling in food processing industries: Preliminary findings of a task oriented approach,* 545-557, Second Int. Conference on Comp. Integrated Manufacturing in the Process Industries.

Vickery, S.K., Calantone, R. and Droge, C., 1999, Supply chain flexibility: An empirical study, *Journal of Supply Chain Management: A Global Review of Purchasing & Supply*, 35, 3, 16-23.

Vidal, C.J. and Goetschalckx, M., 1997, Strategic production–distribution models: A critical review with emphasis on global supply chain models, *European Journal of Operational Research*, 98, 1–18.

Villa, A., 2002, Emerging trends in large-scale supply chain management, *International Journal of Production Research,* 40, 5, 3487-3498.

Visser, J.P., 1998, Developments in HSE management in oil and gas exploration and production, in A.R. Hale and M.Baram, eds., *Safety management: The challenge of organisational change,* Oxford, UK, Pergamon.

Viswanathan, S. and Piplani, R., 2001, Coordinating supply chain inventories through common replenishment epochs, *European Journal of Operational Research,* 129, 277-286.

Weick, K.E., 1979, The social psychology of organizing, 2nd Ed, Reading, MA, Addison-Wesley.

Weick, K.E., 1987, Organization culture as a source of high reliability. *California Management Review,* 29, 116-136.

Weick, K.E., 1990, The vulnerable system: An analysis of Tenerife air disaster, *Journal of Management, 16, 571-593.*

Weick, K.E., 1993, The collapse of sensemaking in organizations: The Mann Gulch disaster, *Administrative Science Quarterly,* 38, 628-652.

Weick, K.E., 1996, Drop your tools: An allegory for organizational studies, *Administrative Science Quarterly, 41, 301-313.*

Weick, K.E., 1998, Improvisation as a mindset for organizational analysis, *Organization Science, 9.*

Weick, K.E., 2001, *Making sense of the organization,* Oxford, Blackwell Business.

Weick, K.E., 2004, Normal accident theory as frame, link, and provocation, *Organization and Environment,* 17, 1, 27-31.

Weick, K.E., Sutcliffe, K.M. and Obstfeld, D., 1999, Organizing for high reliability: Processes of collective mindfulness, *Research in Organizational Behaviour, 21, 13-81.*

Weick, K.E. and Sutcliffe, K.M., 2001, *Managing the unexpected,* San Francisco, Josey Bass.

Wheatley, M and Kellner-Rogers, M., 1996, Self-organization: The irresistible future of organizing, *Strategy & Leadership,* Jul/Aug, 24, 4, 18-24.

Whiting, R., 2001, Biz intelligence turns to suppliers, *Information Week,* October 15.

Wildavsky, A.,1988, *Searching for safety,* New Brunswick, NJ, Transaction Books.

Wilding, R., 1998, The supply chain complexity triangle: Uncertainty generation in the supply chain, *International Journal of Physical Distribution & Logistics Management*, 28, 8, 519-616.

William, A. and Winfrey, F.L., 1995, The resilient organization: Sustaining organizational renewal and performance, *Journal of Strategic Change,* 3, 165-173.

Williams, L.R., Esper, T.L. and Ozment, J., 2002, The electronic supply chain Its impact on the current and future structure of strategic alliances, partnerships and logistics leadership, *International Journal of Physical distribution and Management*, 32, 8, 703-719.

Wong, C.Y., McFarlane, D., Zaharudin, A. and Agarwal, V., 2002, *The intelligent product driven supply chain,* Working paper of Auto-ID Centre, Institute for Manufacturing, University of Cambridge.

Woods, D.D., 2006, Essential characteristics of resilience, in, E. Hollnagel, D.Woods and Leveson, N., eds., *Resilience engineering: Concepts and precepts,* Aldershot, UK, Ashgate.

Wooldridge, M. and Jennings, N. R., 1995, Intelligent agents: Theory and practice, *The Knowledge Engineering Review*, 10, 2, 115–152.

Wooldridge, M., 1999, Intelligent agents, in, G. Weiss, ed., *Multiagent systems - A modern approach to distributed artificial intelligence*, 28–77, Cambridge (Massachusetts, USA), MIT Press.

Wooldridge, M., 2001, *An introduction to multi-agent systems*, New York, NY, USA, John Wiley & Sons, Inc.

Worline, M.C., Dutton, J.E., Frost, P.J., Janov, J., Lillius, J. and Maitlis, S., 2004, *Creating fertile soil: The organizing dynamics of resilience*, Working paper, Ann Arbor, University of Michigan School of Business.

Yuan, Y., Liang, T. P. and Zhang, J. J., 2001, *Using agent technology to support supply chain management: Potentials and challenges*, Working Paper, School of Business, McMaster University, Hamilton, Ontario, Canada.

Zhou Z, Cheng S, and Hua B, 2000, Supply chain optimisation of continuous process industries with sustainability considerations, *Computers and Chemical Engineering,* 24, 1151–1158

Zsidisin, G.A., 2003, A grounded definition of supply risk, *Journal of Purchasing & Supply Management,* 9, 5/6, 217-224.

Zsidisin, G., Ellram, L., Carter, J., and Cavinato, J., 2004, An analysis of supply risk assessment techniques, *International Journal of Physical Distribution & Logistics Management*, 34, 5, 397-422.

Appendix - A

Programming Language and Platform used

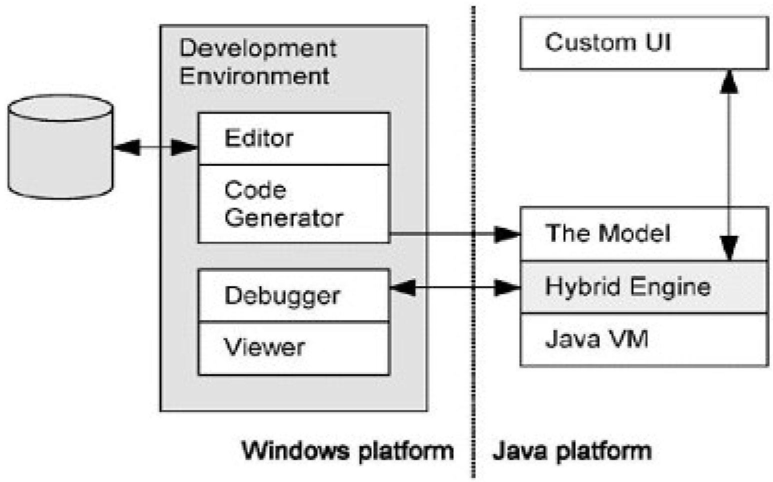


Fig. A.1 Architecture of AnyLogic modeling and simulation environment

From the formulation of the agents, their internal functioning and decision making stages, the assembly configurations required to study a complex supply chain, a model is required which can depict both continuous time and discrete time behaviour. To model such systems successfully and to get accurate and reliable results from simulation experiments, one needs an executable language naturally describing hybrid behaviour, and a simulation engine capable of simulating discrete events interleaved with continuous time processes.

For modelling, I chose to use a relatively new piece of software called AnyLogic™, Version 5.5 [XJtek 2005]. AnyLogic itself is a very flexible tool; it is essentially an environment for programming on Java with modelled system visual specification support in terms of simulation class library.

AnyLogic architecture is shown in Figure A.1. Windows-based development environment includes graphical model editor and code generator that maps the model into

Java code. The model runs on any Java platform on the top of AnyLogic hybrid simulation engine, supporting modeling of hybrid system behaviour. A running model exposes an interface to control its execution and to retrieve information via a text-based protocol over TCP/IP. That interface is used by Viewer and Debugger that runs on Java platform as well. Any model can be customized using custom code to extend its capabilities. Since the application is written entirely in the Java language, the resulting model can be exported as a cross-platform Java applet with a user-defined interface that can then be given to policy-makers to use.

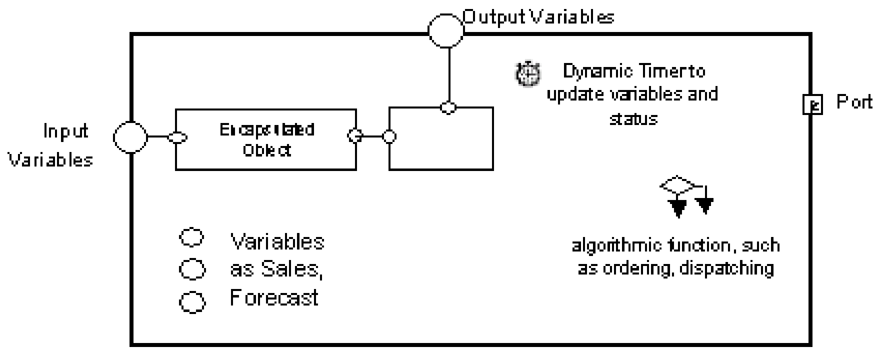


Fig. A.2 . AnyLogic structure diagram of an active object, connections between objects

The main building block of a hybrid model is called an active object. The object interface elements can be of two types: ports and variables. Objects interact by passing messages through ports, or by exposing continuous time variables one to another. The basic class representing the flow is that of a Message class, which can belong to one of the following types:

• order,
• products
• truck,
• factory order,
• country specific delivery.

Each Message is parameterized by an ID, a precursor ID and an internal information table, which specifies uniquely the content, origin, quality etc. of the delivery or the delivery relevant information that is passed. Object may encapsulate other objects, and so on to any depth. Encapsulated objects can export ports and variables to the container interface. An object may have multiple concurrent activities that share object local data and object interface. Activities can be created and destroyed at any moment of the model execution by use of dynamic timers. An activity can be described by a Java function. So AnyLogic is ideal in modelling complex systems consisting of agents with timing, event ordering and other kinds of individual behaviours. The structure diagram of a typical Anylogic building block, the objects is shown in Fig.A.2 above.

Appendix B.1

```
// The program RDC.java representing Czech RDC
// This code shows the calculation of FETS and TICF
if (msg instanceof Order){
Order o = (Order)msg;
Order=o.sales;
Forecast=o.fcst;
MeanDemand=o.md;
SD=o.sd;
Order1.add(o);
int i=(int)(getTime());
if (i==0) {
EnumItem s = Kleenex6765;
do{
 if (Forecast.get(s).doubleValue()==0 && MeanDemand.get(s).doubleValue()>0)
{Forecast.set(s,MeanDemand.get(s).doubleValue());}
 double e=(Forecast.get(s).doubleValue()-Order.get(s).doubleValue());
 double e2=MeanDemand.get(s).doubleValue()-Forecast.get(s).doubleValue();
 double e1=Math.abs(e);
 Error.set(s,d1,e);
 AbsError.set(s,d1,e1);
 MeanDiff.set(s,e2);
 double t=e1/(Forecast.get(s).doubleValue());
 double f=e/(Forecast.get(s).doubleValue());
 FETS.set(s,1-f/t);
 TICF.set(s,t); tsales.set(s,Order.get(s).doubleValue());
 s=s.next();
}while(!s.equals(Wypall7290));
}
else{
EnumItem s = Kleenex6765;
do{
if (Forecast.get(s).doubleValue()==0 && MeanDemand.get(s).doubleValue()>0)
{Forecast.set(s,MeanDemand.get(s).doubleValue());}
double e= Error.get(s,d2).doubleValue();
 double e1=AbsError.get(s,d2).doubleValue();
 double e2=MeanDiff.get(s).doubleValue();
 e=Forecast.get(s).doubleValue()-Order.get(s).doubleValue();
 e2=MeanDemand.get(s).doubleValue()-Forecast.get(s).doubleValue();
 e1=Math.abs(e);
 Error.set(s,d2,e);
 AbsError.set(s,d2,e1);
 Gradient.set(s,d1,Gradient.get(s,d2).doubleValue());
 Gradient.set(s,d2,(e2-MeanDiff.get(s).doubleValue())/MeanDiff.get(s).doubleValue());
 MeanDiff.set(s,e2);
 double f=(0.2)*(Error.get(s,d3).doubleValue()/main.czechOrderBank.ForecastUpdate(i-4).get(s).doubleValue()+
Error.get(s,d4).doubleValue()/main.czechOrderBank.ForecastUpdate(i-
3).get(s).doubleValue()+Error.get(s,d5).doubleValue()/main.czechOrderBank.ForecastUpdate(i-
2).get(s).doubleValue()+Error.get(s,d1).doubleValue()/main.czechOrderBank.ForecastUpdate(i-
1).get(s).doubleValue()+Error.get(s,d2).doubleValue()/main.czechOrderBank.ForecastUpdate(i).get(s).doubleValue());
double t=(0.2)*(AbsError.get(s,d3).doubleValue()/main.czechOrderBank.ForecastUpdate(i-4).get(s).doubleValue()+
AbsError.get(s,d4).doubleValue()/main.czechOrderBank.ForecastUpdate(i-
3).get(s).doubleValue()+AbsError.get(s,d5).doubleValue()/main.czechOrderBank.ForecastUpdate(i-
2).get(s).doubleValue()+AbsError.get(s,d1).doubleValue()/main.czechOrderBank.ForecastUpdate(i-
1).get(s).doubleValue()+AbsError.get(s,d2).doubleValue()/main.czechOrderBank.ForecastUpdate(i).get(s).doubleValu
e());
 FETS.set(s,1-f/t);TICF.set(s,t);
```

```
 }}
if (TICF.get(s).doubleValue()==0 || FETS.get(s).doubleValue()==0 && Forecast.get(s).doubleValue()>0)
{TICF.set(s,1);FETS.set(s,1);}
{Forecast.set(s,MeanDemand.get(s).doubleValue());}
 tsales.set(s,tsales.get(s).doubleValue()+Order.get(s).doubleValue());
s=s.next();
}while(!s.equals(Wypall7290));
}
}
   }
      return false;
    }
  }
```

// This part of the code decides on the ordering amount based on adjustable safety stock methods

```
public class decision extends DynamicTimer {
  public decision( double _timeout    ) {
    super(CzechRDC.this, _timeout);
  }
  public void action() {
EnumItem s1 = Kleenex6765;
do{
FactoryRequest.set(s1,0);
s1=s1.next();
}while(!s1.equals(Wypall7290));
double q;
if (((getTime()-2.06)%7)!=0 && ((getTime()-3.06)%7)!=0){
EnumItem s = Kleenex6765;
do{
O.set(s,stock.get(s).doubleValue()+IT.get(s).doubleValue()-backlog.get(s).doubleValue()-
LT*Forecast.get(s).doubleValue());
if (Forecast.get(s).doubleValue()==0 && Order.get(s).doubleValue()==0){
Gradient.set(s,d2,0);
}
if (Forecast.get(s).doubleValue()==MeanDemand.get(s).doubleValue() && Order.get(s).doubleValue()>0){
Gradient.set(s,d2,-Order.get(s).doubleValue()+Forecast.get(s).doubleValue());
}
if (stock.get(s).doubleValue()+IT.get(s).doubleValue()<=Forecast.get(s).doubleValue() ||
stock.get(s).doubleValue()+IT.get(s).doubleValue()<=Order.get(s).doubleValue() ||
Order.get(s).doubleValue()>=Forecast.get(s).doubleValue() && main.kobRDC.PCT.get(s).doubleValue()>=15 &&
main.kobRDC.PCT.get(s).doubleValue()<=30){
 if (Forecast.get(s).doubleValue()==0 && MeanDemand.get(s).doubleValue()>0)
{Forecast.set(s,MeanDemand.get(s).doubleValue());}
  double cs=Forecast.get(s).doubleValue()*LT;
if (TF.get(s).doubleValue()>10000){
 double
ss=SafetyFactor(96)*Forecast.get(s).doubleValue()*LT*FETS.get(s).doubleValue()*TICF.get(s).doubleValue();

  q =backlog.get(s).doubleValue()+ss+cs-stock.get(s).doubleValue()-IT.get(s).doubleValue();}
  else{
 double
ss=SafetyFactor(96)*Forecast.get(s).doubleValue()*LT*FETS.get(s).doubleValue()*TICF.get(s).doubleValue();

  q =backlog.get(s).doubleValue()+ss+cs-stock.get(s).doubleValue()-IT.get(s).doubleValue();}
  if (q>0){
  int palletNo= (int)(q/CP.get(s).doubleValue());
  if (palletNo==0) palletNo+=1;
  q=(palletNo)*CP.get(s).doubleValue();
  FactoryRequest.set(s,q);
  }
```

```
  else{
  FactoryRequest.set(s,0);}
 }
if (FactoryRequest.get(s).doubleValue()==0){
if (Gradient.get(s,d2).doubleValue()<0) {
  double cs=Forecast.get(s).doubleValue()*LT;
  if (TF.get(s).doubleValue()>10000){
 double
ss=SafetyFactor(96)*Forecast.get(s).doubleValue()*LT*FETS.get(s).doubleValue()*TICF.get(s).doubleValue();

  q =backlog.get(s).doubleValue()+ss+cs-stock.get(s).doubleValue()-IT.get(s).doubleValue();}
  else{
 double
ss=SafetyFactor(96)*Forecast.get(s).doubleValue()*LT*FETS.get(s).doubleValue()*TICF.get(s).doubleValue();

  q =backlog.get(s).doubleValue()+ss+cs-stock.get(s).doubleValue()-IT.get(s).doubleValue();}
  if (q>0){
  int palletNo= (int)(q/CP.get(s).doubleValue());
  if (palletNo==0) palletNo+=1;
  q=(palletNo)*CP.get(s).doubleValue();
  FactoryRequest.set(s,q);
}
  else{
  FactoryRequest.set(s,0);}
 }}
s=s.next();
}while(!s.equals(Wypall7290));

FactoryOrder t = new FactoryOrder();
t.amount = FactoryRequest;
t.from=CzechRDC.this;
t.F=O;
Nport.send(t);}
if (getTime()<368)
{decision nn = new decision(1);}
 }
}
// This part of the code decides on the dispatching function
public class dispatching extends DynamicTimer {
public dispatching( double _timeout ) {
    super(CzechRDC.this, _timeout);
  }

public void action() {
if (((getTime()-2.05)%7)!=0 && ((getTime()-3.05)%7)!=0){
EnumItem s = Kleenex6765;
do{
  if (stock.get(s).doubleValue()>=backlog.get(s).doubleValue()+Order.get(s).doubleValue()){
  OrderD.set(s,Order.get(s).doubleValue());
  stock.set(s,stock.get(s).doubleValue()-Order.get(s).doubleValue()-backlog.get(s).doubleValue());
  backlog.set(s,0);}
  else {
  if (stock.get(s).doubleValue()>backlog.get(s).doubleValue() )
  {OrderD.set(s,stock.get(s).doubleValue()-backlog.get(s).doubleValue());}
  else
  {OrderD.set(s,0);}
  backlog.set(s,backlog.get(s).doubleValue()+Order.get(s).doubleValue()-stock.get(s).doubleValue());
  stock.set(s,0);
  }
TotalDelivered.set(s,TotalDelivered.get(s).doubleValue()+OrderD.get(s).doubleValue());
```

```
 s=s.next();
}while(!s.equals(Wypall7290));

Product pm = new Product();
pm.amount=OrderD;
port.send(pm);}
else{
EnumItem s = Kleenex6765;
do{
OrderD.set(s,0);
s=s.next();
}while(!s.equals(Wypall7290));}
if (getTime()<368)
{dispatching nT = new dispatching(1);}
}
}
```

// This part of the code actually places the order

```
public class ordering extends DynamicTimer {

  public ordering( double _timeout    ) {
    super(CzechRDC.this, _timeout);
  }
public void action() {
if (((getTime()-2.1)%7)!=0 && ((getTime()-3.1)%7)!=0){
EnumItem s = Kleenex6765;
do{if (Order.get(s).doubleValue()>MaxSales.get(s).doubleValue()) MaxSales.set(s,Order.get(s).doubleValue());

 double qq1 =0;
if (stock.get(s).doubleValue()+IT.get(s).doubleValue()>DaysCover.get(s).doubleValue()*Forecast.get(s).doubleValue()
&& alpha.get(s).doubleValue()>0.2)
{alpha.set(s,alpha.get(s).doubleValue()-0.2);}
else { if (alpha.get(s).doubleValue()+0.2<=1){alpha.set(s,alpha.get(s).doubleValue()+0.2);}
else {alpha.set(s,1);}}
if (TF.get(s).doubleValue()<5000) qq1=TF.get(s).doubleValue();
else qq1=250*Forecast.get(s).doubleValue();
if (SD.get(s).doubleValue()>0) DaysCover.set(s,1207.2*Math.pow(qq1,-
0.4654)+alpha.get(s).doubleValue()*Math.log(SD.get(s).doubleValue()));
else DaysCover.set(s,1207.2*Math.pow(qq1,-0.4654));
double xp=main.kobRDC.TotalStock.get(s).doubleValue()-main.kobRDC.DirectSales.get(s).doubleValue()-
4.5*main.kobRDC.ForecastDirect.get(s).doubleValue();
double
fr=Math.exp(sstock.get(s).doubleValue())/(Math.exp(sstock.get(s).doubleValue())+Math.exp(main.czechRDC.sstock.g
et(s).doubleValue())+Math.exp(main.uKRDC.sstock.get(s).doubleValue())+Math.exp(main.franceRDC.sstock.get(s).do
ubleValue())+Math.exp(main.italyRDC.sstock.get(s).doubleValue())+Math.exp(main.niederbippRDC.sstock.get(s).dou
bleValue())+Math.exp(main.russiaRDC.sstock.get(s).doubleValue()));
  double qq;
   if (xp>0)
  {int palletN;
if
(stock.get(s).doubleValue()+IT.get(s).doubleValue()+main.kobRDC.OBL1.get(s,Czech).doubleValue()<LT*Forecast.g
et(s).doubleValue()*FETS.get(s).doubleValue()*TICF.get(s).doubleValue()){
    qq=backlog.get(s).doubleValue()+LT*Forecast.get(s).doubleValue()*FETS.get(s).doubleValue() -
main.kobRDC.OBL1.get(s,Czech).doubleValue()- stock.get(s).doubleValue()-IT.get(s).doubleValue();
    palletN= (int)(qq/CP.get(s).doubleValue());
    if (qq>0 && TF.get(s).doubleValue()>0 && palletN==0) palletN+=1;
   qq=(palletN)*CP.get(s).doubleValue();
  if (qq>0)FactoryRequest.set(s,qq);}}
  else{
  FactoryRequest.set(s,0);}
```

```
if ( FactoryRequest.get(s).doubleValue()>DaysCover.get(s).doubleValue()*Forecast.get(s).doubleValue() &&
backlog.get(s).doubleValue()==0)
{qq=DaysCover.get(s).doubleValue()*Forecast.get(s).doubleValue()-
main.kobRDC.OBL1.get(s,Czech).doubleValue()- stock.get(s).doubleValue()-IT.get(s).doubleValue();
int palletN;
   palletN = (int)(qq/CP.get(s).doubleValue());
  qq=(palletN)*CP.get(s).doubleValue();
if (qq>0) FactoryRequest.set(s,qq);
else FactoryRequest.set(s,0);}

else{
if
(stock.get(s).doubleValue()+IT.get(s).doubleValue()+main.kobRDC.OBL1.get(s,Czech).doubleValue()<=DaysCover.g
et(s).doubleValue()*Forecast.get(s).doubleValue())
{qq=DaysCover.get(s).doubleValue()*Forecast.get(s).doubleValue()-
main.kobRDC.OBL1.get(s,Czech).doubleValue()- stock.get(s).doubleValue()-IT.get(s).doubleValue();
int palletN;
   palletN = (int)(qq/CP.get(s).doubleValue());
  if (qq>0 && MeanDemand.get(s).doubleValue()>0  && TF.get(s).doubleValue()>0 && palletN==0) palletN+=1;
qq=(palletN)*CP.get(s).doubleValue();
if (qq>0) FactoryRequest.set(s,qq);
else FactoryRequest.set(s,0);}

}
if (MaxSales.get(s).doubleValue()>TF.get(s).doubleValue() &&
stock.get(s).doubleValue()+IT.get(s).doubleValue()>TF.get(s).doubleValue() && TF.get(s).doubleValue()<5000)
{FactoryRequest.set(s,0);}

OtherOrders.set(s,0);if (TF.get(s).doubleValue()==0) FactoryRequest.set(s,0);

s=s.next();
}while(!s.equals(Wypall7290));

FactoryOrder t = new FactoryOrder();
t.amount = FactoryRequest;
t.from=CzechRDC.this;
t.F=O;
input.send(t);}
write();
if (getTime()<368)
{ordering newTimer = new ordering(1);}
// _XJ_SECTION_END
  }

}
```

Appendix B.2

```
// KobFactory.java
// This actually decides the stop time for production
public double ProductionStopTime( EnumItem h ) {
double time;
time=(main.kobRDC.MaxStock.get(h).doubleValue()-
main.kobRDC.TotalStock.get(h).doubleValue())/(ProductionRate.get(h).doubleValue()-
main.kobRDC.TotalForecast.get(h).doubleValue());

if ((getTime()-2)%7==0 || (getTime()-3)%7==0)
{
EnumItem s = Kleenex6765;
do{
main.kobRDC.TotalForecast.set(s,main.kobRDC.AvgFcst.get(s).doubleValue());
if (main.kobRDC.TotalStock.get(s).doubleValue()>0){
if (time>main.kobRDC.TotalStock.get(s).doubleValue()/(main.kobRDC.TotalForecast.get(s).doubleValue()))
{time=main.kobRDC.TotalStock.get(s).doubleValue()/(main.kobRDC.TotalForecast.get(s).doubleValue());}
else {time=time;}}
s=s.next();
}while(!s.equals(Wypall7290));
}
else
{
EnumItem s = Kleenex6765;
do{
if (main.kobRDC.TotalStock.get(s).doubleValue()>0){
if (time>main.kobRDC.TotalStock.get(s).doubleValue()/(main.kobRDC.TotalForecast.get(s).doubleValue()))
{time=main.kobRDC.TotalStock.get(s).doubleValue()/(main.kobRDC.TotalForecast.get(s).doubleValue());}
else {time=time;}}
s=s.next();
}while(!s.equals(Wypall7290));
}
if (time<0) time=0;
if (main.kobRDC.PCT.get(h).doubleValue()==15)
{if (time<tLow) time=tLow;}
else if (main.kobRDC.PCT.get(h).doubleValue()==30)
{if (time<tLow1) time=tLow1;
}
else
{if (time<=4 && time>0) time=tLow2;
if(time>4) time=tLow2;}

if (main.kobRDC.PCT.get(h).doubleValue()==15 &&
main.kobRDC.TotalStock.get(h).doubleValue()/(main.kobRDC.TotalForecast.get(h).doubleValue())>70)
{time=tLow;}

return time;
}

public class change extends DynamicTimer {

  public change( double _timeout    ) {
    super(KobFactory.this, _timeout);
  }

  public void action() {
int y=0;
```

```
int y1=0;
idle=0;
EnumItem ss=Kleenex6765;
do{
if (ss!=pr){
if (main.kobRDC.ForecastDirect.get(ss).doubleValue()>0){
   if (main.kobRDC.PCT.get(ss).doubleValue()==15 &&
main.kobRDC.TotalStock.get(ss).doubleValue()/(main.kobRDC.TotalForecast.get(ss).doubleValue())<AvRunLen+6){
y+=1;}
   else if (main.kobRDC.PCT.get(ss).doubleValue()==30 &&
main.kobRDC.TotalStock.get(ss).doubleValue()/(main.kobRDC.TotalForecast.get(ss).doubleValue())<AvRunLen+6){
y+=1;}
   else if (main.kobRDC.PCT.get(ss).doubleValue()==60 &&
main.kobRDC.TotalStock.get(ss).doubleValue()/(main.kobRDC.TotalForecast.get(ss).doubleValue())<AvRunLen+6){
y+=1;}
   else if (main.kobRDC.PCT.get(ss).doubleValue()==90 &&
main.kobRDC.TotalStock.get(ss).doubleValue()/(main.kobRDC.TotalForecast.get(ss).doubleValue())<AvRunLen+6){
y+=1;}
   else {y+=0;}
   }
else{
   if
((main.kobRDC.TotalStock.get(ss).doubleValue()+main.edeRDC.stock.get(ss).doubleValue()+main.edeRDC.IT.get(ss)
.doubleValue()+main.niederbippRDC.stock.get(ss).doubleValue()+main.niederbippRDC.IT.get(ss).doubleValue())/(ma
in.kobRDC.TotalForecast.get(ss).doubleValue())<AvRunLen+15)y1+=1;
   }}
ss=ss.next();
}while(!ss.equals(Wypall7290));

if (y>0 || y1>0) {
double time=ProductionStopTime(pr);
new production(time);
/*EnumItem s = Kleenex6765;
do{
if (main.kobRDC.TotalStock.get(s).doubleValue()>0){
if (time>main.kobRDC.TotalStock.get(s).doubleValue()/(main.kobRDC.TotalForecast.get(s).doubleValue()))
{time=main.kobRDC.TotalStock.get(s).doubleValue()/(main.kobRDC.TotalForecast.get(s).doubleValue());}
else {
if
(time>(main.kobRDC.TotalStock.get(s).doubleValue()+main.edeRDC.stock.get(s).doubleValue()+main.edeRDC.IT.ge
t(s).doubleValue()+main.niederbippRDC.stock.get(s).doubleValue()+main.niederbippRDC.IT.get(s).doubleValue())/(m
ain.kobRDC.TotalForecast.get(s).doubleValue()))
{time=(main.kobRDC.TotalStock.get(s).doubleValue()+main.edeRDC.stock.get(s).doubleValue()+main.edeRDC.IT.ge
t(s).doubleValue()+main.niederbippRDC.stock.get(s).doubleValue()+main.niederbippRDC.IT.get(s).doubleValue())/(m
ain.kobRDC.TotalForecast.get(s).doubleValue());}
}}
s=s.next();
}while(!s.equals(Wypall7290));
}
else {
new change(0.1);} }

}
// This code shows which product the factory chooses
public class production extends DynamicTimer {
  public production( double _timeout    ) {
    super(KobFactory.this, _timeout);
  }

  public void action() {
```

```
AP.set(pr,AmountProduced.get(pr).doubleValue());
pr3=pr;
EnumItem s=Kleenex6765;
do{
  if (main.kobRDC.Rank1.get(s).doubleValue()==1) {pr=s;}
  s=s.next();
}while(!s.equals(Wypall7290));


if (main.kobRDC.MaxStock.get(pr).doubleValue()==0){
EnumItem s1=Kleenex6765;
do{
  if (main.kobRDC.Rank1.get(s1).doubleValue()==2) {pr=s1;}
  s1=s1.next();
}while(!s1.equals(Wypall7290));}

if (main.kobRDC.GrandTotalSales.get(pr).doubleValue()==0){
EnumItem s1=Kleenex6765;
do{
  if (main.kobRDC.Rank1.get(s1).doubleValue()==2 &&
main.kobRDC.TotalStock.get(s1).doubleValue()<=main.kobRDC.FETS.get(s1).doubleValue()*main.kobRDC.Forecast
Direct.get(s1).doubleValue()*main.kobRDC.PCT.get(s1).doubleValue()) {pr=s1;}
  s1=s1.next();
}while(!s1.equals(Wypall7290));
if (main.kobRDC.GrandTotalSales.get(pr).doubleValue()==0){
EnumItem s2=Kleenex6765;
do{
  if (main.kobRDC.Rank1.get(s2).doubleValue()==3 &&
main.kobRDC.TotalStock.get(s2).doubleValue()<=main.kobRDC.FETS.get(s2).doubleValue()*main.kobRDC.Forecast
Direct.get(s2).doubleValue()*main.kobRDC.PCT.get(s2).doubleValue()) {pr=s2;}
  s2=s2.next();
}while(!s2.equals(Wypall7290));
if (main.kobRDC.GrandTotalSales.get(pr).doubleValue()==0){
EnumItem s3=Kleenex6765;
do{
  if (main.kobRDC.Rank1.get(s3).doubleValue()==4 &&
main.kobRDC.TotalStock.get(s3).doubleValue()<=main.kobRDC.FETS.get(s3).doubleValue()*main.kobRDC.Forecast
Direct.get(s3).doubleValue()*main.kobRDC.PCT.get(s3).doubleValue()) {pr=s3;}
  s3=s3.next();
}while(!s3.equals(Wypall7290));
}
}
}
EnumItem s6=Kleenex6765;
do{
  if (main.kobRDC.Rank1.get(s6).doubleValue()>1 && main.kobRDC.Rank1.get(s6).doubleValue()<4 &&
main.kobRDC.PCT.get(pr).doubleValue()>30 &&
main.kobRDC.TotalStock.get(pr).doubleValue()/PR.get(pr).doubleValue()>=1)
  {pr=s6;}
  s6=s6.next();
}while(!s6.equals(Wypall7290));

if (0.9*main.kobRDC.MaxStock.get(pr).doubleValue()<main.kobRDC.TotalStock.get(pr).doubleValue())
{
EnumItem s1=Kleenex6765;
do{
  if (main.kobRDC.Rank1.get(s1).doubleValue()==2) {pr=s1;}
  s1=s1.next();
}while(!s1.equals(Wypall7290));
```

```
if (0.9*main.kobRDC.MaxStock.get(pr).doubleValue()<main.kobRDC.TotalStock.get(pr).doubleValue())
{
EnumItem s2=Kleenex6765;
do{
  if (main.kobRDC.Rank1.get(s2).doubleValue()==3) {pr=s2;}
  s2=s2.next();
}while(!s2.equals(Wypall7290));

if (0.9*main.kobRDC.MaxStock.get(pr).doubleValue()<main.kobRDC.TotalStock.get(pr).doubleValue())
{
EnumItem s3=Kleenex6765;
do{
  if (main.kobRDC.Rank1.get(s3).doubleValue()==4) {pr=s3;}
  s3=s3.next();
}while(!s3.equals(Wypall7290));

if (0.9*main.kobRDC.MaxStock.get(pr).doubleValue()<main.kobRDC.TotalStock.get(pr).doubleValue())
{
EnumItem s4=Kleenex6765;
do{
  if (main.kobRDC.Rank1.get(s4).doubleValue()==5) {pr=s4;}
  s4=s4.next();
}while(!s4.equals(Wypall7290));

if (0.9*main.kobRDC.MaxStock.get(pr).doubleValue()<main.kobRDC.TotalStock.get(pr).doubleValue())
{
EnumItem s5=Kleenex6765;
do{
  if (main.kobRDC.Rank1.get(s5).doubleValue()>5) {pr=s5;}
  s5=s5.next();
}while(!s5.equals(Wypall7290));}
}
}
}
}
EnumItem s19=Kleenex6765;
do{
  if (main.kobRDC.Rank1.get(s19).doubleValue()==2 && main.kobRDC.TotalStock.get(s19).doubleValue()>0 &&
main.kobRDC.GrandTotalSales.get(s19).doubleValue()/main.kobRDC.TotalStock.get(s19).doubleValue()>main.kobR
DC.GrandTotalSales.get(pr).doubleValue()/main.kobRDC.TotalStock.get(pr).doubleValue()) {pr=s19;}
  s19=s19.next();
}while(!s19.equals(Wypall7290));

EnumItem s21=Kleenex6765;
do{
  if (main.kobRDC.Rank1.get(s21).doubleValue()==3 && main.kobRDC.TotalStock.get(s21).doubleValue()>0 &&
main.kobRDC.GrandTotalSales.get(s21).doubleValue()/main.kobRDC.TotalStock.get(s21).doubleValue()>main.kobR
DC.GrandTotalSales.get(pr).doubleValue()/main.kobRDC.TotalStock.get(pr).doubleValue()) {pr=s21;}
  s21=s21.next();
}while(!s21.equals(Wypall7290));

EnumItem s22=Kleenex6765;
do{
  if (main.kobRDC.Rank1.get(s22).doubleValue()==4 && main.kobRDC.TotalStock.get(s22).doubleValue()>0 &&
main.kobRDC.GrandTotalSales.get(s22).doubleValue()/main.kobRDC.TotalStock.get(s22).doubleValue()>main.kobR
DC.GrandTotalSales.get(pr).doubleValue()/main.kobRDC.TotalStock.get(pr).doubleValue()) {pr=s22;}
  s22=s22.next();
}while(!s22.equals(Wypall7290));
double fc=1000000;
EnumItem s8=Kleenex6765;
```

```
do{
 if (main.kobRDC.Rank1.get(s8).doubleValue()<=11) {
 if (s8==Kimcel7025 || s8==Wypall7126 || s8==Wypall7195 || s8==Wypall7196)
 { if (main.kobRDC.TotAdv.get(s8).doubleValue()==0 && main.kobRDC.CumSales.get(s8).doubleValue()==0) {
s8=s8.next();}
  else{
 double ffc;
 double ny=main.kobRDC.PCT.get(s8).doubleValue();
 double np=main.kobRDC.TotalForecast.get(s8).doubleValue();
 double pm=main.kobRDC.ForecastDirect.get(s8).doubleValue()*main.kobRDC.FETS.get(s8).doubleValue();
if (main.kobRDC.PCT.get(s8).doubleValue()>30) ny=AvRunLen+7;
 if (s8==Kimcel7025 || s8==Wypall7126 || s8==Wypall7195 || s8==Wypall7196)
np=main.kobRDC.TotAdv.get(s8).doubleValue();
 if (main.kobRDC.ForecastDirect.get(s8).doubleValue()==0 &&
main.kobRDC.TotalStock.get(s8).doubleValue()+main.edeRDC.stock.get(s8).doubleValue()+main.edeRDC.IT.get(s8).
doubleValue()+main.niederbippRDC.stock.get(s8).doubleValue()+main.niederbippRDC.IT.get(s8).doubleValue()-
ny*np>0){s8=s8.next();}
 else{
  if (s8==Kimcel7025 || s8==Wypall7126 || s8==Wypall7195 || s8==Wypall7196)
pm=main.kobRDC.TotAdv.get(s8).doubleValue();
 ffc=main.kobRDC.TotalStock.get(s8).doubleValue()-AvRunLen*pm;
 if (ffc<fc) {fc=ffc;
 pr=s8;}
 s8=s8.next();}}
  }
 else{
 double ffc;
 double ny=main.kobRDC.PCT.get(s8).doubleValue();
 double np=main.kobRDC.TotalForecast.get(s8).doubleValue();
 double pm=main.kobRDC.ForecastDirect.get(s8).doubleValue()*main.kobRDC.FETS.get(s8).doubleValue();

 if (main.kobRDC.PCT.get(s8).doubleValue()>30) ny=AvRunLen+7;
 np=main.kobRDC.TotAdv.get(s8).doubleValue();
 if (main.kobRDC.ForecastDirect.get(s8).doubleValue()==0 &&
main.kobRDC.TotalStock.get(s8).doubleValue()+main.edeRDC.stock.get(s8).doubleValue()+main.edeRDC.IT.get(s8).
doubleValue()+main.niederbippRDC.stock.get(s8).doubleValue()+main.niederbippRDC.IT.get(s8).doubleValue()-
ny*np>0){s8=s8.next();}
 else{
pm=main.kobRDC.TotAdv.get(s8).doubleValue();
 ffc=main.kobRDC.TotalStock.get(s8).doubleValue()-AvRunLen*pm;
 if (ffc<fc) {fc=ffc;
 pr=s8;}

 s8=s8.next();}}}
}while(!s8.equals(Wypall7290));

if (pr==pr2 &&
main.kobRDC.CumSales.get(pr).doubleValue()<main.kobRDC.AvgFcst.get(pr).doubleValue()*getTime() &&
main.kobRDC.PCT.get(pr).doubleValue()>15 ){
double fc1=1000000;
EnumItem s81=Kleenex6765;
do{
if (s81==pr) {s81=s81.next();}
else{
 if (s81==Wypall7195 || s81==Wypall7196)
 { if (main.kobRDC.TotAdv.get(s81).doubleValue()==0 && main.kobRDC.CumSales.get(s81).doubleValue()==0) {
s81=s81.next();}
  else{
 double ffc;
 double ny=main.kobRDC.PCT.get(s81).doubleValue();
```

```
 double np=main.kobRDC.TotalForecast.get(s81).doubleValue();
 double pm=main.kobRDC.ForecastDirect.get(s81).doubleValue()*main.kobRDC.FETS.get(s81).doubleValue();

 if (main.kobRDC.PCT.get(s81).doubleValue()>30) ny=AvRunLen+7;
 np=main.kobRDC.TotAdv.get(s81).doubleValue();
 if (main.kobRDC.ForecastDirect.get(s81).doubleValue()==0 &&
main.kobRDC.TotalStock.get(s81).doubleValue()+main.edeRDC.stock.get(s81).doubleValue()+main.edeRDC.IT.get(s
81).doubleValue()+main.niederbippRDC.stock.get(s81).doubleValue()+main.niederbippRDC.IT.get(s81).doubleValue(
)-ny*np>0){s81=s81.next();}
 else{
 pm=main.kobRDC.TotAdv.get(s81).doubleValue();
 ffc=main.kobRDC.TotalStock.get(s81).doubleValue()-AvRunLen*pm;
 if (ffc<fc1) {fc1=ffc;
 pr=s81;}

 s81=s81.next();}}
 }
 else{
 if (main.kobRDC.PCT.get(s81).doubleValue()>15) {s81=s81.next();}
 else{
 double ffc;
 double ny=main.kobRDC.PCT.get(s81).doubleValue();
  double np=main.kobRDC.TotalForecast.get(s81).doubleValue();
 double pm=main.kobRDC.ForecastDirect.get(s81).doubleValue()*main.kobRDC.FETS.get(s81).doubleValue();
 if (main.kobRDC.PCT.get(s81).doubleValue()>30) ny=AvRunLen+7;
 if (main.kobRDC.ForecastDirect.get(s81).doubleValue()==0 &&
main.kobRDC.TotalStock.get(s81).doubleValue()+main.edeRDC.stock.get(s81).doubleValue()+main.edeRDC.IT.get(s
81).doubleValue()+main.niederbippRDC.stock.get(s81).doubleValue()+main.niederbippRDC.IT.get(s81).doubleValue(
)-ny*np>0){s81=s81.next();}
 else{
pm=main.kobRDC.TotAdv.get(s81).doubleValue();
 ffc=main.kobRDC.TotalStock.get(s81).doubleValue()-AvRunLen*pm;
 if (ffc<fc1) {fc1=ffc;
 pr=s81;}
 s81=s81.next();}}}}
}while(!s81.equals(Wypall7290));}

if (main.kobRDC.TotalStock.get(pr).doubleValue()/main.kobRDC.TotalForecast.get(pr).doubleValue()>366-getTime()
&& main.kobRDC.PCT.get(pr).doubleValue()>15){
double fc1=1000000;
EnumItem s81=Kleenex6765;
do{
if (s81==pr) {s81=s81.next();}
else{
 if (s81==Kimcel7025 || s81==Wypall7126 || s81==Wypall7195 || s81==Wypall7196)
 { if (main.kobRDC.TotAdv.get(s81).doubleValue()==0 && main.kobRDC.CumSales.get(s81).doubleValue()==0) {
s81=s81.next();}
 else{
 double ffc;
 double ny=main.kobRDC.PCT.get(s81).doubleValue();
 double np=main.kobRDC.TotalForecast.get(s81).doubleValue();
 double pm=main.kobRDC.ForecastDirect.get(s81).doubleValue()*main.kobRDC.FETS.get(s81).doubleValue();

 if (main.kobRDC.PCT.get(s81).doubleValue()>30) ny=AvRunLen+7;
 np=main.kobRDC.TotAdv.get(s81).doubleValue();
 if (main.kobRDC.ForecastDirect.get(s81).doubleValue()==0 &&
main.kobRDC.TotalStock.get(s81).doubleValue()+main.edeRDC.stock.get(s81).doubleValue()+main.edeRDC.IT.get(s
81).doubleValue()+main.niederbippRDC.stock.get(s81).doubleValue()+main.niederbippRDC.IT.get(s81).doubleValue(
)-ny*np>0){s81=s81.next();}
 else{
```

```
 pm=main.kobRDC.TotAdv.get(s81).doubleValue();
 ffc=main.kobRDC.TotalStock.get(s81).doubleValue()-AvRunLen*pm;
 if (main.kobRDC.TotalStock.get(s81).doubleValue()/main.kobRDC.TotAdv.get(s81).doubleValue()>366-getTime()
&& main.kobRDC.PCT.get(s81).doubleValue()>15)ffc=1000000;
 if (ffc<fc1) {fc1=ffc;
 pr=s81;}
 s81=s81.next();}}
 }
 else{
 double ffc;
 double ny=main.kobRDC.PCT.get(s81).doubleValue();
  double np=main.kobRDC.TotalForecast.get(s81).doubleValue();
 double pm=main.kobRDC.ForecastDirect.get(s81).doubleValue()*main.kobRDC.FETS.get(s81).doubleValue();
 if (main.kobRDC.PCT.get(s81).doubleValue()>30) ny=AvRunLen+7;
  if (main.kobRDC.ForecastDirect.get(s81).doubleValue()==0 &&
main.kobRDC.TotalStock.get(s81).doubleValue()+main.edeRDC.stock.get(s81).doubleValue()+main.edeRDC.IT.get(s
81).doubleValue()+main.niederbippRDC.stock.get(s81).doubleValue()+main.niederbippRDC.IT.get(s81).doubleValue(
)-ny*np>0){s81=s81.next();}
 else{
 ffc=main.kobRDC.TotalStock.get(s81).doubleValue()-AvRunLen*pm;
 if (main.kobRDC.TotalStock.get(s81).doubleValue()/main.kobRDC.TotalForecast.get(s81).doubleValue()>366-
getTime() && main.kobRDC.PCT.get(s81).doubleValue()>15)ffc=1000000;
 if (ffc<fc1) {fc1=ffc;
 pr=s81;}

 s81=s81.next();}}}
}while(!s81.equals(Wypall7290));}

if (main.kobRDC.InitStock.get(pr).doubleValue()+TotalProduced.get(pr).doubleValue()-
main.kobRDC.CumSales.get(pr).doubleValue()>main.kobRDC.AvgFcst.get(pr).doubleValue()*(366-getTime()) &&
main.kobRDC.PCT.get(pr).doubleValue()>15){
double fc1=1000000;
EnumItem s81=Kleenex6765;
do{
if (s81==pr) {s81=s81.next();}
else{
 if (s81==Kimcel7025 || s81==Wypall7126 || s81==Wypall7195 || s81==Wypall7196)
 { if (main.kobRDC.TotAdv.get(s81).doubleValue()==0 && main.kobRDC.CumSales.get(s81).doubleValue()==0) {
s81=s81.next();}
 else{
 double ffc;
 double ny=main.kobRDC.PCT.get(s81).doubleValue();
 double np=main.kobRDC.TotalForecast.get(s81).doubleValue();
 double pm=main.kobRDC.ForecastDirect.get(s81).doubleValue()*main.kobRDC.FETS.get(s81).doubleValue();

 if (main.kobRDC.PCT.get(s81).doubleValue()>30) ny=AvRunLen+7;
 np=main.kobRDC.TotAdv.get(s81).doubleValue();
 if (main.kobRDC.ForecastDirect.get(s81).doubleValue()==0 &&
main.kobRDC.TotalStock.get(s81).doubleValue()+main.edeRDC.stock.get(s81).doubleValue()+main.edeRDC.IT.get(s
81).doubleValue()+main.niederbippRDC.stock.get(s81).doubleValue()+main.niederbippRDC.IT.get(s81).doubleValue(
)-ny*np>0){s81=s81.next();}
 else{
 pm=main.kobRDC.TotAdv.get(s81).doubleValue();
 ffc=main.kobRDC.TotalStock.get(s81).doubleValue()-AvRunLen*pm;
 if (main.kobRDC.TotalStock.get(s81).doubleValue()/main.kobRDC.TotAdv.get(s81).doubleValue()>366-getTime()
&& main.kobRDC.PCT.get(s81).doubleValue()>15)ffc=1000000;
 if (ffc<fc1) {fc1=ffc;
 pr=s81;}
 s81=s81.next();}}
 }
```

```
 else{
 double ffc;
 double ny=main.kobRDC.PCT.get(s81).doubleValue();
  double np=main.kobRDC.TotalForecast.get(s81).doubleValue();
 double pm=main.kobRDC.ForecastDirect.get(s81).doubleValue()*main.kobRDC.FETS.get(s81).doubleValue();
 if (main.kobRDC.PCT.get(s81).doubleValue()>30) ny=AvRunLen+7;
  if (main.kobRDC.ForecastDirect.get(s81).doubleValue()==0 &&
main.kobRDC.TotalStock.get(s81).doubleValue()+main.edeRDC.stock.get(s81).doubleValue()+main.edeRDC.IT.get(s
81).doubleValue()+main.niederbippRDC.stock.get(s81).doubleValue()+main.niederbippRDC.IT.get(s81).doubleValue(
)-ny*np>0){s81=s81.next();}
 else{
 ffc=main.kobRDC.TotalStock.get(s81).doubleValue()-AvRunLen*pm;
 if (main.kobRDC.TotalStock.get(s81).doubleValue()/main.kobRDC.TotalForecast.get(s81).doubleValue()>366-
getTime() && main.kobRDC.PCT.get(s81).doubleValue()>15)ffc=1000000;
 if (ffc<fc1) {fc1=ffc;
 pr=s81;}

 s81=s81.next();}}}
}while(!s81.equals(Wypall7290));}

int y=0;
int y1=0;
int cc=0;
EnumItem ss=Kleenex6765;
do{
if (main.kobRDC.ForecastDirect.get(ss).doubleValue()>0){
   if (main.kobRDC.PCT.get(ss).doubleValue()==15 &&
main.kobRDC.TotalStock.get(ss).doubleValue()/(main.kobRDC.TotalForecast.get(ss).doubleValue())<AvRunLen+6){
y+=1;ChangeOver(pr1,ss); if (p==0.04) cc+=1;}
   else if (main.kobRDC.PCT.get(ss).doubleValue()==30 &&
main.kobRDC.TotalStock.get(ss).doubleValue()/(main.kobRDC.TotalForecast.get(ss).doubleValue())<AvRunLen+6){
y+=1;ChangeOver(pr1,ss); if (p==0.04) cc+=1;}
   else if (main.kobRDC.PCT.get(ss).doubleValue()==60 &&
main.kobRDC.TotalStock.get(ss).doubleValue()/(main.kobRDC.TotalForecast.get(ss).doubleValue())<AvRunLen+6){
y+=1;ChangeOver(pr1,ss); if (p==0.04) cc+=1;}
   else if (main.kobRDC.PCT.get(ss).doubleValue()==90 &&
main.kobRDC.TotalStock.get(ss).doubleValue()/(main.kobRDC.TotalForecast.get(ss).doubleValue())<AvRunLen+6){
y+=1;ChangeOver(pr1,ss); if (p==0.04) cc+=1;}
   else {y+=0;}
   }
else{
   if
((main.kobRDC.TotalStock.get(ss).doubleValue()+main.edeRDC.stock.get(ss).doubleValue()+main.edeRDC.IT.get(ss)
.doubleValue()+main.niederbippRDC.stock.get(ss).doubleValue()+main.niederbippRDC.IT.get(ss).doubleValue())/(ma
in.kobRDC.TotalForecast.get(ss).doubleValue())<AvRunLen+15)
   {y1+=1;ChangeOver(pr1,ss); if (p==0.04) cc+=1;}
   }ss=ss.next();
}while(!ss.equals(Wypall7290));
ChangeOver(pr1,pr);

if (cc>4 && p>0.04){
double fc1=1000000;
EnumItem s81=Kleenex6765;
do{
ChangeOver(pr1,s81);
if (s81==pr || p>0.04) {s81=s81.next();}
else{
 if (s81==Kimcel7025 || s81==Wypall7126 || s81==Wypall7195 || s81==Wypall7196)
 { if (main.kobRDC.TotAdv.get(s81).doubleValue()==0 && main.kobRDC.CumSales.get(s81).doubleValue()==0) {
s81=s81.next();}
```

```
 else{
 double ffc;
 double ny=main.kobRDC.PCT.get(s81).doubleValue();
 double np=main.kobRDC.TotalForecast.get(s81).doubleValue();
 double pm=main.kobRDC.ForecastDirect.get(s81).doubleValue()*main.kobRDC.FETS.get(s81).doubleValue();

 if (main.kobRDC.PCT.get(s81).doubleValue()>30) ny=AvRunLen+7;
 np=main.kobRDC.TotAdv.get(s81).doubleValue();
 if (main.kobRDC.ForecastDirect.get(s81).doubleValue()==0 &&
main.kobRDC.TotalStock.get(s81).doubleValue()+main.edeRDC.stock.get(s81).doubleValue()+main.edeRDC.IT.get(s
81).doubleValue()+main.niederbippRDC.stock.get(s81).doubleValue()+main.niederbippRDC.IT.get(s81).doubleValue(
)-ny*np>0){s81=s81.next();}
 else{
 pm=main.kobRDC.TotAdv.get(s81).doubleValue();
 ffc=main.kobRDC.TotalStock.get(s81).doubleValue()-AvRunLen*pm;
 if (main.kobRDC.TotalStock.get(s81).doubleValue()/main.kobRDC.TotAdv.get(s81).doubleValue()>366-getTime()
&& main.kobRDC.PCT.get(s81).doubleValue()>15)ffc=1000000;
 if (ffc<fc1) {fc1=ffc;
 pr=s81;}

 s81=s81.next();}}



 }
 else{
 double ffc;
 double ny=main.kobRDC.PCT.get(s81).doubleValue();
  double np=main.kobRDC.TotalForecast.get(s81).doubleValue();
 double pm=main.kobRDC.ForecastDirect.get(s81).doubleValue();
 if (main.kobRDC.PCT.get(s81).doubleValue()>30) ny=AvRunLen+7;
  if (main.kobRDC.ForecastDirect.get(s81).doubleValue()==0 &&
main.kobRDC.TotalStock.get(s81).doubleValue()+main.edeRDC.stock.get(s81).doubleValue()+main.edeRDC.IT.get(s
81).doubleValue()+main.niederbippRDC.stock.get(s81).doubleValue()+main.niederbippRDC.IT.get(s81).doubleValue(
)-ny*np>0){s81=s81.next();}
 else{
 ffc=main.kobRDC.TotalStock.get(s81).doubleValue()-AvRunLen*pm;
 if (main.kobRDC.TotalStock.get(s81).doubleValue()/main.kobRDC.TotalForecast.get(s81).doubleValue()>366-
getTime() && main.kobRDC.PCT.get(s81).doubleValue()>15)ffc=1000000;
 if (ffc<fc1) {fc1=ffc;
 pr=s81;}

 s81=s81.next();}}}
}while(!s81.equals(Wypall7290));}
if (main.kobRDC.PCT.get(pr3).doubleValue()==15 && y==0 && y1==0 &&
main.kobRDC.TotalStock.get(pr3).doubleValue()/main.kobRDC.AvgFcst.get(pr3).doubleValue()<70) {
pr=pr3;
}


if (y1>0){
double fc1=1000000;
EnumItem s81=Kleenex6765;
do{
if (main.kobRDC.ForecastDirect.get(s81).doubleValue()==0){ double ffc=0;
ffc=main.kobRDC.TotalStock.get(s81).doubleValue()+main.edeRDC.stock.get(s81).doubleValue()+main.edeRDC.IT.g
et(s81).doubleValue()+main.niederbippRDC.stock.get(s81).doubleValue()+main.niederbippRDC.IT.get(s81).doubleVa
lue()-(15+AvRunLen)*main.kobRDC.TotalForecast.get(s81).doubleValue();
if (ffc<fc1) {fc1=ffc;pr=s81;}}
s81=s81.next();
```

```
}while(!s81.equals(Wypall7290));}

if (y>0 && main.kobRDC.CumSales.get(pr).doubleValue()==0)
{double fc1=1000000;
EnumItem s81=Kleenex6765;
do{
if (main.kobRDC.CumSales.get(s81).doubleValue()!=0 && main.kobRDC.ForecastDirect.get(s81).doubleValue()>0){
 double ffc;
 double ny=main.kobRDC.PCT.get(s81).doubleValue();
 double np=main.kobRDC.TotalForecast.get(s81).doubleValue();
 double pm=main.kobRDC.ForecastDirect.get(s81).doubleValue()*main.kobRDC.FETS.get(s8).doubleValue();
 if (main.kobRDC.PCT.get(s81).doubleValue()>30) ny=AvRunLen+7;
 ffc=main.kobRDC.TotalStock.get(s81).doubleValue()-AvRunLen*pm;
 if (ffc<fc1)
 {fc1=ffc; pr=s81;}}
s81=s81.next();
}while(!s81.equals(Wypall7290));}


ChangeOver(pr1,pr);
CO+=p;
pr2=pr1;
pr1=pr;
T.set(pr2,getTime());
//int y=0;

if (pr!=pr2){
if (main.kobRDC.PCT.get(pr).doubleValue()==15)
{tLow+=0.05;tLow1-=0.01;tLow2-=0.01;}
else if (main.kobRDC.PCT.get(pr).doubleValue()==30)
{tLow-=0.01;tLow1+=0.05;tLow2-=0.01;}
else
{tLow-=0.01;tLow1-=0.01;tLow2+=0.05;}}

if (pr!=pr2)
{RunLength+=getTime()-start-idle-p;
if (idle>0) idle=0;
DelRunLen=getTime()-start-idle-PrevRunLen;
PrevRunLen=getTime()-start-idle;
start=getTime();noCO+=1;}
if (PrevRunLen>MaxRunLen) MaxRunLen=PrevRunLen;
double xr = ProductionRate.get(pr).doubleValue();
EnumItem ss1=Kleenex6765;
do{
   ProductionRate.set(ss1,0);
   ss1=ss1.next();
}while(!ss1.equals(Wypall7290));
if (y==0 && y1==0 &&
(main.kobRDC.TotalStock.get(pr).doubleValue()+xr*ProductionRate.get(pr).doubleValue())/main.kobRDC.AvgFcst.g
et(pr).doubleValue()>45) {
new Maintenance(1);idleTime+=1;idle=1;}
else{idle=0;
new CTimer(p);}
  }
}
```

Appendix B.3

```
// KobRDC.java
// This function decides the Ranks of different products for production
public void InsertionSort1( HyperArray LL ) {
EnumItem s = Kleenex6765;
int f, i;
int l=0;
double temp;
double[] A = new double[12];

do{
   A[i] = LL.get(s).doubleValue();
   l=l+1;
   s=s.next();
}while(!s.equals(Wypall7290));

for (f = 1; f < 12; f++) {
 if (A[f] >A[f-1]) continue;
  temp = A[f];
  i = f-1;
 while ((i>=0)&&(A[i]>temp)) {
  A[i+1] = A[i];
  i--;
 }
  A[i+1]=temp;
}
int k;
EnumItem s0=Kleenex6765;
do{
for (k=0;k<11;k++){
if (A[k]==LL.get(s0).doubleValue())
{Rank1.set(s0,k+1);
if(A[k]==0) {A[k]=150000;break;}
}
}
s0=s0.next();
}while(!s0.equals(Wypall7290));
  }

//Dispatching of products to different RDCs
public class dispatching extends DynamicTimer {
  public dispatching( double _timeout    ) {
    super(KobRDC.this, _timeout);
  }
public void action() {

EnumItem s = Kleenex6765;
do{
// First dispatching to markets directly supplied from the central warehouse
  if
(stockE5.get(s).doubleValue()>=BacklogSales.get(s,DDXMFr).doubleValue()+Sales.get(s,DDXMFr).doubleValue()
&& BacklogSales.get(s,DDXMFr).doubleValue()+Sales.get(s,DDXMFr).doubleValue()>=0){
  OrderD.set(s,DDXMFr,BacklogSales.get(s,DDXMFr).doubleValue()+Sales.get(s,DDXMFr).doubleValue());
  stockE5.set(s,stockE5.get(s).doubleValue()-BacklogSales.get(s,DDXMFr).doubleValue()-
Sales.get(s,DDXMFr).doubleValue());
```

```
DeliveryDDXMFr.set(s,DeliveryDDXMFr.get(s).doubleValue()+BacklogSales.get(s,DDXMFr).doubleValue()+Sales.g
et(s,DDXMFr).doubleValue());
  Sales.set(s,DDXMFr,0);
  BacklogSales.set(s,DDXMFr,0);
  sumDDXMFr+=DeliveryDDXMFr.get(s).doubleValue();
  }
  else {
  if
(stockE3.get(s).doubleValue()>=BacklogSales.get(s,DDXMFr).doubleValue()+Sales.get(s,DDXMFr).doubleValue()-
(BacklogSales.get(s,DDXMFr).doubleValue()+Sales.get(s,DDXMFr).doubleValue())*stockE5.get(s).doubleValue()/(T
otalBacklog.get(s).doubleValue()+BSize.get(s).doubleValue()) &&
BacklogSales.get(s,DDXMFr).doubleValue()+Sales.get(s,DDXMFr).doubleValue()>=0)
  {double rp1 = BacklogSales.get(s,DDXMFr).doubleValue()+Sales.get(s,DDXMFr).doubleValue()-
(int)((BacklogSales.get(s,DDXMFr).doubleValue()+Sales.get(s,DDXMFr).doubleValue())*stockE5.get(s).doubleValue
()/(TotalBacklog.get(s).doubleValue()+BSize.get(s).doubleValue()));
   Repal.set(s,Repal.get(s).doubleValue()+rp1);
   stockE3.set(s,stockE3.get(s).doubleValue()-
(int)((BacklogSales.get(s,DDXMFr).doubleValue()+Sales.get(s,DDXMFr).doubleValue()-
(BacklogSales.get(s,DDXMFr).doubleValue()+Sales.get(s,DDXMFr).doubleValue())*stockE5.get(s).doubleValue()/(T
otalBacklog.get(s).doubleValue()+BSize.get(s).doubleValue())));

DeliveryDDXMFr.set(s,DeliveryDDXMFr.get(s).doubleValue()+BacklogSales.get(s,DDXMFr).doubleValue()+Sales.g
et(s,DDXMFr).doubleValue());
   Sales.set(s,DDXMFr,0);  BacklogSales.set(s,DDXMFr,0);
   sumDDXMFr+=DeliveryDDXMFr.get(s).doubleValue();}
  else{
   if (BacklogSales.get(s,DDXMFr).doubleValue()+Sales.get(s,DDXMFr).doubleValue()>0)
   {
   BacklogSales.set(s,DDXMFr,BacklogSales.get(s,DDXMFr).doubleValue()+Sales.get(s,DDXMFr).doubleValue()-
(int)((BacklogSales.get(s,DDXMFr).doubleValue()+Sales.get(s,DDXMFr).doubleValue())*stockE5.get(s).doubleValue
()/(TotalBacklog.get(s).doubleValue()+BSize.get(s).doubleValue())));
   if (stockE5.get(s).doubleValue()>0)
DeliveryDDXMFr.set(s,DeliveryDDXMFr.get(s).doubleValue()+(int)((BacklogSales.get(s,DDXMFr).doubleValue()+S
ales.get(s,DDXMFr).doubleValue())*stockE5.get(s).doubleValue()/(TotalBacklog.get(s).doubleValue()+BSize.get(s).d
oubleValue())));}
   sumDDXMFr+=DeliveryDDXMFr.get(s).doubleValue();
   }
 if (BacklogSales.get(s,DDXMFr).doubleValue()+Sales.get(s,DDXMFr).doubleValue()>0)
   {
   stockE5.set(s,stockE5.get(s).doubleValue()-
(int)((BacklogSales.get(s,DDXMFr).doubleValue()+Sales.get(s,DDXMFr).doubleValue())*stockE5.get(s).doubleValue
()/(TotalBacklog.get(s).doubleValue()+BSize.get(s).doubleValue())));}}
```

// Next dispatching the products to RDCs

```
  if (stockE5.get(s).doubleValue()>=OBL1.get(s,France).doubleValue()+FR.get(s,FranceDC).doubleValue() &&
OBL1.get(s,France).doubleValue()+FR.get(s,FranceDC).doubleValue()>=0){
  OrderD.set(s,France,OBL1.get(s,France).doubleValue()+FR.get(s,FranceDC).doubleValue());
  stockE5.set(s,stockE5.get(s).doubleValue()-OBL1.get(s,France).doubleValue()-FR.get(s,FranceDC).doubleValue());

DeliveryFrance.set(s,DeliveryFrance.get(s).doubleValue()+OBL1.get(s,France).doubleValue()+FR.get(s,FranceDC).do
ubleValue());
  FR.set(s,FranceDC,0);OBL1.set(s,France,0);
  sumFrance+=DeliveryFrance.get(s).doubleValue();
  }
  else {
  if (stockE3.get(s).doubleValue()>=OBL1.get(s,France).doubleValue()+FR.get(s,FranceDC).doubleValue()-
stockE5.get(s).doubleValue() && OBL1.get(s,France).doubleValue()+FR.get(s,FranceDC).doubleValue()>=0)
  {double rp = OBL1.get(s,France).doubleValue()+FR.get(s,FranceDC).doubleValue()-stockE5.get(s).doubleValue();
   Repal.set(s,Repal.get(s).doubleValue()+rp);
```

```
   stockE3.set(s,stockE3.get(s).doubleValue()-OBL1.get(s,France).doubleValue()-
FR.get(s,FranceDC).doubleValue()+stockE5.get(s).doubleValue());

DeliveryFrance.set(s,DeliveryFrance.get(s).doubleValue()+OBL1.get(s,France).doubleValue()+FR.get(s,FranceDC).do
ubleValue());
   FR.set(s,FranceDC,0);stockE5.set(s,0);OBL1.set(s,France,0);
   sumFrance+=DeliveryFrance.get(s).doubleValue();}
  else{
   if (stockE5.get(s).doubleValue()>0 && OBL1.get(s,France).doubleValue()+FR.get(s,FranceDC).doubleValue()>0)

{DeliveryFrance.set(s,DeliveryFrance.get(s).doubleValue()+(int)(Fraction2.get(s,FranceDC).doubleValue()*stockE5.g
et(s).doubleValue()));
    OBL1.set(s,France,OBL1.get(s,France).doubleValue()+FR.get(s,FranceDC).doubleValue()-
DeliveryFrance.get(s).doubleValue());
    stockE5.set(s,(int)(stockE5.get(s).doubleValue()*(1-Fraction2.get(s,FranceDC).doubleValue())));
    sumFrance+=DeliveryFrance.get(s).doubleValue();}
   }
   }
s=s.next();
}while(!s.equals(Wypall7290));
```

Appendix B.4

// CenPlanning.java**, this code shows the central planning agent's function and the changes made in all the different members of the supply chain**

```
public class MonthlyTimer extends DynamicTimer {
//Each month the amount planned to be produced is coded as below
  public MonthlyTimer( double _timeout    ) {
    super(CenPlanning.this, _timeout);
  }
  public void action() {
if (getTime()==0.25){
double totalP=0;
EnumItem s=Kleenex6765;
do{
double xxx=0;
if (s==Wypall7195 || s==Wypall7196 || s==Wypall7121 || s==Wypall7120){
xxx=(MonthlyForecast.get(s,m1).doubleValue()+0.5*MonthlyForecast.get(s,m2).doubleValue()-
main.kobRDC.TotalStock.get(s).doubleValue()-main.niederbippRDC.IT.get(s).doubleValue()-
main.edeRDC.IT.get(s).doubleValue()-main.niederbippRDC.stock.get(s).doubleValue()-
main.edeRDC.stock.get(s).doubleValue())/(main.kobFactory.PR.get(s).doubleValue());}
else{
xxx=(MonthlyForecast.get(s,m1).doubleValue()+0.5*MonthlyForecast.get(s,m2).doubleValue()-
main.kobRDC.TotalStock.get(s).doubleValue())/(main.kobFactory.PR.get(s).doubleValue());}
if (xxx>0 && xxx<1) xxx=1;
if (xxx<0) xxx=0;
DofP.set(s,m1,xxx);
totalP+=xxx;
s=s.next();
}while(!s.equals(Wypall7290));

if (totalP>AvailableDays.get(m1).doubleValue()){
double excess=-AvailableDays.get(m1).doubleValue()+totalP;

EnumItem s1=Kleenex6765;
do{
if (DofP.get(s1,m1).doubleValue()==1)totalP-=1;
s1=s1.next();
}while(!s1.equals(Wypall7290));

EnumItem s2=Kleenex6765;
do{
if (DofP.get(s2,m1).doubleValue()>1){
DofP.set(s2,m1,DofP.get(s2,m1).doubleValue()-excess*DofP.get(s2,m1).doubleValue()/totalP);}
s2=s2.next();
}while(!s2.equals(Wypall7290));

EnumItem s3=Kleenex6765;
do{
if (DofP.get(s3,m1).doubleValue()>0){
PlannedProduction.set(s3,DofP.get(s3,m1).doubleValue()*main.kobFactory.PR.get(s3).doubleValue());
}
else{PlannedProduction.set(s3,0);}
s3=s3.next();
}while(!s3.equals(Wypall7290));}

else{
double excess=AvailableDays.get(m1).doubleValue()-totalP;
```

```
EnumItem s1=Kleenex6765;
do{
if (DofP.get(s1,m1).doubleValue()==1)totalP-=1;
s1=s1.next();
}while(!s1.equals(Wypall7290));

EnumItem s2=Kleenex6765;
do{
if (DofP.get(s2,m1).doubleValue()>1){
DofP.set(s2,m1,DofP.get(s2,m1).doubleValue()+excess*DofP.get(s2,m1).doubleValue()/totalP);}
s2=s2.next();
}while(!s2.equals(Wypall7290));

EnumItem s3=Kleenex6765;
do{
if (DofP.get(s3,m1).doubleValue()>0){
PlannedProduction.set(s3,DofP.get(s3,m1).doubleValue()*main.kobFactory.PR.get(s3).doubleValue());
}
else{PlannedProduction.set(s3,0);}
s3=s3.next();
}while(!s3.equals(Wypall7290));}
}
MonthlyTimer newTimer = new MonthlyTimer(1);
}

}

// RDC.java
```

//This piece of code shows the ordering function of the Czech RDC

```
public class ordering extends DynamicTimer {

  public ordering( double _timeout    ) {
    super(CzechRDC.this, _timeout);
  }

  public void action() {
EnumItem s1 = Kleenex6765;
do{
FactoryRequest.set(s1,0);
s1=s1.next();
}while(!s1.equals(Wypall7290));
double q;
if (((getTime()-2.1)%7)!=0 && ((getTime()-3.1)%7)!=0){
EnumItem s = Kleenex6765;
do{
double cs=Forecast.get(s).doubleValue()*LT;
double ss=SafetyFactor(CSL)*SD.get(s).doubleValue()*Math.pow(LT,0.5);

if
(stock.get(s).doubleValue()+IT.get(s).doubleValue()+main.kobRDC.AmCommittedCz.get(s).doubleValue()<=backlog.
get(s).doubleValue()+cs+ss)
{
  q =backlog.get(s).doubleValue()+cs+ss-stock.get(s).doubleValue()-IT.get(s).doubleValue()-
main.kobRDC.AmCommittedCz.get(s).doubleValue();
  if (q>0){
  int palletNo= (int)(q/CP.get(s).doubleValue());
  if (palletNo==0) palletNo+=1;
  q=(palletNo)*CP.get(s).doubleValue();
```

```
 FactoryRequest.set(s,q);
 }
 else{
 FactoryRequest.set(s,0);}
}
else
{
 FactoryRequest.set(s,0);}

s=s.next();
}while(!s.equals(Wypall7290));

FactoryOrder t = new FactoryOrder();
t.amount = FactoryRequest;
t.from=CzechRDC.this;
t.F=O;
input.send(t);}
write();
if (getTime()<368)
{ordering newTimer = new ordering(1);}
 }
```

```
// KobFactory.java
```
//This determines the stop time for production

```
public double ProductionStopTime( EnumItem h ) {
double time;
time=(ToProduce.get(h).doubleValue())/ProductionRate.get(h).doubleValue();
if ((getTime()-2)%7==0 || (getTime()-3)%7==0)
{
EnumItem s = Kleenex6765;
do{
main.kobRDC.TotalForecast.set(s,main.kobRDC.AvgFcst.get(s).doubleValue());
if (main.kobRDC.TotalStock.get(s).doubleValue()>0){
if (time>main.kobRDC.TotalStock.get(s).doubleValue()/main.kobRDC.TotalForecast.get(s).doubleValue())
{time=main.kobRDC.TotalStock.get(s).doubleValue()/main.kobRDC.TotalForecast.get(s).doubleValue();}
else {time=time;}}
s=s.next();
}while(!s.equals(Wypall7290));
}
else
{
EnumItem s = Kleenex6765;
do{
if (main.kobRDC.TotalStock.get(s).doubleValue()>0){
if (time>main.kobRDC.TotalStock.get(s).doubleValue()/main.kobRDC.TotalForecast.get(s).doubleValue())
{time=main.kobRDC.TotalStock.get(s).doubleValue()/main.kobRDC.TotalForecast.get(s).doubleValue();}
else {time=time;}}
s=s.next();
}while(!s.equals(Wypall7290));
}
else if (main.kobRDC.PCT.get(h).doubleValue()==30)
{if (time<1) time=1;}
else
{if (time<=4) time=1;
if(time>4) time=1;}

return time;  }
```

```
public class production extends DynamicTimer {

  public production( double _timeout    ) {
    super(KobFactory.this, _timeout);
  }

  public void action() {
if
(getTime()==31.3||getTime()==60.3||getTime()==91.3||getTime()==121.3||getTime()==152.3||getTime()==182.3||getTi
me()==213.3||getTime()==244.3||getTime()==274.3||getTime()==305.3||getTime()==335.3)
{
EnumItem s21=Kleenex6765;
do{
TotalProduced.set(s21,0);
s21=s21.next();
}while(!s21.equals(Wypall7290));
new Maintenance(0);}

else{
double toproduce=0;
AP.set(pr,AmountProduced.get(pr).doubleValue());
EnumItem s21=Kleenex6765;
do{
ToProduce.set(s21,(int)(main.cenPlanning.PlannedProduction.get(s21).doubleValue()-
TotalProduced.get(s21).doubleValue()));
if (ToProduce.get(s21).doubleValue()<0)TotalProduced.set(s21,0);
ToProduce.set(s21,(int)(main.cenPlanning.PlannedProduction.get(s21).doubleValue()-
TotalProduced.get(s21).doubleValue()));
toproduce+=ToProduce.get(s21).doubleValue();
s21=s21.next();
}while(!s21.equals(Wypall7290));
T1=getTime();

EnumItem s=Kleenex6765;
do{
  if (main.kobRDC.Rank.get(s).doubleValue()==1) {pr=s;}
  s=s.next();
}while(!s.equals(Wypall7290));

if (pr==pr2 && ToProduce.get(pr).doubleValue()==0 ||
ToProduce.get(pr).doubleValue()/ProductionRate.get(pr).doubleValue()<1)
{
EnumItem s2=Kleenex6765;
do{
  if (main.kobRDC.Rank.get(s2).doubleValue()==2 && ToProduce.get(s2).doubleValue()>0) {pr=s2;}
  s2=s2.next();
}while(!s2.equals(Wypall7290));}

if (pr==pr2 && (int)(ToProduce.get(pr).doubleValue())==0 ||
ToProduce.get(pr).doubleValue()/ProductionRate.get(pr).doubleValue()<1)
{
EnumItem s2=Kleenex6765;
do{
  if (main.kobRDC.Rank.get(s2).doubleValue()==3 && (int)(ToProduce.get(s2).doubleValue())>0) {pr=s2;}
  s2=s2.next();
}while(!s2.equals(Wypall7290));}

if (pr==pr2 && (int)(ToProduce.get(pr).doubleValue())==0 ||
ToProduce.get(pr).doubleValue()/ProductionRate.get(pr).doubleValue()<1)
{
```

```
EnumItem s2=Kleenex6765;
do{
  if (main.kobRDC.Rank.get(s2).doubleValue()==4 && (int)(ToProduce.get(s2).doubleValue())>0) {pr=s2;}
  s2=s2.next();
}while(!s2.equals(Wypall7290));}
double p01=0;
if (ToProduce.get(pr).doubleValue()==0 || ToProduce.get(pr).doubleValue()/ProductionRate.get(pr).doubleValue()<1)
{
EnumItem s2=Kleenex6765;
do{
  if (main.kobRDC.Rank.get(s2).doubleValue()==2 && ToProduce.get(s2).doubleValue()>0 ||
ToProduce.get(s2).doubleValue()/ProductionRate.get(s2).doubleValue()>=1) {pr=s2;}
  s2=s2.next();
}while(!s2.equals(Wypall7290));}

if (ToProduce.get(pr).doubleValue()==0 || ToProduce.get(pr).doubleValue()/ProductionRate.get(pr).doubleValue()<1)
{
EnumItem s2=Kleenex6765;
do{
  if (main.kobRDC.Rank.get(s2).doubleValue()==3 && ToProduce.get(s2).doubleValue()>0 ||
ToProduce.get(s2).doubleValue()/ProductionRate.get(s2).doubleValue()>=1) {pr=s2;}
  s2=s2.next();
}while(!s2.equals(Wypall7290));}

if (ToProduce.get(pr).doubleValue()==0 || ToProduce.get(pr).doubleValue()/ProductionRate.get(pr).doubleValue()<1)
{
EnumItem s2=Kleenex6765;
do{
  if (main.kobRDC.Rank.get(s2).doubleValue()==4 && ToProduce.get(s2).doubleValue()>0 ||
ToProduce.get(s2).doubleValue()/ProductionRate.get(s2).doubleValue()>=1) {pr=s2;}
  s2=s2.next();
}while(!s2.equals(Wypall7290));}
if (ToProduce.get(pr).doubleValue()==0 || ToProduce.get(pr).doubleValue()/ProductionRate.get(pr).doubleValue()<1)
{
EnumItem s2=Kleenex6765;
do{
  if (main.kobRDC.Rank.get(s2).doubleValue()==5 && ToProduce.get(s2).doubleValue()>0 ||
ToProduce.get(s2).doubleValue()/ProductionRate.get(s2).doubleValue()>=1) {pr=s2;}
  s2=s2.next();
}while(!s2.equals(Wypall7290));}
if (ToProduce.get(pr).doubleValue()==0 || ToProduce.get(pr).doubleValue()/ProductionRate.get(pr).doubleValue()<1)
{
EnumItem s2=Kleenex6765;
do{
  if (main.kobRDC.Rank.get(s2).doubleValue()==6 && ToProduce.get(s2).doubleValue()>0 ||
ToProduce.get(s2).doubleValue()/ProductionRate.get(s2).doubleValue()>=1) {pr=s2;}
  s2=s2.next();
}while(!s2.equals(Wypall7290));}

ChangeOver(pr1,pr);p01=p;

CO+=p01;
pr2=pr1;
pr1=pr;
T.set(pr2,getTime());
int y=0;

EnumItem ss1=Kleenex6765;
do{
   ProductionRate.set(ss1,0);
```

```
  ss1=ss1.next();
}while(!ss1.equals(Wypall7290));
if (getTime()<31 && getTime()+1>31) {idleTime+=31.3-getTime();new production(31.3-getTime());}
else if (getTime()<60 && getTime()+1>60) {idleTime+=60.3-getTime();new production(60.3-getTime());}
else if (getTime()<91 && getTime()+1>91) {idleTime+=91.3-getTime();new production(91.3-getTime());}
else if (getTime()<121 && getTime()+1>121){idleTime+=121.3-getTime(); new production(121.3-getTime());}
else if (getTime()<152 && getTime()+1>152) {idleTime+=152.3-getTime();new production(152.3-getTime());}
else if (getTime()<182 && getTime()+1>182) {idleTime+=182.3-getTime();new production(182.3-getTime());}
else if (getTime()<213 && getTime()+1>213) {idleTime+=213.3-getTime();new production(213.3-getTime());}
else if (getTime()<244 && getTime()+1>244) {idleTime+=244.3-getTime();new production(244.3-getTime());}
else if (getTime()<274 && getTime()+1>274) {idleTime+=274.3-getTime();new production(274.3-getTime());}
else if (getTime()<305 && getTime()+1>305) {idleTime+=305.3-getTime();new production(305.3-getTime());}
else if (getTime()<335 && getTime()+1>335) {idleTime+=335.3-getTime();new production(335.3-getTime());}
else {idleTime+=1;new production(1);}}
else{
EnumItem ss1=Kleenex6765;
do{
  ProductionRate.set(ss1,0);
  ss1=ss1.next();
}while(!ss1.equals(Wypall7290));

new CTimer(p01);}
}
else{ProductionRate.set(pr,PR.get(pr).doubleValue());
new production(ProductionStopTime(pr));}

else{
EnumItem ss=Kleenex6765;
do{
  if (ss!=pr) ProductionRate.set(ss,0);
  ss=ss.next();
}while(!ss.equals(Wypall7290));

ProductionRate.set(pr,PR.get(pr).doubleValue());

}
 }
}
```

Appendix C – A fragment of collected data

Table 1. The Production Amounts of product* X1 *at the Factory during December, 2004

Material	Movement number	Posting date	Cs Qty
X1	4906150674	20.12.2004	216
X1	4906152553	20.12.2004	216
X1	4906154027	20.12.2004	72
X1	4906149625	19.12.2004	252
X1	4906149118	19.12.2004	2,844
X1	4906148670	18.12.2004	2,016
X1	4906131425	17.12.2004	144
X1	4906131425	17.12.2004	120
X1	4906130387	17.12.2004	264
X1	4906128929	17.12.2004	240
X1	4906127274	17.12.2004	24
X1	4906137792	17.12.2004	972
X1	4906135184	17.12.2004	396
X1	4906134635	17.12.2004	324
X1	4906133917	17.12.2004	324
X1	4906132851	17.12.2004	396
X1	4906120771	16.12.2004	312
X1	4906119626	16.12.2004	216
X1	4906118537	16.12.2004	144
X1	4906117304	16.12.2004	240
X1	4906115493	16.12.2004	24
X1	4906126275	16.12.2004	24
X1	4906125427	16.12.2004	528
X1	4906123544	16.12.2004	240
X1	4906122786	16.12.2004	24
X1	4906121923	16.12.2004	72
X1	4906114414	15.12.2004	96
X1	4905979315	01.12.2004	120
X1	4905978244	01.12.2004	336
X1	4905976993	01.12.2004	192
X1	4905975900	01.12.2004	120
X1	4905979315	01.12.2004	216
X1	4905983244	01.12.2004	144
X1	4905982566	01.12.2004	756
X1	4905980935	01.12.2004	288
X1	4905979969	01.12.2004	252

Table 2. Products sent by Factory to different RDCs during January 2004

Location of the ship-to party	Material	Delivery Qty	Pallet Qty	Pallets	Mat.av.dt.	Deliv.date	Weight	Volume	Batch	Purch.doc.
Marene	X11	624	24	26	29/12/2003	02/01/2004	4,300.61	30.576	E5	4500388431
Koblenz	X1	72	24	3	02/01/2004	06/01/2004	468	3.6	E5	4500392472
Arceniega	X1	336	24	14	02/01/2004	07/01/2004	2,184.00	16.8	E5	4500390717
Arceniega	X5	0	36	0	02/01/2004	07/01/2004	0	0	E5	4500390717
Arceniega	X10	432	24	18	02/01/2004	07/01/2004	3,132.00	21.168	E5	4500390717
Arceniega	X11	72	24	3	02/01/2004	07/01/2004	496.224	3.528	E5	4500390717
Arceniega	X12	144	24	6	02/01/2004	07/01/2004	1,008.00	7.056	E5	4500390717
Flint, Wales	X10	840	30	28	02/01/2004	07/01/2004	6,090.00	41.16	S2	4500390626
Flint, Wales	X12	120	30	4	02/01/2004	07/01/2004	840	5.88	S2	4500390626
Niederbipp	X12	32	32	1	05/01/2004	07/01/2004	224	1.568	E3	4500391622
Koblenz	X1	720	36	20	05/01/2004	07/01/2004	4,680.00	36	E3	4500393073
Koblenz	X1	540	36	15	05/01/2004	07/01/2004	3,510.00	27	E3	4500393487
Flint, Wales	X10	930	30	31	05/01/2004	08/01/2004	6,742.50	45.57	S2	4500390630
Flint, Wales	X11	120	30	4	05/01/2004	08/01/2004	827.04	5.88	S2	4500388354
Meung Sur Loire	X5	108	36	3	05/01/2004	09/01/2004	532.548	3.348	E5	4500392431
Meung Sur Loire	X10	264	24	11	05/01/2004	09/01/2004	1,914.00	12.936	E5	4500392431
Meung Sur Loire	X12	48	24	2	05/01/2004	09/01/2004	336	2.352	E5	4500392431
Meung Sur Loire	X10	120	24	5	06/01/2004	09/01/2004	870	5.88	E5	4500394129
Niederbipp	X3	32	32	1	08/01/2004	12/01/2004	240	1.536	E3	4500393338
Niederbipp	X5	48	48	1	08/01/2004	12/01/2004	236.688	1.488	E3	4500393338
Meung Sur Loire	X1	888	24	37	07/01/2004	12/01/2004	5,772.00	44.4	E5	4500393281
Flint, Wales	X1	960	30	32	07/01/2004	12/01/2004	6,240.00	48	S2	4500393188
Flint, Wales	X10	570	30	19	07/01/2004	12/01/2004	4,132.50	27.93	S2	4500393193
Budaors	X1	10	36	0.2778	08/01/2004	12/01/2004	65	0.5	E3	963619
Koblenz	X1	792	24	33	08/01/2004	12/01/2004	5,148.00	39.6	E5	4500396178
Koblenz	X1	792	24	33	08/01/2004	12/01/2004	5,148.00	39.6	E5	4500396183
Flint, Wales	X1	720	30	24	08/01/2004	13/01/2004	4,680.00	36	S2	4500394131
Flint, Wales	X5	288	36	8	08/01/2004	13/01/2004	1,420.13	8.928	S2	4500394131
Flint, Wales	X1	540	30	18	09/01/2004	14/01/2004	3,510.00	27	S2	4500395022
Flint, Wales	X10	780	30	26	09/01/2004	14/01/2004	5,655.00	38.22	S2	4500395022
Meung Sur Loire	X1	408	24	17	09/01/2004	14/01/2004	2,652.00	20.4	E5	4500396134
Meung Sur Loire	X5	72	48	1.5	09/01/2004	14/01/2004	355.032	2.232	E3	4500396134
Marene	X1	96	24	4	12/01/2004	14/01/2004	624	4.8	E5	4500396261
Marene	X5	122	36	3.3889	12/01/2004	14/01/2004	601.582	3.782	E5	4500396261
Flint, Wales	X1	210	30	7	12/01/2004	15/01/2004	1,365.00	10.5	S2	4500396217
Flint, Wales	X5	72	36	2	12/01/2004	15/01/2004	355.032	2.232	S2	4500396217
Flint, Wales	X10	510	30	17	12/01/2004	15/01/2004	3,697.50	24.99	S2	4500396217
Marki kolo Warszawy	X10	72	32	2.25	13/01/2004	15/01/2004	522	3.528	E3	970794
Flint, Wales	X1	360	30	12	13/01/2004	16/01/2004	2,340.00	18	S2	4500397191
Meung Sur Loire	X10	240	24	10	13/01/2004	16/01/2004	1,740.00	11.76	E5	4500398400
Koblenz	X5	540	36	15	14/01/2004	16/01/2004	2,662.74	16.74	E5	4500400212
Koblenz	X1	96	24	4	14/01/2004	16/01/2004	624	4.8	E5	4500400630
Himki	X1	72	24	3	14/01/2004	17/01/2004	468	3.6	E5	953730
Himki	X10	320	32	10	14/01/2004	18/01/2004	2,320.00	15.68	E3	953732
Vilnius	X1	36	36	1	15/01/2004	19/01/2004	234	1.8	E3	976016
Flint, Wales	X1	240	30	8	14/01/2004	19/01/2004	1,560.00	12	S2	4500398417
Flint, Wales	X5	288	36	8	14/01/2004	19/01/2004	1,420.13	8.928	S2	4500398417
Flint, Wales	X10	540	30	18	14/01/2004	19/01/2004	3,915.00	26.46	S2	4500398417
POHORELICE	X5	96	48	2	16/01/2004	20/01/2004	473.376	2.976	E3	974028
POHORELICE	X10	192	32	6	16/01/2004	20/01/2004	1,392.00	9.408	E3	974028
Arceniega	X5	72	36	2	15/01/2004	20/01/2004	355.032	2.232	E5	4500400461
Budaors	X11	36	32	1.125	16/01/2004	20/01/2004	248.112	1.764	E3	979785
Koblenz	X10	256	32	8	16/01/2004	20/01/2004	1,856.00	12.544	E3	4500402546
Koblenz	X5	540	36	15	16/01/2004	20/01/2004	2,662.74	16.74	E5	4500402877
Koblenz	X11	1,056	32	33	16/01/2004	20/01/2004	7,277.95	51.744	E3	4500402882
Flint, Wales	X1	450	30	15	16/01/2004	21/01/2004	2,925.00	22.5	S2	4500400399
Flint, Wales	X5	216	36	6	16/01/2004	21/01/2004	1,065.10	6.696	S2	4500400399
Niederbipp	X5	48	48	1	19/01/2004	21/01/2004	236.688	1.488	E3	4500400539
Tarn¾w	X5	48	48	1	19/01/2004	21/01/2004	236.688	1.488	E3	985036
Tarn¾w	X11	20	32	0.625	19/01/2004	21/01/2004	137.84	0.98	E3	985036
Koblenz	X11	1,056	32	33	19/01/2004	21/01/2004	7,277.95	51.744	E3	4500403428
Koblenz	X11	792	24	33	19/01/2004	21/01/2004	5,458.46	38.808	E5	4500403455
Koblenz	X11	792	24	33	19/01/2004	21/01/2004	5,458.46	38.808	E5	4500403456
Koblenz	X11	792	24	33	19/01/2004	21/01/2004	5,458.46	38.808	E5	4500403458
Koblenz	X11	792	24	33	19/01/2004	21/01/2004	5,163.84	40.392	E5	4500403844
Poznan	X5	48	48	1	19/01/2004	21/01/2004	236.688	1.488	E3	985349
Himki	X1	72	36	2	20/01/2004	22/01/2004	468	3.6	E3	963711
Himki	X10	352	32	11	20/01/2004	22/01/2004	2,552.00	17.248	E3	963711
Niederbipp	X5	48	48	1	20/01/2004	22/01/2004	236.688	1.488	E3	4500402931
Niederbipp	X11	288	32	9	20/01/2004	22/01/2004	1,984.90	14.112	E3	4500402921
Marene	X1	192	24	8	20/01/2004	22/01/2004	1,248.00	9.6	E5	4500402646
Marene	X5	288	36	8	20/01/2004	22/01/2004	1,420.13	8.928	E5	4500402646
Marene	X11	672	24	28	20/01/2004	22/01/2004	4,631.42	32.928	E5	4500402646

Table 3. Orders for different products delivered to different customers from different RDCs during first week of January, 2004

Name of the ship-to party	laterial	Delivery Qty	Mat.av.dt.	Deliv.date	Weight	Volume	Batch	Plnt	SOrg.	Purch.doc.
ALDIS SUD EST 2	X1	48	29/12/2003	02/01/2004	312	2.4	E5	3351	2334	949157
Vogt GmbH	X11	8	02/01/2004	02/01/2004	55.136	0.392	E3	3322	2340	951315
Vogt GmbH	X11	32	09/01/2004	02/01/2004	220.544	1.568	E3	3322	2340	951315
Vogt GmbH	X11	24	15/01/2004	02/01/2004	165.408	1.176	E3	3322	2340	951315
BUNZL CATERING SUPPLIES	X10	10	31/12/2003	05/01/2004	72.5	0.49	S2	3221	2310	942139
LYNDALE IND SUPPLIES LTD	X10	4	31/12/2003	05/01/2004	29	0.196	S2	3221	2310	943147
VIKING Direct	X11	2	30/12/2003	05/01/2004	13.784	0.098	E5	3022	2334	944373
VIKING Direct	X11	2	30/12/2003	05/01/2004	13.784	0.098	E5	3022	2334	944373
SYNDIAL SPA	X5	166	31/12/2003	05/01/2004	818.546	5.146	E5	3429	2789	938665
Delta Zofingen AG	X7	108	30/12/2003	05/01/2004	783	5.292	E3	3322	2647	953633
BLANC ET FILS	X7	140	30/12/2003	05/01/2004	1,015.00	6.86	E5	3022	2334	942341
Julius Brune GmbH & Co KG.	X7	15	30/12/2003	05/01/2004	108.75	0.735	E3	3322	2340	925752
Julius Brune GmbH & Co KG.	X13	32	30/12/2003	05/01/2004	285.76	1.6	E3	3322	2340	949770
Marco-Martin & Co., 930089	X13	32	30/12/2003	05/01/2004	285.76	1.6	E3	3322	2340	953435
Hegro Eichler	X13	64	30/12/2003	05/01/2004	571.52	3.2	E3	3322	2340	954040
KING BELGIUM N.V	X5	42	05/01/2004	05/01/2004	207.102	1.302	E3	3322	2786	954479
Groveko-Ede B.V.	X10	36	05/01/2004	05/01/2004	261	1.764	E3	3322	2376	955600
Van Ginkel	X10	28	05/01/2004	05/01/2004	203	1.372	E3	3322	2376	955615
King Nederland B.V.	X7	40	05/01/2004	05/01/2004	290	1.96	E3	3322	2376	955637
King Nederland B.V.	X7	15	05/01/2004	05/01/2004	108.75	0.735	E3	3322	2376	956039
RIDGEWAY SUPPLIES	X10	150	31/12/2003	05/01/2004	1,087.50	7.35	S2	3221	2310	955668
NEWHALL JANITORIAL	X10	25	31/12/2003	05/01/2004	181.25	1.225	S2	3221	2310	955598
RIDGEWAY SUPP LTD	X10	25	31/12/2003	05/01/2004	181.25	1.225	S2	3221	2310	953271
GREENHAM T L (BR 09)	X10	30	31/12/2003	05/01/2004	217.5	1.47	S2	3221	2310	951332
K C JOHNS LTD	X5	5	31/12/2003	05/01/2004	24.655	0.155	S2	3221	2310	947379
ICP Hygiene Ltd	X5	2	31/12/2003	05/01/2004	9.862	0.062	S2	3221	2310	947372
MINATOL LTD	X1	30	31/12/2003	05/01/2004	195	1.5	S2	3221	2310	946620
BUNZL CATERING SUPPLIES	X11	5	31/12/2003	05/01/2004	34.46	0.245	S2	3221	2310	944333
BUNZL CATERING SUPPLIES	X10	60	31/12/2003	05/01/2004	435	2.94	S2	3221	2310	944333
GREENHAM T L (BR 10)	X10	15	31/12/2003	05/01/2004	108.75	0.735	S2	3221	2310	941652
UNICO LIMITED	X5	10	31/12/2003	05/01/2004	49.31	0.31	S2	3221	2310	949776
INDUSTRIAL CLEANING SUPPLIES	X1	60	31/12/2003	05/01/2004	390	3	S2	3221	2310	948815
BUNZL CATERING SUPPLIES	X1	5	31/12/2003	05/01/2004	32.5	0.25	S2	3221	2310	939285
BUNZL CATERING SUPPLIES	X12	10	31/12/2003	05/01/2004	70	0.49	S2	3221	2310	939285
BUNZL CATERING SUPPLIES	X10	30	31/12/2003	05/01/2004	217.5	1.47	S2	3221	2310	939285
Bunzl Cleaning & Hygiene Supplies	X5	6	31/12/2003	05/01/2004	29.586	0.186	S2	3221	2310	935594
Julius Holluschek Ges.m.b.H.	X7	1	31/12/2003	05/01/2004	7.25	0.049	E3	3322	2340	939208
OH22DATA AG	X5	1	31/12/2003	05/01/2004	4.931	0.031	E3	3322	2340	946596
OH22DATA AG	X7	1	31/12/2003	05/01/2004	7.25	0.049	E3	3322	2340	946596
KING BELGIUM N.V	X1	36	05/01/2004	05/01/2004	234	1.8	E3	3322	2786	954479
Arndt Landshut	X1	11	06/01/2004	05/01/2004	71.5	0.55	E3	3322	2340	937063
Arndt Landshut	X1	25	06/01/2004	05/01/2004	162.5	1.25	E3	3322	2340	937063
V O G T GmbH	X1	12	06/01/2004	05/01/2004	78	0.6	E3	3322	2340	956173
Harry Wegner	X11	32	15/01/2004	05/01/2004	220.544	1.568	E3	3322	2340	932741
HYGIADIS	X5	36	31/12/2003	06/01/2004	177.516	1.116	E5	3022	2334	944130
MANUTAN	X11	18	31/12/2003	06/01/2004	124.056	0.882	E5	3022	2334	954079
Br^{3}ggershemke+Reinkemeier	X12	96	06/01/2004	06/01/2004	672	4.704	E3	3322	2340	956178
VERPA BENELUX N.V.	X5	1	02/01/2004	06/01/2004	4.931	0.031	E3	3322	2786	956172
VERPA BENELUX N.V.	X10	1	02/01/2004	06/01/2004	7.25	0.049	E3	3322	2786	956172
VERPA BENELUX N.V.	X7	1	02/01/2004	06/01/2004	7.25	0.049	E3	3322	2786	956172
Hysa Berlin	X11	0	06/01/2004	06/01/2004	0	0	E3	3322	2340	953760
Haagclean Products BV	X10	1	06/01/2004	06/01/2004	7.25	0.049	E3	3322	2376	957305
King Nederland B.V.	X10	18	06/01/2004	06/01/2004	130.5	0.882	E3	3322	2376	956412
King Nederland B.V.	X7	16	06/01/2004	06/01/2004	116	0.784	E3	3322	2376	956412
MANUTAN	X1	5	01/01/2004	06/01/2004	32.5	0.25	E5	3022	2334	887881
ORRU	X1	48	01/01/2004	06/01/2004	312	2.4	E5	3022	2334	936902
JPG	X1	24	01/01/2004	06/01/2004	156	1.2	E5	3022	2334	938781
TOUSSAINT	X1	81	01/01/2004	06/01/2004	526.5	4.05	E5	3022	2334	941842
SOFRASTOCK	X1	6	01/01/2004	06/01/2004	39	0.3	E5	3022	2334	942043
ADISCO VACHET	X1	15	01/01/2004	06/01/2004	97.5	0.75	E5	3022	2334	949185
ANAXIS	X1	1	01/01/2004	06/01/2004	6.5	0.05	E5	3022	2334	951194
TISSERAND S A R L	X1	24	01/01/2004	06/01/2004	156	1.2	E5	3022	2334	952767
ALLO DICS	X1	24	01/01/2004	06/01/2004	156	1.2	E5	3022	2334	954056
MANUTAN	X1	2	01/01/2004	06/01/2004	13	0.1	E5	3022	2334	954079
BUNZL CLEANING & HYGIENE SUPPLIES	X1	10	02/01/2004	06/01/2004	65	0.5	S2	3221	2310	946658
GREENHAM T L (BR 08)	X12	24	02/01/2004	06/01/2004	168	1.176	S2	3221	2310	946920
UNICO LIMITED	X1	60	02/01/2004	06/01/2004	390	3	S2	3221	2310	948808
GREEN OF LINCOLN	X11	10	02/01/2004	06/01/2004	68.92	0.49	S2	3221	2310	948902
CANNON HYGIENE LTD	X10	25	02/01/2004	06/01/2004	181.25	1.225	S2	3221	2310	949479
LIGHTOWLER	X10	1	02/01/2004	06/01/2004	6.892	0.049	S2	3221	2310	951116
Bunzl Cleaning & Hygiene Supplies	X1	30	02/01/2004	06/01/2004	195	1.5	S2	3221	2310	955586
ALLYN SUPPLIES	X10	75	02/01/2004	06/01/2004	543.75	3.675	S2	3221	2310	955754
Sahlberg GmbH & Co. KG	X10	1	02/01/2004	06/01/2004	7.25	0.049	E3	3322	2340	949017

Table 4. Fixed Monthly Forecasts of X1 during 2004

Markets	Jan-04	Feb-04	Mar-04	Apr-04	May-04	Jun-04	Jul-04	Aug-04	Sep-04	Oct-04	Nov-04	Dec-04
Belgium	307	259	247	258	328	358	428	336	342	441	360	414
Switzerland	20	21	17	29	29	36	27	25	30	36	22	17
Czech	105	163	120	121	124	136	159	164	159	38	28	30
Germany	1,303.00	1,065.00	1,129.00	1,112.00	1,157.00	1,007.00	1,212.00	1,063.00	1,043.00	945	1,113.00	1,092.00
Nordic	44	40	66	18	16	18	36	20	25	30	20	22
Spain	218	223	245	224	242	181	144	141	156	133	135	102
France	3,465.00	2,389.00	3,279.00	2,889.00	3,050.00	2,487.00	2,605.00	2,044.00	3,020.00	3,131.00	2,829.00	3,340.00
UK	3,400.00	3,377.00	3,697.00	3,026.00	3,395.00	3,522.00	3,388.00	3,365.00	3,592.00	3,332.00	3,542.00	3,726.00
Italy	780	693	850	739	721	728	650	650	680	621	595	700
Holland	188	179	176	181	160	181	189	126	175	142	142	149
Portugal	76	80	73	76	84	69	59	67	95	111	91	87
Russia	416	486	499	418	539	507	517	659	670	756	792	828

Table 5: Monthly Sales of X1 during 2004

Markets	Jan-04	Feb-04	Mar-04	Apr-04	May-04	Jun-04	Jul-04	Aug-04	Sep-04	Oct-04	Nov-04	Dec-04
Belgium	792	186	341	360	360	324	612	144	308	510	468	64
Switzerland	36	4	40	0	0	38	40	0	2	46	5	80
Czech	111	112	188	190	118	76	166	1	30	25	54	29
Germany	1,397.00	952	1,087.00	1,047.00	1,040.00	1,153.00	985	1,126.00	1,066.00	1,246.00	937	822
Nordic	40	35	20	56	15	28	15	14	0	68	26	36
Spain	26	6	84	144	146	176	102	53	146	102	206	128
France	3,579.00	3,075.00	2,738.00	3,007.00	3,368.00	3,053.00	3,447.00	1,433.00	3,436.00	3,501.00	2,666.00	3,645.00
UK	3,370.00	3,416.00	3,776.00	3,388.00	3,305.00	3,942.00	3,828.00	3,003.00	3,698.00	3,323.00	3,668.00	3,238.00
Italy	457	654	592	333	775	640	893	266	921	504	325	939
Holland	223	121	207	165	112	209	93	160	147	173	147	190
Portugal	48	96	24	96	104	120	120	24	72	96	48	48
Russia	499	510	516	712	715	586	648	768	704	871	865	1,038.00

Appendix D.1

The desired number of replications is found by applying an incremental approach in the following algorithm:

1) Make an initial number of m>=2 runs and calculate initial estimates $\overline{X}(m)$ and $S^2(m)$.
2) Decide the size of the allowable percentage error $\varepsilon' = \left|\overline{X}(m) - \mu\right| / |\mu|$
3) Calculate the adjusted percentage error $\varepsilon' = \varepsilon / (1 + \varepsilon)$
4) Decide the level of significance α
5) Calculate the new $\overline{X}(n)$ and $S^2(n)$.
6) Calculate the half-length of the confidence interval: $\delta(n,\alpha) = t_{n-1,1-\alpha/2}\sqrt{\dfrac{S^2(n)}{n}}$
7) If $\dfrac{\delta(n,\alpha)}{\left|\overline{X}(n)\right|} \le \varepsilon'$ use $\overline{X}(n)$ as an unbiased point estimate for μ, else make one more replication and go back to 5.

$\overline{X}(m)$: estimate of real mean μ from m simulation runs

$S^2(m)$: estimate of real standard deviation σ from m simulation runs

$t_{n-1,1-\alpha/2}$: Critical value of the t-test for n-1 degrees of freedom and significance α

For m=3, $\overline{X}(3) = 140562$, *S(3)*= 4158, $\varepsilon' = 0.035$, $\dfrac{\delta(3,0.05)}{\left|\overline{X}(3)\right|} = 0.037 > \varepsilon'$

For m=4, $\overline{X}(4) = 143365$, *S(4)*= 6554, $\varepsilon' = 0.054$, $\dfrac{\delta(4,0.05)}{\left|\overline{X}(4)\right|} = 0.057 > \varepsilon'$

For m=5, $\overline{X}(5) = 144519$, *S(5)*= 6236, $\varepsilon' = 0.062$, $\dfrac{\delta(5,0.05)}{\left|\overline{X}(5)\right|} = 0.054 < \varepsilon'$

Hence the number of simulation runs is 5.

Appendix D.2

Test of Homogeneity of Variances

	Levene Statistic	df1	df2	Sig.
NAVI	.947	9	40	.496
NetworkCSL	6.649	9	40	.000
Average_Respnse	2.518	9	40	.022
Average_RunLength	1.828	9	40	.093

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
NAVI	Between Groups	6.40E+09	9	710791729.5	10.900	.000
	Within Groups	2.61E+09	40	65209301.91		
	Total	9.01E+09	49			
NetworkCSL	Between Groups	.013	9	.001	41.215	.000
	Within Groups	.001	40	.000		
	Total	.014	49			
Average_Respnse	Between Groups	87.682	9	9.742	8.009	.000
	Within Groups	48.656	40	1.216		
	Total	136.339	49			
Average_RunLength	Between Groups	24.840	9	2.760	23.700	.000
	Within Groups	4.658	40	.116		
	Total	29.498	49			

Robust Tests of Equality of Means

		Statistic[a]	df1	df2	Sig.
NAVI	Welch	9.565	9	16.224	.000
	Brown-Forsythe	10.900	9	27.984	.000
NetworkCSL	Welch	104.336	9	15.514	.000
	Brown-Forsythe	41.215	9	11.450	.000
Average_Respnse	Welch	10.395	9	16.258	.000
	Brown-Forsythe	8.009	9	8.843	.003
Average_RunLength	Welch	21.004	9	16.232	.000
	Brown-Forsythe	23.700	9	21.499	.000

a. Asymptotically F distributed.

Anova Test Results for Average Network Inventory

Multiple Comparisons
Dependent Variable: NAVI
Tukey HSD

(I) Model configuration	(J) Model configuration	Mean Difference (I-J)	Significance	95% Confidence Interval	
				Lower Bound	Upper Bound
Baseline	Baseline with weekly Production Review	-902.41118	1.000	-18000.4019	16195.5795
	Decentralised information structure	-2352.47144	1.000	-19450.4621	14745.51924
	Adjustable safety stock	21048.86398	0.006 *	3950.873299	38146.85466
	Collaborative RDC+pull	20959.76856	0.007 *	3861.777879	38057.75924
	Push based on partial information	30658.56144	0.000 *	13560.57076	47756.55212
	Production based on partial global information	4419.33172	0.997	-12678.659	21517.3224
	Production based on full global information	-2497.90884	1.000	-19595.8995	14600.08184
	Learning RDCs	1162.29116	1.000	-15935.6995	18260.28184
	Flexible Maintenance	10962.09116	0.508	-6135.89952	28060.08184
Baseline with weekly Production Review	Baseline	902.41118	1.000	-16195.5795	18000.40186
	Decentralised information structure	-1450.06026	1.000	-18548.0509	15647.93042
	Adjustable safety stock	21951.27516	0.004 *	4853.284479	39049.26584
	Collaborative RDC+pull	21862.17974	0.004 *	4764.189059	38960.17042
	Push based on partial information	31560.97262	0.000 *	14462.98194	48658.9633
	Production based on partial global information	5321.7429	0.987	-11776.2478	22419.73358
	Production based on full global information	-1595.49766	1.000	-18693.4883	15502.49302
	Learning RDCs	2064.70234	1.000	-15033.2883	19162.69302
	Flexible Maintenance	11864.50234	0.397	-5233.48834	28962.49302
Decentralised information structure	Baseline	2352.47144	1.000	-14745.5192	19450.46212
	Baseline with weekly Production Review	1450.06026	1.000	-15647.9304	18548.05094
	Adjustable safety stock	23401.33542	0.002 *	6303.344739	40499.3261
	Collaborative RDC+pull	23312.24	0.002 *	6214.249319	40410.23068
	Push based on partial information	33011.03288	0.000 *	15913.0422	50109.02356
	Production based on partial global information	6771.80316	0.941	-10326.1875	23869.79384
	Production based on full global information	-145.4374	1.000	-17243.4281	16952.55328
	Learning RDCs	3514.7626	0.999	-13583.2281	20612.75328
	Flexible Maintenance	13314.5626	0.248	-3783.42808	30412.55328
Adjustable safety stock	Baseline	-21048.86398	0.006 *	-38146.8547	-3950.8733
	Baseline with weekly Production Review	-21951.27516	0.004 *	-39049.2658	-4853.28448
	Decentralised information structure	-23401.33542	0.002 *	-40499.3261	-6303.34474
	Collaborative RDC+pull	-89.09542	1.000	-17187.0861	17008.89526
	Push based on partial information	9609.69746	0.681	-7488.29322	26707.68814
	Production based on partial global information	-16629.53226	0.062	-33727.5229	468.458421
	Production based on full global information	-23546.77282	0.002 *	-40644.7635	-6448.78214
	Learning RDCs	-19886.57282	0.012 *	-36984.5635	-2788.58214
	Flexible Maintenance	-10086.77282	0.620	-27184.7635	7011.217861
Collaborative RDC+pull	Baseline	-20959.76856	0.007 *	-38057.7592	-3861.77788
	Baseline with weekly Production Review	-21862.17974	0.004 *	-38960.1704	-4764.18906
	Decentralised information structure	-23312.24	0.002 *	-40410.2307	-6214.24932
	Adjustable safety stock	89.09542	1.000	-17008.8953	17187.0861
	Push based on partial information	9698.79288	0.670	-7399.1978	26796.78356
	Production based on partial global information	-16540.43684	0.065	-33638.4275	557.553841
	Production based on full global information	-23457.6774	0.002 *	-40555.6681	-6359.68672
	Learning RDCs	-19797.4774	0.013 *	-36895.4681	-2699.48672
	Flexible Maintenance	-9997.6774	0.632	-27095.6681	7100.313281

* denotes The mean difference is significant at the .05 level.

Anova Test Results for Average Network Inventory

Multiple Comparisons
Dependent Variable: NAVI
Tukey HSD

(I) Model configuration	(J) Model configuration	Mean Difference (I-J)	Significance	95% Confidence Interval	
				Lower Bound	Upper Bound
Push based on partial information	Baseline	-30658.56144	0.000 *	-47756.5521	-13560.5708
	Baseline with weekly Production Review	-31560.97262	0.000 *	-48658.9633	-14462.9819
	Decentralised information structure	-33011.03288	0.000 *	-50109.0236	-15913.0422
	Adjustable safety stock	-9609.69746	0.681	-26707.6881	7488.293221
	Collaborative RDC+pull	-9698.79288	0.670	-26796.7836	7399.197801
	Production based on partial global information	-26239.22972	0.000 *	-43337.2204	-9141.23904
	Production based on full global information	-33156.47028	0.000 *	-50254.461	-16058.4796
	Learning RDCs	-29496.27028	0.000 *	-46594.261	-12398.2796
	Flexible Maintenance	-19696.47028	0.013 *	-36794.461	-2598.4796
Production based on partial global information	Baseline	-4419.33172	0.997	-21517.3224	12678.65896
	Baseline with weekly Production Review	-5321.7429	0.987	-22419.7336	11776.24778
	Decentralised information structure	-6771.80316	0.941	-23869.7938	10326.18752
	Adjustable safety stock	16629.53226	0.062	-468.458421	33727.52294
	Collaborative RDC+pull	16540.43684	0.065	-557.553841	33638.42752
	Push based on partial information	26239.22972	0.000 *	9141.239039	43337.2204
	Production based on full global information	-6917.24056	0.934	-24015.2312	10180.75012
	Learning RDCs	-3257.04056	1.000	-20355.0312	13840.95012
	Flexible Maintenance	6542.75944	0.952	-10555.2312	23640.75012
Production based on full global information	Baseline	2497.90884	1.000	-14600.0818	19595.89952
	Baseline with weekly Production Review	1595.49766	1.000	-15502.493	18693.48834
	Decentralised information structure	145.4374	1.000	-16952.5533	17243.42808
	Adjustable safety stock	23546.77282	0.002 *	6448.782139	40644.7635
	Collaborative RDC+pull	23457.6774	0.002 *	6359.686719	40555.66808
	Push based on partial information	33156.47028	0.000 *	16058.4796	50254.46096
	Production based on partial global information	6917.24056	0.934	-10180.7501	24015.23124
	Learning RDCs	3660.2	0.999	-13437.7907	20758.19068
	Flexible Maintenance	13460	0.235	-3637.99068	30557.99068
Learning RDCs	Baseline	-1162.29116	1.000	-18260.2818	15935.69952
	Baseline with weekly Production Review	-2064.70234	1.000	-19162.693	15033.28834
	Decentralised information structure	-3514.7626	0.999	-20612.7533	13583.22808
	Adjustable safety stock	19886.57282	0.012 *	2788.582139	36984.5635
	Collaborative RDC+pull	19797.4774	0.013 *	2699.486719	36895.46808
	Push based on partial information	29496.27028	0.000 *	12398.2796	46594.26096
	Production based on partial global information	3257.04056	1.000	-13840.9501	20355.03124
	Production based on full global information	-3660.2	0.999	-20758.1907	13437.79068
	Flexible Maintenance	9799.8	0.657	-7298.19068	26897.79068
Flexible Maintenance	Baseline	-10962.09116	0.508	-28060.0818	6135.899521
	Baseline with weekly Production Review	-11864.50234	0.397	-28962.493	5233.488341
	Decentralised information structure	-13314.5626	0.248	-30412.5533	3783.428081
	Adjustable safety stock	10086.77282	0.620	-7011.21786	27184.7635
	Collaborative RDC+pull	9997.6774	0.632	-7100.31328	27095.66808
	Push based on partial information	19696.47028	0.013 *	2598.479599	36794.46096
	Production based on partial global information	-6542.75944	0.952	-23640.7501	10555.23124
	Production based on full global information	-13460	0.235	-30557.9907	3637.990681
	Learning RDCs	-9799.8	0.657	-26897.7907	7298.190681

* denotes The mean difference is significant at the .05 level.

Anova Test Results for Average Network CSL

Dependent Variable: Network CSL
Games-Howell

(I) Strategy	(J) Strategy	Mean Difference (I-J)	Sig.		95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Baseline	Baseline with weekly Production Review	4.20014E-05	1.000		-0.017628936	0.017712939
	Decentralised information structure	-0.007610583	0.352		-0.020880287	0.005659121
	Adjustable safety stock	-0.014663616	0.046	*	-0.029115201	-0.000212031
	Collaborative RDC+pull	-0.027711387	0.002	*	-0.043299743	-0.012123031
	Push based on partial information	-0.021608602	0.214		-0.053931987	0.010714783
	Production based on partial global information	-0.039758812	0.001	*	-0.053696332	-0.025821291
	Production based on full global information	-0.040880488	0.001	*	-0.055053465	-0.02670751
	Learning RDCs	-0.040158469	0.001	*	-0.054258285	-0.026058653
	Flexible Maintenance	-0.040983548	0.001	*	-0.05517288	-0.026794216
Baseline with weekly Production Review	Baseline	-4.20014E-05	1.000		-0.017712939	0.017628936
	Decentralised information structure	-0.007652585	0.549		-0.024732719	0.00942755
	Adjustable safety stock	-0.014705618	0.104		-0.031969183	0.002557947
	Collaborative RDC+pull	-0.027753388	0.004	*	-0.04567211	-0.009834666
	Push based on partial information	-0.021650604	0.226		-0.053746544	0.010445337
	Production based on partial global information	-0.039800813	0.002	*	-0.057684459	-0.021917167
	Production based on full global information	-0.040922489	0.002	*	-0.059000178	-0.0228448
	Learning RDCs	-0.04020047	0.003	*	-0.058219598	-0.022181343
	Flexible Maintenance	-0.041025549	0.002	*	-0.059116141	-0.022934958
Decentralised information structure	Baseline	0.007610583	0.352		-0.005659121	0.020880287
	Baseline with weekly Production Review	0.007652585	0.549		-0.00942755	0.024732719
	Adjustable safety stock	-0.007053033	0.335		-0.01891884	0.004812774
	Collaborative RDC+pull	-0.020100804	0.009	*	-0.034064301	-0.006137306
	Push based on partial information	-0.013998019	0.546		-0.047569143	0.019573105
	Production based on partial global information	-0.032148228	0.000	*	-0.038838836	-0.025457621
	Production based on full global information	-0.033269905	0.000	*	-0.040281098	-0.026258711
	Learning RDCs	-0.032547886	0.000	*	-0.039433644	-0.025662127
	Flexible Maintenance	-0.033372965	0.000	*	-0.040415631	-0.026330299
Adjustable safety stock	Baseline	0.014663616	0.046	*	0.000212031	0.029115201
	Baseline with weekly Production Review	0.014705618	0.104		-0.002557947	0.031969183
	Decentralised information structure	0.007053033	0.335		-0.004812774	0.01891884
	Collaborative RDC+pull	-0.013047771	0.095		-0.027969656	0.001874115
	Push based on partial information	-0.006944986	0.972		-0.039472088	0.025582116
	Production based on partial global information	-0.025095195	0.003	*	-0.037503414	-0.012686976
	Production based on full global information	-0.026216871	0.003	*	-0.038880172	-0.013553571
	Learning RDCs	-0.025494853	0.004	*	-0.038077373	-0.012912332
	Flexible Maintenance	-0.026319932	0.003	*	-0.039001462	-0.013638402
Collaborative RDC+pull	Baseline	0.027711387	0.002	*	0.012123031	0.043299743
	Baseline with weekly Production Review	0.027753388	0.004	*	0.009834666	0.04567211
	Decentralised information structure	0.020100804	0.009	*	0.006137306	0.034064301
	Adjustable safety stock	0.013047771	0.095		-0.001874115	0.027969656
	Push based on partial information	0.006102785	0.989		-0.026143129	0.038348698
	Production based on partial global information	-0.012047425	0.098		-0.02672073	0.002625881
	Production based on full global information	-0.013169101	0.075		-0.028069146	0.001730945
	Learning RDCs	-0.012447082	0.090		-0.027277178	0.002383014
	Flexible Maintenance	-0.013272161	0.074		-0.028187787	0.001643465

* denotes The mean difference is significant at the .05 level

Anova Test Results for Average Network CSL

Dependent Variable: Network CSL
Games-Howell

(I) Strategy	(J) Strategy	Mean Difference (I-J)	Sig.		95% Confidence Interval Lower Bound	Upper Bound
Push based on partial information	Baseline	0.021608602	0.214		-0.010714783	0.053931987
	Baseline with weekly Production Review	0.021650604	0.226		-0.010445337	0.053746544
	Decentralised information structure	0.013998019	0.546		-0.019573105	0.047569143
	Adjustable safety stock	0.006944986	0.972		-0.025582116	0.039472088
	Collaborative RDC+pull	-0.006102785	0.989		-0.038348698	0.026143129
	Production based on partial global information	-0.018150209	0.320		-0.052387551	0.016087133
	Production based on full global information	-0.019271886	0.278		-0.053617451	0.015073679
	Learning RDCs	-0.018549867	0.304		-0.052863859	0.015764125
	Flexible Maintenance	-0.019374946	0.274		-0.053727351	0.014977459
Production based on partial global informatio	Baseline	0.039758812	0.001	*	0.025821291	0.053696332
	Baseline with weekly Production Review	0.039800813	0.002	*	0.021917167	0.057684459
	Decentralised information structure	0.032148228	0.000	*	0.025457621	0.038838836
	Adjustable safety stock	0.025095195	0.003	*	0.012686976	0.037503414
	Collaborative RDC+pull	0.012047425	0.098		-0.002625881	0.02672073
	Push based on partial information	0.018150209	0.320		-0.016087133	0.052387551
	Production based on full global information	-0.001121676	0.501		-0.003592581	0.001349229
	Learning RDCs	-0.000399657	0.997		-0.00281417	0.002014856
	Flexible Maintenance	-0.001224736	0.408		-0.003754112	0.001304639
Production based on full global information	Baseline	0.040880488	0.001	*	0.02670751	0.055053465
	Baseline with weekly Production Review	0.040922489	0.002	*	0.0228448	0.059000178
	Decentralised information structure	0.033269905	0.000	*	0.026258711	0.040281098
	Adjustable safety stock	0.026216871	0.003	*	0.013553571	0.038880172
	Collaborative RDC+pull	0.013169101	0.075		-0.001730945	0.028069146
	Push based on partial information	0.019271886	0.278		-0.015073679	0.053617451
	Production based on partial global information	0.001121676	0.501		-0.001349229	0.003592581
	Learning RDCs	0.000722019	0.473		-0.000704844	0.002148881
	Flexible Maintenance	-0.00010306	0.999		-0.00082424	0.00061812
Learning RDCs	Baseline	0.040158469	0.001	*	0.026058653	0.054258285
	Baseline with weekly Production Review	0.04020047	0.003	*	0.022181343	0.058219598
	Decentralised information structure	0.032547886	0.000	*	0.025662127	0.039433644
	Adjustable safety stock	0.025494853	0.004	*	0.012912332	0.038077373
	Collaborative RDC+pull	0.012447082	0.090		-0.002383014	0.027277178
	Push based on partial information	0.018549867	0.304		-0.015764125	0.052863859
	Production based on partial global information	0.000399657	0.997		-0.002014856	0.00281417
	Production based on full global information	-0.000722019	0.473		-0.002148881	0.000704844
	Flexible Maintenance	-0.000825079	0.314		-0.002287905	0.000637747
Flexible Maintenance	Baseline	0.040983548	0.001	*	0.026794216	0.05517288
	Baseline with weekly Production Review	0.041025549	0.002	*	0.022934958	0.059116141
	Decentralised information structure	0.033372965	0.000	*	0.026330299	0.040415631
	Adjustable safety stock	0.026319932	0.003	*	0.013638402	0.039001462
	Collaborative RDC+pull	0.013272161	0.074		-0.001643465	0.028187787
	Push based on partial information	0.019374946	0.274		-0.014977459	0.053727351
	Production based on partial global information	0.001224736	0.408		-0.001304639	0.003754112
	Production based on full global information	0.00010306	0.999		-0.00061812	0.00082424
	Learning RDCs	0.000825079	0.314		-0.000637747	0.002287905

* denotes The mean difference is significant at the .05 level

Anova Test Results for Average Response Period

Dependent Variable: Average-Response
Games-Howell

(I) Strategy	(J) Strategy	Mean Difference (I-J)	Sig.		95% Confidence Interval Lower Bound	Upper Bound
Baseline	Baseline with weekly Production Review	0.02	1.00		-1.57	1.62
	Decentralised information structure	0.20	1.00		-1.38	1.78
	Adjustable safety stock	-1.31	0.12		-2.90	0.27
	Collaborative RDC+pull	-0.43	0.96		-1.94	1.09
	Push based on partial information	-1.91	0.86		-8.77	4.94
	Production based on partial global information	0.03	1.00		-1.72	1.78
	Production based on full global information	2.23	0.02	*	0.31	4.16
	Learning RDCs	1.63	0.10		-0.28	3.54
	Flexible Maintenance	2.23	0.02	*	0.31	4.16
Baseline with weekly Production Review	Baseline	-0.02	1.00		-1.62	1.57
	Decentralised information structure	0.18	1.00		-1.39	1.74
	Adjustable safety stock	-1.34	0.11		-2.91	0.24
	Collaborative RDC+pull	-0.45	0.94		-1.95	1.05
	Push based on partial information	-1.94	0.85		-8.79	4.92
	Production based on partial global information	0.01	1.00		-1.73	1.75
	Production based on full global information	2.21	0.02	*	0.30	4.13
	Learning RDCs	1.61	0.11		-0.29	3.51
	Flexible Maintenance	2.21	0.02	*	0.30	4.13
Decentralised information structure	Baseline	-0.20	1.00		-1.78	1.38
	Baseline with weekly Production Review	-0.18	1.00		-1.74	1.39
	Adjustable safety stock	-1.51	0.06		-3.07	0.05
	Collaborative RDC+pull	-0.62	0.74		-2.10	0.85
	Push based on partial information	-2.11	0.79		-8.97	4.75
	Production based on partial global information	-0.17	1.00		-1.89	1.56
	Production based on full global information	2.04	0.04	*	0.13	3.94
	Learning RDCs	1.44	0.17		-0.46	3.33
	Flexible Maintenance	2.04	0.04	*	0.13	3.94
Adjustable safety stock	Baseline	1.31	0.12		-0.27	2.90
	Baseline with weekly Production Review	1.34	0.11		-0.24	2.91
	Decentralised information structure	1.51	0.06		-0.05	3.07
	Collaborative RDC+pull	0.89	0.38		-0.60	2.38
	Push based on partial information	-0.60	1.00		-7.46	6.26
	Production based on partial global information	1.35	0.16		-0.39	3.08
	Production based on full global information	3.55	0.00	*	1.64	5.46
	Learning RDCs	2.95	0.00	*	1.05	4.85
	Flexible Maintenance	3.55	0.00	*	1.64	5.46
Collaborative RDC+pull	Baseline	0.43	0.96		-1.09	1.94
	Baseline with weekly Production Review	0.45	0.94		-1.05	1.95
	Decentralised information structure	0.62	0.74		-0.85	2.10
	Adjustable safety stock	-0.89	0.38		-2.38	0.60
	Push based on partial information	-1.49	0.95		-8.38	5.40
	Production based on partial global information	0.46	0.96		-1.22	2.14
	Production based on full global information	2.66	0.01	*	0.78	4.54
	Learning RDCs	2.06	0.03	*	0.20	3.92
	Flexible Maintenance	2.66	0.01	*	0.78	4.54

* denotes The mean difference is significant at the .05 level

Anova Test Results for Average Response Period

(I) Strategy	(J) Strategy	Mean Difference (I-J)	Sig.		95% Confidence Interval Lower Bound	Upper Bound
Push based on partial information	Baseline	1.91	0.86		-4.94	8.77
	Baseline with weekly Production Review	1.94	0.85		-4.92	8.79
	Decentralised information structure	2.11	0.79		-4.75	8.97
	Adjustable safety stock	0.60	1.00		-6.26	7.46
	Collaborative RDC+pull	1.49	0.95		-5.40	8.38
	Production based on partial global information	1.95	0.85		-4.86	8.75
	Production based on full global information	4.15	0.25		-2.61	10.91
	Learning RDCs	3.55	0.37		-3.21	10.31
	Flexible Maintenance	4.15	0.25		-2.61	10.91
Production based on partial global informatio	Baseline	-0.03	1.00		-1.78	1.72
	Baseline with weekly Production Review	-0.01	1.00		-1.75	1.73
	Decentralised information structure	0.17	1.00		-1.56	1.89
	Adjustable safety stock	-1.35	0.16		-3.08	0.39
	Collaborative RDC+pull	-0.46	0.96		-2.14	1.22
	Push based on partial information	-1.95	0.85		-8.75	4.86
	Production based on full global information	2.20	0.03	*	0.20	4.21
	Learning RDCs	1.60	0.14		-0.39	3.59
	Flexible Maintenance	2.20	0.03	*	0.20	4.21
Production based on full global information	Baseline	-2.23	0.02	*	-4.16	-0.31
	Baseline with weekly Production Review	-2.21	0.02	*	-4.13	-0.30
	Decentralised information structure	-2.04	0.04	*	-3.94	-0.13
	Adjustable safety stock	-3.55	0.00	*	-5.46	-1.64
	Collaborative RDC+pull	-2.66	0.01	*	-4.54	-0.78
	Push based on partial information	-4.15	0.25		-10.91	2.61
	Production based on partial global information	-2.20	0.03	*	-4.21	-0.20
	Learning RDCs	-0.60	0.95		-2.72	1.51
	Flexible Maintenance	0.00	1.00		-2.12	2.12
Learning RDCs	Baseline	-1.63	0.10		-3.54	0.28
	Baseline with weekly Production Review	-1.61	0.11		-3.51	0.29
	Decentralised information structure	-1.44	0.17		-3.33	0.46
	Adjustable safety stock	-2.95	0.00	*	-4.85	-1.05
	Collaborative RDC+pull	-2.06	0.03	*	-3.92	-0.20
	Push based on partial information	-3.55	0.37		-10.31	3.21
	Production based on partial global information	-1.60	0.14		-3.59	0.39
	Production based on full global information	0.60	0.95		-1.51	2.72
	Flexible Maintenance	0.60	0.95		-1.51	2.72
Flexible Maintenance	Baseline	-2.23	0.02	*	-4.16	-0.31
	Baseline with weekly Production Review	-2.21	0.02	*	-4.13	-0.30
	Decentralised information structure	-2.04	0.04	*	-3.94	-0.13
	Adjustable safety stock	-3.55	0.00	*	-5.46	-1.64
	Collaborative RDC+pull	-2.66	0.01	*	-4.54	-0.78
	Push based on partial information	-4.15	0.25		-10.91	2.61
	Production based on partial global information	-2.20	0.03	*	-4.21	-0.20
	Production based on full global information	0.00	1.00		-2.12	2.12
	Learning RDCs	-0.60	0.95		-2.72	1.51

* denotes The mean difference is significant at the .05 level

Anova Test Results for Average Run Length

Dependent Variable: Average Run-Length
Tukey HSD

(I) Strategy	(J) Strategy	Mean Difference (I-J)	Sig.		95% Confidence Interval Lower Bound	Upper Bound
Baseline	Baseline with weekly Production Review	-0.000446939	1.000		-0.723001507	0.72210763
	Decentralised information structure	0.003553061	1.000		-0.719001507	0.72610763
	Adjustable safety stock	-1.092446939	0.000	*	-1.815001507	-0.36989237
	Collaborative RDC+pull	-1.070446939	0.001	*	-1.793001507	-0.34789237
	Push based on partial information	0.525553061	0.333		-0.197001507	1.24810763
	Production based on partial global information	0.927553061	0.004	*	0.204998493	1.65010763
	Production based on full global information	-1.050446939	0.001	*	-1.773001507	-0.32789237
	Learning RDCs	-0.912446939	0.005	*	-1.635001507	-0.18989237
	Flexible Maintenance	-0.918446939	0.004	*	-1.641001507	-0.19589237
Baseline with weekly Production Review	Baseline	0.000446939	1.000		-0.72210763	0.723001507
	Decentralised information structure	0.004	1.000		-0.718554568	0.726554568
	Adjustable safety stock	-1.092	0.000	*	-1.814554568	-0.369445432
	Collaborative RDC+pull	-1.07	0.001	*	-1.792554568	-0.347445432
	Push based on partial information	0.526	0.332		-0.196554568	1.248554568
	Production based on partial global information	0.928	0.004	*	0.205445432	1.650554568
	Production based on full global information	-1.05	0.001	*	-1.772554568	-0.327445432
	Learning RDCs	-0.912	0.005	*	-1.634554568	-0.189445432
	Flexible Maintenance	-0.918	0.004	*	-1.640554568	-0.195445432
Decentralised information structure	Baseline	-0.003553061	1.000		-0.72610763	0.719001507
	Baseline with weekly Production Review	-0.004	1.000		-0.726554568	0.718554568
	Adjustable safety stock	-1.096	0.000	*	-1.818554568	-0.373445432
	Collaborative RDC+pull	-1.074	0.000	*	-1.796554568	-0.351445432
	Push based on partial information	0.522	0.342		-0.200554568	1.244554568
	Production based on partial global information	0.924	0.004	*	0.201445432	1.646554568
	Production based on full global information	-1.054	0.001	*	-1.776554568	-0.331445432
	Learning RDCs	-0.916	0.004	*	-1.638554568	-0.193445432
	Flexible Maintenance	-0.922	0.004	*	-1.644554568	-0.199445432
Adjustable safety stock	Baseline	1.092446939	0.000	*	0.36989237	1.815001507
	Baseline with weekly Production Review	1.092	0.000	*	0.369445432	1.814554568
	Decentralised information structure	1.096	0.000	*	0.373445432	1.818554568
	Collaborative RDC+pull	0.022	1.000		-0.700554568	0.744554568
	Push based on partial information	1.618	0.000	*	0.895445432	2.340554568
	Production based on partial global information	2.02	0.000	*	1.297445432	2.742554568
	Production based on full global information	0.042	1.000		-0.680554568	0.764554568
	Learning RDCs	0.18	0.998		-0.542554568	0.902554568
	Flexible Maintenance	0.174	0.998		-0.548554568	0.896554568
Collaborative RDC+pull	Baseline	1.070446939	0.001	*	0.34789237	1.793001507
	Baseline with weekly Production Review	1.07	0.001	*	0.347445432	1.792554568
	Decentralised information structure	1.074	0.000	*	0.351445432	1.796554568
	Adjustable safety stock	-0.022	1.000		-0.744554568	0.700554568
	Push based on partial information	1.596	0.000	*	0.873445432	2.318554568
	Production based on partial global information	1.998	0.000	*	1.275445432	2.720554568
	Production based on full global information	0.02	1.000		-0.702554568	0.742554568
	Learning RDCs	0.158	0.999		-0.564554568	0.880554568
	Flexible Maintenance	0.152	0.999		-0.570554568	0.874554568

* denotes The mean difference is significant at the .05 level

Anova Test Results for Average Run Length

Dependent Variable: Average Run-Length
Tukey HSD

(I) Strategy	(J) Strategy	Mean Difference (I-J)	Sig.		95% Confidence Interval Lower Bound	Upper Bound
Push based on partial information	Baseline	-0.525553061	0.333		-1.24810763	0.197001507
	Baseline with weekly Production Review	-0.526	0.332		-1.248554568	0.196554568
	Decentralised information structure	-0.522	0.342		-1.244554568	0.200554568
	Adjustable safety stock	-1.618	0.000	*	-2.340554568	-0.895445432
	Collaborative RDC+pull	-1.596	0.000	*	-2.318554568	-0.873445432
	Production based on partial global information	0.402	0.693		-0.320554568	1.124554568
	Production based on full global information	-1.576	0.000	*	-2.298554568	-0.853445432
	Learning RDCs	-1.438	0.000	*	-2.160554568	-0.715445432
	Flexible Maintenance	-1.444	0.000	*	-2.166554568	-0.721445432
Production based on partial global informatio	Baseline	-0.927553061	0.004	*	-1.65010763	-0.204998493
	Baseline with weekly Production Review	-0.928	0.004	*	-1.650554568	-0.205445432
	Decentralised information structure	-0.924	0.004	*	-1.646554568	-0.201445432
	Adjustable safety stock	-2.02	0.000	*	-2.742554568	-1.297445432
	Collaborative RDC+pull	-1.998	0.000	*	-2.720554568	-1.275445432
	Push based on partial information	-0.402	0.693		-1.124554568	0.320554568
	Production based on full global information	-1.978	0.000	*	-2.700554568	-1.255445432
	Learning RDCs	-1.84	0.000	*	-2.562554568	-1.117445432
	Flexible Maintenance	-1.846	0.000	*	-2.568554568	-1.123445432
Production based on full global information	Baseline	1.050446939	0.001	*	0.32789237	1.773001507
	Baseline with weekly Production Review	1.05	0.001	*	0.327445432	1.772554568
	Decentralised information structure	1.054	0.001	*	0.331445432	1.776554568
	Adjustable safety stock	-0.042	1.000		-0.764554568	0.680554568
	Collaborative RDC+pull	-0.02	1.000		-0.742554568	0.702554568
	Push based on partial information	1.576	0.000	*	0.853445432	2.298554568
	Production based on partial global information	1.978	0.000	*	1.255445432	2.700554568
	Learning RDCs	0.138	1.000		-0.584554568	0.860554568
	Flexible Maintenance	0.132	1.000		-0.590554568	0.854554568
Learning RDCs	Baseline	0.912446939	0.005	*	0.18989237	1.635001507
	Baseline with weekly Production Review	0.912	0.005	*	0.189445432	1.634554568
	Decentralised information structure	0.916	0.004	*	0.193445432	1.638554568
	Adjustable safety stock	-0.18	0.998		-0.902554568	0.542554568
	Collaborative RDC+pull	-0.158	0.999		-0.880554568	0.564554568
	Push based on partial information	1.438	0.000	*	0.715445432	2.160554568
	Production based on partial global information	1.84	0.000	*	1.117445432	2.562554568
	Production based on full global information	-0.138	1.000		-0.860554568	0.584554568
	Flexible Maintenance	-0.006	1.000		-0.728554568	0.716554568
Flexible Maintenance	Baseline	0.918446939	0.004	*	0.19589237	1.641001507
	Baseline with weekly Production Review	0.918	0.004	*	0.195445432	1.640554568
	Decentralised information structure	0.922	0.004	*	0.199445432	1.644554568
	Adjustable safety stock	-0.174	0.998		-0.896554568	0.548554568
	Collaborative RDC+pull	-0.152	0.999		-0.874554568	0.570554568
	Push based on partial information	1.444	0.000	*	0.721445432	2.166554568
	Production based on partial global information	1.846	0.000	*	1.123445432	2.568554568
	Production based on full global information	-0.132	1.000		-0.854554568	0.590554568
	Learning RDCs	0.006	1.000		-0.716554568	0.728554568

* denotes The mean difference is significant at the .05 level

Appendix E

Table 1: Average Inventory for the Baseline Model

Replication	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
Average Inventory at Koblenz												
1	12770.76	11040.68	2370.975	2557.537	22265.63	10070.63	15471.93	5348.403	4109.591	23839.89	11019.56	6628.681
2	9773.142	10995.27	1956.272	731.4741	45755.29	17088.05	15644.84	1689.744	2838.458	9092.474	9754.169	5318.302
3	14839.01	6902.322	3145.526	720.3134	17787.05	5968.997	17553.4	3191.738	3341.379	16892.17	17539.19	14835.14
4	17525.95	7109.91	3367.52	730.6022	19983.04	14419.76	19142.63	3151.324	3794.714	19015.87	15474.06	15369.51
5	17790.63	7024.793	2696.67	728.0736	18056.63	12848.98	20333.1	3421.275	3552.67	17771.54	15300.72	15266.62
Average Inventory at UK												
1	467.7221	0	0	0	222.1526	265.6567	660.5559	0	0	841.8719	52.83651	294.3951
2	546.4305	0	0	0	251.0654	353.7657	612.3106	0	0	767.4332	51.29155	341.1008
3	522.0109	0	0	0	253.3924	264.4469	583.9155	0	0	789.4251	53.91826	341.5395
4	500.0845	0	0	0	231.4714	270.8147	559.1907	0	0	785.2643	45.92371	373.6049
5	489.891	0	0	0	232.2016	270.1444	578.0763	0	0	745.0109	50.10082	296.9891
Average Inventory at Russia												
1	376.1035	0	0	0	66.6049	63.88556	153.2343	0	0	465.8556	41.68937	42.22616
2	353.0409	0	0	0	68.58038	73.58856	156.049	0	0	468.327	41.05177	41.13896
3	422.7793	0	0	0	74.20981	77.22071	145.8856	0	0	459.4114	39.34332	42.6921
4	402.9864	0	0	0	65.77384	62.89646	146.5041	0	0	448.1063	45.12534	43.11172
5	369.2943	0	0	0	60.48501	69.07902	152.6567	0	0	469.5586	38.55586	42.6158
Average Inventory at Neiderbipp												
1	31.74114	0	201.3433	50.90463	106.5531	0	118.8147	0	0	44.44959	110.3597	29.95913
2	31.79019	0	181.5913	34.71935	86.58856	0	66.68937	0	0	23.94823	90.88828	26.27793
3	34.31335	0	186.436	32.88283	86.70027	0	65.95368	0	0	25.74114	91.72752	24.40872
4	34.61308	0	193.9155	34.74114	95.90463	0	58.56948	0	0	23.297	99.6703	25.78474
5	38.96458	0	182.6894	32.60218	84.3624	0	58.61035	0	0	26.55041	94.08174	24.04087
		0										
Average Inventory at Italy												
1	247.0599	0	0	0	758.1281	0	720.4986	0	0	0	1359.943	0
2	257.3896	0	0	0	720.3243	0	702.2997	0	0	0	1189.401	0
3	253.8638	0	0	0	742.0518	0	710.97	0	0	0	1076.766	0
4	245.248	0	0	0	660.2125	0	708.3678	0	0	0	1111.54	0
5	235.7766	0	0	0	671.3842	0	817.9564	0	0	0	1242.967	0
Average Inventory at France												
1	558.139	64.08447	0	0	311.7112	33.95368	1439.48	0	0	145.1798	430.1199	22.3406
2	560.515	59.34605	0	0	293.9973	33.01635	1431.251	0	0	161.733	360.9482	24.14986
3	554.9428	58.85831	0	0	309.4169	33.3733	1421.858	0	0	169.1635	387.0163	21.60218
4	537.9946	60.14441	0	0	278.0845	35.01907	1407.046	0	0	151	380.9264	22.58311
5	555.6512	58.02452	0	0	286.2916	32.59401	1441.801	0	0	148.8747	386.2343	20.43324
Average Inventory at Ede												
1	0	0	0	0	0	0	0	1431.812	530.5858	0	0	0
2	0	0	0	0	0	0	0	929.92	468.92	0	0	0
3	0	0	0	0	0	0	0	961.9292	391.9782	0	0	0
4	0	0	0	0	0	0	0	658.7275	403.812	0	0	0
5								923.9537	349.4142			
Average Inventory at Czech												
1	259.8937	0	0	0	37.83379	0	112.1499	0	0	143.4469	44.81199	18.45504
2	243.7684	0	0	0	39.53951	0	114.1117	0	0	142.921	47.19074	15.40054
3	252.2207	0	0	0	37.3842	0	110.5422	0	0	138.9564	44.33787	16.3842
4	268.1826	0	0	0	36.82016	0	109.4114	0	0	145.5695	45.06812	14.78202
5	260.327	0	0	0	37.02452	0	113.4087	0	0	140.4332	45.98365	15.17984
Average Inventory at Arceniega												
1	72.44687	0	0	0	128.7929	142.346	73.58038	0	0	280.3787	54.01907	110.842
2	73.47684	0	0	0	139.7984	162.7112	71.61035	0	0	299.5749	54.28065	104.2316
3	75.0545	0	0	0	131.9264	147.5886	70.68392	0	0	288.4278	61.70027	139.515
4	72.86104	0	0	0	122.7602	151.8719	70.08719	0	0	275.5531	62.97003	106.1717
5	72.31335	0	0	0	127.3951	162.733	71.52316	0	0	270.8256	64.36512	112.5831

Table 2: Average Inventory for the Baseline Model with weekly production plan review

Replication												
Average Inventory at Koblenz												
	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1	15373.15	5644.932	2374.256	3190.354	13503.21	18510.24	15514.77	7637.297	3035.624	23808.26	14185.82	5804.61
2	10495.62	5456.439	2582.757	731.4741	17380.59	15088.31	17831.54	1886.91	2921.738	37076.21	16197.95	7184.812
3	14637	6557.951	3165.586	720.3134	15739.46	6320.51	18441.92	3852.883	4813.946	18494.74	13738.52	15126.92
4	18408.39	7110.302	3384.42	730.6022	14616.82	15720.64	19964.19	2781.515	3992.763	18511.18	19114.12	17334.75
5	11402.45	7052.978	2578.436	728.0736	20083.06	12767.79	19616.07	3349.275	3854.452	18245.59	17892.12	16292.68
Average Inventory at UK												
1	469.2534				222.1526	268.436	660.5559			841.8719	52.83651	353.5913
2	546.4305				251.0654	249.9264	612.3106			767.4332	51.29155	348.3161
3	522.0109	0	0	0	253.3924	267.3896	583.9155	0	0	789.4251	53.97003	354.327
4	500.0845	0	0	0	231.4714	270.8147	559.1907	0	0	785.2643	45.92371	297.2807
5	489.891	0	0	0	232.2016	263.2779	578.0763	0	0	745.0109	50.08174	370.9837
Average Inventory at Russia												
1	375.515				66.6049	63.88556	153.2343			465.8556	41.68937	40.74387
2	353.0409				68.58038	73.58856	156.049			468.327	42.70845	41.13896
3	422.7793	0	0	0	74.20981	77.22071	145.8856	0	0	459.4114	39.34332	44.95913
4	402.9864	0	0	0	65.77384	62.89646	146.5041	0	0	448.1063	45.12534	42.85014
5	369.2943	0	0	0	60.48501	69.07902	152.6567	0	0	469.5586	38.55586	42.52861
Average Inventory at Neiderbipp												
1	31.74114		196.9292	66.84469	106.5531		118.8147			44.44959	110.3597	31.19074
2	31.79019		181.5913	34.71935	86.58856		66.68937			23.94823	91.3951	26.27793
3	34.31335	0	192.0681	32.88283	86.70027	0	65.95368	0	0	25.74114	91.72752	26.15259
4	34.61308	0	180.0545	34.74114	95.90463	0	58.56948	0	0	23.297	99.6703	25.33243
5	38.96458	0	182.6894	32.60218	84.3624	0	58.61035	0	0	26.55041	93.90736	24.93733
Average Inventory at Italy												
1	244.327				758.1281		720.4986				1225.038	
2	257.3896				720.3243		702.2997				1160.183	
3	253.8638	0	0	0	742.0518	0	710.97	0	0	0	1089.074	0
4	245.248	0	0	0	660.2125	0	708.3678	0	0	0	1111.54	0
5	235.7766	0	0	0	671.3842	0	817.9564	0	0	0	1236.82	
Average Inventory at France												
1	557.7466	64.08447			311.7112	33.95368	1439.48			145.1798	427.8965	22.21526
2	560.515	59.34			293.9973	33.01635	1431.251			161.733	360.9482	23.56131
3	554.9428	58.85831	0	0	309.4169	33.3733	1421.858	0	0	169.1635	386.951	22.41962
4	537.9946	60.14441	0	0	278.0845	35.01907	1407.046	0	0	151	380.9264	22.12807
5	555.6512	58.02452	0	0	286.2916	32.59401	1441.801	0	0	148.8747	385.9728	20.51226
Average Inventory at Ede												
1								1232.779	470.752			
2								1044.49	457.1499			
3								705.9074	431.9864			
4								1148.351	398.9918			
5								894.9183	350.6076			
Average Inventory at Czech												
1	259.8937				37.83379	0	112.1499			143.4469	44.89918	18.31063
2	243.7684				39.53951	0	114.1117			142.921	47.01635	15.92098
3	252.2207	0	0	0	37.3842	0	110.5422	0	0	138.9564	44.33787	17.07357
4	268.1826	0	0	0	36.82016	0	109.4114	0	0	145.5695	45.06812	13.70027
5	260.327	0	0	0	37.02452	0	113.4087	0	0	140.4332	46.94278	15.31063
Average Inventory at Arceniega												
1	72.44687				128.7929	142.6158	73.58038			280.3787	54.01907	150.5559
2	73.47684				139.7984	160.6757	71.61035			299.5749	54.60763	107.1253
3	75.0545	0	0	0	131.9264	148.218	70.68392	0	0	288.4278	61.70027	126.2371
4	72.86104	0	0	0	122.7602	151.8719	70.08719	0	0	275.5531	62.97003	104.7684
5	72.31335	0	0	0	127.3951	161.2698	71.52316	0	0	270.8256	64.36512	133.7057

Table 3: Average Inventory for the Model with decentralised informational structure

Replication	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
Average Inventory at Koblenz												
1	13194.54	11179.32	3797.401	4802.537	14292.95	9306.185	24069.46	7266.507	6536.06	14419.99	11550.5	10292.85
2	14020.23	11031.37	5180.027	4970.559	14222.79	10044.71	24267.86	5549.689	10151.41	14504.05	11709.75	10920.56
3	12769.62	11042.09	3501.553	3436.738	13773.59	9107.305	19716.15	7258.463	10432.15	13679.25	11124.16	9326.973
4	14229.97	11937.83	4971.379	5292.564	13910.03	9856.417	21573.84	12599.02	10382.27	15542.16	11474.02	9591.431
5	13515.3	11598.66	4731.33	4260.193	15388.77	9859.12	21400	9423.564	7999.504	14004.69	12892.23	8508.243
	13545.93	11357.85	4436.338	4552.518	14317.63	9634.748	22205.46	8419.449	9100.28	14430.03	11750.13	9728.012
Average Inventory at UK												
1	466.5777				222.1526	269.5804	660.5559			841.8719	52.83651	296.5177
2	546.4305				251.0654	246.0027	612.3106			767.4332	51.29155	339.6757
3	522.0109	0	0	0	253.3924	263.3025	583.9155	0	0	789.4251	53.98638	338.6376
4	500.0845				231.4714	352.1907	559.1907			785.2643	45.92371	307.6594
5	489.891				232.2016	369.7875	578.0763			745.0109	50.10082	308.2289
Average Inventory at Russia												
1	376.1035				66.6049	63.88556	153.2343			465.8556	41.68937	42.22616
2	353.0409				68.58038	73.58856	156.049			468.327	42.88283	41.13896
3	422.7793	0	0	0	74.20981	77.22071	145.8856	0	0	459.4114	39.34332	44.95913
4	402.9864				65.77384	62.89646	146.5041			448.1063	45.12534	43.11172
5	369.2943				60.48501	69.07902	152.6567			469.5586	38.55586	42.87738
Av Inv Neiderbipp												
1	31.74114		201.8392	54.42507	106.5531		118.8147			44.44959	110.3597	31.29973
2	31.79019		212.3515	34.71935	86.58856		66.68937			23.94823	34.76567	26.27793
3	34.31335	0	200.6104	32.88283	86.70027	0	65.88011	0	0	25.74114	91.72752	25.01907
4	34.61308		200.1335	34.74114	95.90463		58.56948			23.297	99.58311	25.9564
5	38.96458	0	182.6894	32.60218	84.3624	0	58.61035	0	0	26.55041	94.08174	25.14441
Av Inv Italy												
1	247.0599				758.1281	0	720.4986				1224.411	0
2	257.3896				720.3243		702.2997				1153.932	
3	253.8638	0	0	0	742.0518	0	710.97	0	0	0	1089.095	0
4	245.248	0	0	0	660.2125	0	708.3678	0	0	0	1073.414	0
5	235.7766				671.3842		817.9564				1244.292	
Av Inv France												
1	558.139	64.08447	0	0	311.7112	33.95368	1439.48	0	0	145.1798	427.8965	22.79837
2	560.515	59.34605	0	0	293.9973	33.01635	1431.251	0	0	161.733	361.3406	23.56131
3	554.9428	58.85831	0	0	309.4169	33.3733	1421.858	0	0	169.1635	387.0163	22.74659
4	537.9946	60.14			278.0845	35.01907	1407.046			151	380.9264	22.84469
5	555.6512	58.02452			286.2916	32.59401	1441.801			148.8747	386.7575	22.39237
Av Inv Ede												
1								1553	494			
2								505.6866	470.3079			
3								1069.635	450.6975			
4								1173.659	444.1526			
5								974.1771	483.1635			
Av Inv Czech												
1	259.8937				37.83379	0	112.1499	0	0	143.4469	44.89918	18.55586
2	243.7684				39.53951		114.1117			142.921	47.01635	15.92098
3	252.2207	0	0	0	37.3842	0	110.5422	0	0	138.9564	44.33787	17.50954
4	268.1826	0	0	0	36.82016	0	109.4114	0	0	145.5695	45.06812	15.3406
5	260.327				37.02452		113.4087			140.4332	45.98365	15.78747
Av Inv Arceniega												
1	72.44687				128.7929	142.2725	73.58038	0	0	280.3787	54.01907	108.733
2	73.47684				139.7984	159.327	71.61035			299.5749	54.67302	107.049
3	75.0545				131.9264	147.4959	70.55313			288.4278	61.70027	105.9782
4	72.86104				122.7602	152.5559	70.08719			275.5531	62.97003	104.7575
5	72.31335				127.3951	172.2343	71.52316			270.8256	64.36512	107.1417

Table 4: Average Inventory for the Model with adjustable safety stock

Replication	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
Average Inventory at Koblenz												
1	11376.36	4885.804	3525.183	2398.7	12101.63	5029.436	18270.99	5176.545	7804.986	12578.53	9273.875	7890.796
2	13441.5	5661.06	3509.313	1910.068	12761.54	9299.583	18070.54	6305.199	11472.87	12789.13	9373.319	7465.343
3	10471.75	4519.259	2809.935	2228.499	10676.79	6841.076	16473.48	5968.937	8663.248	12030.89	9595.668	6683.052
4	12345.71	4188.253	3897.586	2569.687	14371.42	8347.191	19839.74	7244.73	9014.174	14200.6	10327.24	7631.877
5	11883.93	4338.362	3794.872	1943.463	13060.81	9919.39	18460.4	5617.766	11085.16	13140.58	10184.26	7315.398
	11903.85	4718.548	3507.378	2210.083	12594.44	7887.335	18223.03	6062.635	9608.086	12947.95	9750.874	7397.293
Average Inventory at UK												
1	1251.262				402.9946	345.3787	967.1008			1316.926	78.23706	555.5095
2	1057.447				364.1798	342.6185	1076.804			1561.038	76.26158	472.3188
3	1102.161				407.8229	321.4469	974.2098			1383.166	81.76567	501.8801
4	1170.183	0	0	0	406.5422	408.7984	824.7602	0	0	1239.894	90.19346	517.7956
5	1124.327	0	0	0	415.455	382.5831	885.2044	0	0	1395.447	87.70572	533.0218
Average Inventory at Russia												
1	651.9401				115.5313	125.6921	230.4877			808.1771	52.73025	56.87466
2	604.5368				197.8011	130.2807	206.1063			978.4087	64.82561	62.32698
3	611.1526				139.9074	171.3951	238.2643			810.267	58.20436	61.43869
4	522.4605		0	0	98.83379	110.1662	199.3569	0	0	858.9237	52.44959	54.09809
5	583.4741		0	0	116.5995	143.2779	222.1199	0	0	743.5286	59.88011	53.16621
Av Inv Neiderbipp												
1	27.14986		114.7984	17.9455	85.28883		44.12807			60.02997	88.31335	32.89646
2	27.02997		104.376	33.49864	77.82561		63.89646			31.09809	112.139	31.297
3	28.82289		124.4905	28.34877	86.96185		62.29155			27.83379	118.9183	32.65668
4	29.0218	0	114.9646	32.03815	97.47411	0	62.67575	0	0	27.65668	111.2616	28.49591
5	27.04632	0	122.2888	30.77112	85.93188	0	68.90191	0	0	29.42779	114.0463	29.6921
Av Inv Italy												
1	221.8719				753.3406		571.6076				1053.177	
2	220.485				630.3161		531.4959				1185.346	
3	280.6594				794.376		661.4768				1154.793	
4	247.5531	0	0	0	671.0191	0	625.436	0	0	0	1201.3	
5	236.3651	0	0	0	718.7629	0	639.2316	0	0	0	1239.627	0
Av Inv France												
1	561.0763	80.13896			297.9728	47.33787	1133.668			241.8283	448.3052	31.15259
2	519.2561	66.54768			272.6076	46.40054	1142.989			232.6866	294.1117	30.09809
3	518.1335	63.64			332.2589	56.92916	1292.049			238.158	444.3569	31.90191
4	522.8011	55.55041	0	0	315.8365	37.42507	1223.932	0	0	230.5531	440.3515	30.48774
5	510.7193	62.86104	0	0	315.0163	41.99455	1151.779	0	0	231.0054	434.248	31.08992
Av Inv Ede												
1								757.6594	675.7302			
2								687.9864	672.1417			
3								697.7902	524.03			
4								687.5204	674.703			
5								725.8038	528.188			
Av Inv Czech												
1	275.6049				69.45232	0	96.50681			150.5858	45.80926	28.57221
2	252.9019				75.48774	0	103.8229			139.4578	38.65123	24.83651
3	257.3597				66.76839	0	106.4169			136.9292	37.0654	31.35695
4	275.2534	0	0	0	68.13079	0	107.0054	0	0	138.9046	37.56131	30.09537
5	265.6104	0	0	0	78.88011	0	106.8883	0	0	147.3597	39.45504	29.44687
Av Inv Arceniega												
1	116.4578				359.6866	305.5395	233.2752			426.97	64.64033	209.6376
2	103.1226				422.8365	326.6158	184.5477			427.8801	71.21798	204.2834
3	109.7793				395.1035	354.8474	212.5913			470.1935	71.80381	219.4387
4	111.8365	0	0	0	414.2371	331.9809	221.5422	0	0	427.7193	76.29155	223.4496
5	99.83106	0	0	0	366.6757	414.2507	251.1635	0	0	402.4659	66.64033	214.9946

Table 5: Average Inventory for the Model with collaborative RDCs

Replication	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
Average Inventory at Koblenz												
1	9371.03	3525.471	3581.335	1403.719	7833.651	7491.101	15620.34	4809.875	6962.616	9836.082	8868.708	6469.749
2	12905.94	6497.384	3492.921	1579.518	11698.78	5757.371	20412.8	4847.15	10758.65	14483.08	11955.96	6664.978
3	8792.063	3107.946	4032.823	1033.163	8142.406	5404.172	11651.27	5102.387	6123.041	10739.65	8724.749	6644.512
4	10255.87	4719.174	3265.782	1022.526	12382.5	8575.202	14794.74	3914.877	12432.07	11623.9	11529.19	6533.883
5	10532.31	5118.569	2959.21	2318.482	9580.73	7817.384	12539.27	4745.526	9291.237	12585.1	10163.94	6133.349
Average Inventory at UK												
1	1037.635	0	0	0	483.3924	791.7112	1285.436	0	0	1377.52	184.6131	985.9401
2	1085.861	0	0	0	487.9373	875.3951	1617.888	0	0	1438.003	223.5586	1042.311
3	1251.46	0	0	0	594.5886	723.8719	1497.349	0	0	1408.414	211.1172	1252.471
4	1105.736	0	0	0	498.3896	556.5259	1253.651	0	0	1469.817	185.3651	1061.831
5	1064.801	0	0	0	476.2888	747.3025	1209.485	0	0	1293.768	191.515	1114.534
Average Inventory at Russia												
1	1293.662		0	0	255.5858	188.9074	441.2343	0	0	1246.935	87.04632	73.44142
2	1304.624		0	0	285.3297	253.485	446.8392	0	0	1293.351	100.5749	67.3842
3	1452.101		0	0	345.8311	200.2561	574.0463	0	0	1387.392	89.6812	83.32425
4	1511.014		0	0	291.8719	178.9155	362.9319	0	0	1293.67	89.45777	66.65395
5	1254.624		0	0	212.8229	200.1281	369.4768	0	0	1199.112	99.72752	99.9891
Av Inv Neiderbipp												
1	138.0409	0	390.8856	353.7793	405.8501	0	732.812	0	0	575.9264	834.4986	200.2888
2	143.5804	0	407.8529	52.15804	120.3324	0	193.1144	0	0	34.58583	276.0654	38.58583
3	121.0763	0	508.5722	48.0545	129.5995	0	210.6431	0	0	31.84469	304.3787	36.88283
4	137.9755	0	838.0245	52.44142	125.9864	0	165.2616	0	0	37.59673	365.2943	35.03542
5	130.7302	0	498.1853	49.25613	124.2534	0	162.8965	0	0	31.60763	332.9019	37.6267
Av Inv Italy												
1	402.1117	0	0	0	1462.251	0	1275.025	0	0	0	2486.817	
2	431.9292	0	0	0	1163.507	0	2812.03	0	0	0	2725.61	0
3	476.8365	0	0	0	1289.997	0	1839.695	0	0	0	2631.896	0
4	400.1689	0	0	0	1088.877	0	1677.94	0	0	0	2185.319	0
5	410.4469	0	0	0	1101.619	0	2013.681	0	0	0	3274.463	0
Av Inv France												
1	968.4741	167.1035	0	0	558.7084	102.1362	2566.172	0	0	489.9373	809.8038	52.79837
2	899.1962	113.0845	0	0	446.7275	96.42779	2750.728	0	0	621.6076	523.0736	54.10082
3	970.0054	148.1471	0	0	519.8311	145.1471	2847.864	0	0	608.7084	783.8338	58.05995
4	885.6349	122.3243	0	0	437.9755	103.0163	2952.398	0	0	546.7956	740.5341	58.28065
5	842.9319	154.7057	0	0	446.2807	106.4741	2711.512	0	0	540.4959	797.5041	58.94823
Av Inv Ede												
1								824.4387	1236.243			
2								1237.392	1024.91			
3	0	0	0	0	0	0	0	1003.488	945.436	0	0	0
4	0	0	0	0	0	0	0	1479.556	1333.044	0	0	0
5	0	0	0	0	0	0	0	933.3079	1379.85	0	0	0
Av Inv Czech												
1	286.5858	0	0	0	94.30245	0	225.0654	0	0	186.1717	74.80654	75.19619
2	266.5095	0	0	0	92.09809	0	236.1798	0	0	177.5068	70.09809	68.56948
3	273.9455	0	0	0	90.00272	0	230.4305	0	0	192.3025	70.84469	62.75749
4	297.4169	0	0	0	93.55041	0	238.4578	0	0	192.218	70.18801	75.37602
5	287.2807	0	0	0	92.92371	0	235.3052	0	0	185.7248	76.91008	67.78202
Av Inv Arceniega												
1	119.6458	0	0	0	418.346	368.8828	179.9782	0	0	598.7984	90.9673	213.6812
2	126.7302	0	0	0	396.6921	428.6703	180.6894	0	0	904.8937	83.51226	211.3842
3	123.97	0	0	0	406.436	394.0627	186.0409	0	0	576.7875	104.5804	240.5613
4	137.079	0	0	0	497.3215	346.0354	179.624	0	0	492.9183	89.50136	195.1335
5	129.4033	0	0	0	394.564	591.1008	172.951	0	0	472.3079	148.8965	191.9755

Table 6: Average Inventory for model with push based replenishment by collaborative RDCs

Replication	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
Average Inventory at Koblenz												
1	4652.823	1468.243	1451.112	2100.15	5172.597	2747.798	6171.771	2553.155	3062.109	6749.074	7017.379	2933.526
2	5780.725	1915.828	1901.815	2232.684	4819.341	5153.777	8544.485	5439.237	2641.439	6467.39	5909.12	2752.046
3	4297.736	1380.853	1815.341	2374.373	4711.67	3343.692	5887.733	5128.283	11039.1	6691.932	4444.422	2493.185
4	6990.218	1540.572	3263.117	2105.033	7673.428	3936.063	7931.136	3387.924	7313.542	8251.005	6070.463	3575.3
5	5727.294	1799.594	1360.082	2214.373	6594.48	2827.39	9152.275	5366.649	3291.646	7173.785	5762.959	2682.466
Average Inventory at UK												
1	1215.18	0	0	0	475.3896	791.7112	1261.24	0	0	1559.809	2275.785	3142.425
2	1742.673	0	0	0	458.2153	2338.837	1718.025	0	0	1408.003	221.1771	2405.063
3	1269.232	0	0	0	591.7439	721.1744	1494.469	0	0	1415.035	210.7902	1710.507
4	2219.779	0	0	0	498.1935	598.951	1597.875	0	0	2102.678	1952.668	2136.681
5	1680.665	0	0	0	502.2698	875.9673	1381.147	0	0	1480.39	905.7929	2204.708
Average Inventory at Russia												
1	1647.384		0	0	255.5858	3881.638	432.1662	0	0	2127.85	87.04632	931.1635
2	1521.899		0	0	285.3297	3291.218	459.3951	0	0	1442.452	100.4877	3062.392
3	1447.392		0	0	345.8311	200.2561	574.7439	0	0	1518.183	89.94278	3239.64
4	2745.608		0	0	291.218	156.9428	779.7166	0	0	2570.88	89.45777	445.5095
5	2157.076		0	0	214.654	437.9918	370.6975	0	0	2248.223	99.72752	567.9564
Av Inv Neiderbipp												
1	143.6213	0	1210.796	1535.204	394.079	0	732.812	0	0	627.109	1141.943	1132.038
2	2586.676	0	1333.711	739.9401	120.2016	0	192.5913	0	0	47.66485	284.4087	75.55586
3	635.9646	0	920.4114	721.5368	129.2071	0	205.0627	0	0	31.84469	301.0654	179.6785
4	845.3215	0	1596.093	738.7411	125.9864	0	351.2452	0	0	37.50954	1281.436	263.8311
5	528.2997	0	1523.406	737.2997	124.2534	0	161.327	0	0	114.3542	370.5695	441.594
Av Inv Italy												
1	477.97	0	0	0	1461.956	0	1241.346	0	0	0	2527.559	0
2	2323.678	0	0	0	1084.052	0	2159.649	0	0	0	2794.245	0
3	475.267	0	0	0	1293.431	0	1839.695	0	0	0	2698.403	0
4	940.921	0	0	0	1088.583	0	1677.94	0	0	0	2270.005	0
5	1338.926	0	0	0	1106.425	0	2016.886	0	0	0	3181.995	0
Av Inv France												
1	1330.839	793.5777	0	0	550.0763	102.1362	2551.065	0	0	1595.768	1740.049	355.9046
2	1395.545	574.8283	0	0	420.733	892.8093	2752.886	0	0	532.8011	1975.202	3574.515
3	965.297	1001.068	0	0	518.4578	145.1471	2847.275	0	0	597.5913	790.5695	157.8529
4	3210.692	308.6785	0	0	437.8774	247.0163	3015.308	0	0	538.5559	804.4905	2131.044
5	1187.433	849.921	0	0	470.1172	810.8447	3366.313	0	0	646.9591	844	916.8011
Av Inv Ede												
1								3172.777	3579.354			
2								3553.033	8690.932			
3								3722.937	4196.504			
4								3369.711	3382.016			
5								5425.362	5804.54			
Av Inv Czech												
1	337.2016	0	0	0	92.07902	0	225.0654	0	0	186.1717	1408.431	2680.188
2	490.951	0	0	0	88.56676	0	235.7439	0	0	505.703	119.2725	668.1117
3	273.5531	0	0	0	87.6485	0	229.8202	0	0	211.8338	70.84469	1805.793
4	683.2153	0	0	0	105.1907	0	238.3706	0	0	1156.665	151.0163	777.0218
5	1501.275	0	0	0	91.48501	0	716.7003	0	0	189.9973	213.8038	1504.033
Av Inv Arceniega												
1	853.6403	0	0	0	382.4441	2034.234	178.3542	0	0	566.2616	1042.662	5128.46
2	1210.327	0	0	0	401.9891	2013.259	455.8719	0	0	916.5014	426.0518	725.5204
3	1796.384	0	0	0	374.8992	725.6158	178.5204	0	0	856.8093	1304.515	1542.512
4	1428.632	0	0	0	498.4986	1633.142	363.9074	0	0	543.9428	160.782	2896.605
5	264.0518	0	0	0	503.4469	720.7793	735.8065	0	0	6878.913	448.7984	2639.583

Table 7 Average Inventory for partial global information based production

Replication

Average Inventory at Koblenz

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1	9536.534	7497.183	591.1226	631.376	12475.85	10023.45	11649.13	178.921	1863.515	10610.86	10033.53	9245.755
2	10412.44	8396.537	478.2071	451.1471	11977.28	11102.39	12839	1409.591	598.8556	11419.08	10903.78	9885.213
3	8364.499	6536.741	500.9646	422.4605	10227.57	8348.354	10547.43	2103.695	663.7439	11775.3	10050.26	8177.54
4	11397.92	8383.757	244.5286	448.0082	13312.81	12466.21	11605.92	264.8501	439.2098	13247.74	13332.61	11089.03
5	10583.2	8166.744	244.0054	448.0082	11954.65	10386.36	11426.52	101.624	594.8828	11353.36	11763.22	10431.73

Average Inventory at UK

1	3270.362	0	0	0	1612.537	952.0109	2556.253	0	0	3068.738	312.1853	3691.09
2	3661.962	0	0	0	1064.97	3077.411	3334.673	0	0	4527.823	392.188	3995.861
3	2998.676	0	0	0	1495.275	1261.174	2288.057	0	0	3879.123	307.3297	4788.796
4	3980.379	0	0	0	1120.787	1107.643	2665.123	0	0	3911.747	399.3706	3756.935
5	4352.651	0	0	0	1716.466	1325.722	3123.67	0	0	3948.319	340.861	4246.542

Average Inventory at Russia

1	1253.15		0	0	255.5858	188.9074	492.4169	0	0	1375.807	86.87193	73.703
2	1298.052		0	0	285.3297	254.7057	436.1144	0	0	1334.071	103.8011	67.3842
3	1435.719		0	0	345.8311	200.8665	573.7847	0	0	1392.45	89.85559	86.81199
4	1547.896		0	0	291.8719	179.1771	362.4087	0	0	1375.807	89.19619	66.65395
5	1242.657		0	0	215.0463	200.7384	365.9019	0	0	1237.913	99.9891	135.7384

Av Inv Neiderbipp

1	144.406	0	1020.016	578.2807	407.4196	0	729.3243	0	0	575.9264	832.7984	202.6431
2	143.4823	0	902.5559	314	120.3324	0	197.4741	0	0	34.58583	317.9782	64.04632
3	120.3896	0	728.5395	331.346	137.8392	0	206.9809	0	0	31.84469	324.2589	60.2752
4	128.0328	0	792.4863	312.9208	132.7541	0	168.9016	0	0	31.56557	350.6475	77.24863
5	127.7875	0	855.3297	312.1444	130.2698	0	158.8856	0	0	31.60763	353.1308	77.03815

Av Inv Italy

1	440.4332	0	0	0	1626.948	0	1353.172	0	0	0	2620.681	0
2	492.5504	0	0	0	1250.809	0	2918.951	0	0	0	3374.234	0
3	643.5286	0	0	0	1463.817	0	1975.847	0	0	0	2815.199	0
4	722.3052	0	0	0	1213.847	0	1749.809	0	0	0	3696.469	0
5	640.6376	0	0	0	1970.719	0	3016.646	0	0	0	4017.09	0

Av Inv France

1	1061.379	741.703	0	0	677.2044	102.1362	2666.292	0	0	561.8065	1253.64	93.08174
2	973.4196	640.812	0	0	589.2561	99.10899	2676.177	0	0	699.5586	587.9101	89.74114
3	1147.88	728.8283	0	0	686.5886	145.6049	2895.144	0	0	688.6213	1092.433	91.08447
4	1296.381	796.4823	0	0	593.6485	103.3433	2954.36	0	0	689.7493	1048.087	95.62125
5	1208.883	767.7193	0	0	677.3869	106.9319	2659.916	0	0	627.406	1222.327	92.75749

Av Inv Ede

1								4430.052	4425.774			
2	0	0	0	0	0	0	0	3549.831	8152.55	0	0	0
3	0	0	0	0	0	0	0	3697.191	8050.03	0	0	0
4								6965.395	4621.97			
5	0	0	0	0	0	0	0	2147.891	1563.591	0	0	0

Av Inv Czech

1	313.5613	0	0	0	136.6785	0	227.158	0	0	323.5014	192.0817	187.7629
2	329.8774	0	0	0	164.8174	0	274.6866	0	0	298.4441	128.8038	130.3787
3	296.1144	0	0	0	170.1771	0	293.297	0	0	372.0954	76.77384	131.267
4	368.8283	0	0	0	163.2616	0	301.4114	0	0	325.8856	82.56948	128.6512
5	339.1717	0	0	0	175.9755	0	264.7766	0	0	252.3406	138.0954	122.3651

Av Inv Arceniega

1	143.5967	0	0	0	343.5014	525.1117	221.4387	0	0	814.0436	106.139	810.0954
2	155.6839	0	0	0	408.8556	603.346	288.9837	0	0	791.8256	112.7439	873.8719
3	187.6866	0	0	0	487.9019	541.8556	270.0082	0	0	792.1335	120.5368	821.139
4	183.0518	0	0	0	465.3433	644.9755	227.1008	0	0	843.3052	170.4605	839.3406
5	137.3188	0	0	0	534.4441	787.327	267.4142	0	0	1011.322	166.6185	794.4605

Table 8: Average Inventory for full global information based production with fixed maintenance

Replication	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
Average Inventory at Koblenz												
1	12589.06	5165.717	91.53678	73.84741	19302.09	7720.975	14146.34	133.406	388.8883	21958.77	15121.73	6152.327
2	14415.89	5521.703	83.35695	6.978202	17251.56	7782.853	28260.56	127.7166	342.2452	17711.35	15557.86	6873.371
3	12277.32	3603.466	133.0245	15.10627	11391.6	5498.065	18623.03	96.71935	265.733	19842.98	26093.38	5454.673
4	13812.62	4691.73	69.54768	6.978202	15655.81	8598.482	31319.25	98.48501	303.9891	18839.01	16866.49	7478.981
5	16518.07	4499.561	55.47684	8.583106	13122.9	8315.42	25000.83	86.91008	227.1826	20886.81	15060.24	6935.948
Average Inventory at UK												
1	1357.046	0	0	0	750.7493	743.3188	1373.812	0	0	1862.199	407.1063	832.4959
2	1410.715				772.3753	740.2192	1526.529			1776.989	363.2301	868.8466
3	1397.376	0	0	0	767.9946	821.6376	1331.373	0	0	1823.275	395.2044	842.3869
4	1374.88	0	0	0	766.0845	725.5695	1361.12	0	0	1815.839	365.1199	845.1771
5	1389.158				762.7112	730.9537	1388.91			1774.902	411.6512	846.7112
Average Inventory at Russia												
1	844.3433				461.7384	807.0327	330.1962			1219.556	188.3978	157.5831
2	876.673				430.5804	861.9918	365.0518			1000.556	210.7629	183.5259
3	724.9292				457.3188	994.5886	381.3106			1140.283	203.0054	181.6567
4	754.3896				409.1907	722.4196	344.6948			1035.616	190.3406	147.9183
5	1197.589				352.891	846.0354	314.3597			1168.763	220.6703	156.2289
Av Inv Neiderbipp												
1	123.158		1444.73	1303.104	341.2398		232.2752			1717.33	361.8747	268.0599
2	144.0956		1134.505	757.5902	319.8934		239.0027			130.1148	339.2022	168.4481
3	136.2371		1563.003	737.0245	312.0518		248.9101			128.7166	317.6322	154.7902
4	139.376		1310.294	754.406	319.5559		227.564			129.4986	312.5422	163.2207
5	134.2316		1143.537	749.3542	326.0627		225.8011			132.0545	317.9918	164.654
Av Inv Italy												
1	607.7929				1150.708	0	1038.272				1613.351	
2	605.1639				1155.639	0	1090.194				1540.661	
3	605.1144				1172.09	0	1038.553				2040.005	
4	603.0845				1140.18	0	1053.809				1681.777	
5	607.0954				1150.076	0	1011.155				1598.458	
Av Inv France												
1	1217.531	356.9837			671.6131	297.8638	2821.662			475.4196	903.406	127.8011
2	1223.561	373.0191			678.8147	290.1935	2862.749			466.4251	891.8229	126.3025
3	1217.703	333.2534			673.7384	296.7984	2862.136			524.1008	897.9482	127.4332
4	1239.73	311.7084			673.1035	301.4905	2946.747			466.2289	897.5477	125.2834
5	1232.351	331.2725			666.9891	290.4959	2858.251			448.7466	888.0654	125.7657
Av Inv Ede												
1								2823.294	2732.204			
2								2370	2353			
3								2353.125	2191.839			
4								3230.812	1978.619			
5								2282.278	2957.21			
Av Inv Czech												
1	372.4169				374.7166		447.4087			409.8229	266.7684	168.5995
2	363.4891				370.112		449.8579			411.582	269.7514	172.6175
3	374.1962				360.2153		446.3297			403.8338	268.861	203.9074
4	379.2262				343.6213		446.7629			417.8747	267.7602	324.6921
5	369.3842				409.9591		448.2044			411.2943	269.1172	220.9973
Av Inv Arceniega												
1	339.4005				607.4687	600.2643	633.1907			687.8965	259.0654	429.485
2	338.3869				641.6294	622.2698	652.842			698.109	259.1526	430.9019
3	340.7166				621.406	624.2561	623.6649			698.8147	265.6485	427.7602
4	337.6185				606.7929	614.1608	624.5886			686.8883	275.812	429.0654
5	337.1117				638.8147	643.9891	656.6131			687.2616	263.0654	428.6076

Table 9: Average Inventory for full global information based production with learning RDCs

Replication	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
Average Inventory at Koblenz												
1	14065.91	4325.586	71.74387	67.97003	15057.91	7333.951	18260.59	152.8283	304.5777	18081.09	15265.59	7751.3
2	19049.25	5020.777	93.90736	6.978202	18902.72	7275.501	23143.63	115.7493	226.0054	17043.99	16263.11	7119.736
3	14201.94	4797.515	48.12534	16.67575	17237.7	7284.572	20039.43	254.6485	125.2153	15569.2	16517.96	8512.997
4	14696.16	4784.984	121.9292	6.978202	17812.34	7619.308	22715.35	237.7766	139.4877	17661.11	16693.01	7054.204
5	13302.43	4799.986	59.53678	8.583106	16072.79	7334.161	22306.91	130.6594	89.16621	23053.8	14140.86	8138.559
Average Inventory at UK												
1	1155.708	0	0	0	613.1253	879.9128	991.6921	0	0	1140.155	1225.428	741.0463
2	977.2016	0	0	0	639.0872	770.1907	1297.657	0	0	1147.305	603.9864	748.1362
3	865.4605	0	0	0	605.8474	775.9428	1223.545	0	0	1414.202	811.0763	855.3079
4	4727.125	0	0	0	604.2316	787.2861	886.812	0	0	1143.578	394.7439	963.0572
5	1763.599	0	0	0	617.3379	791.6076	1153.962	0	0	1155.202	710.3597	775.9046
Average Inventory at Russia												
1	334.3379	0	0	0	211.1444	93.06812	2211.842	0	0	342.1281	292.9973	129.0708
2	246.5613	0	0	0	236.0163	92.0109	1297.237	0	0	332.654	245.0845	123.4496
3	455.1826	0	0	0	223.7275	88.6594	1906.523	0	0	330.9864	237.8828	131.2807
4	299.2752	0	0	0	259.3052	90.6158	1379.071	0	0	334.5804	251.9864	124.3297
5	361.4959	0	0	0	259.5068	93.32698	2198.621	0	0	321.1553	326.7302	125.4496
Av Inv Neiderbipp												
1	378.3351	0	1480.218	1404.381	604.2589	0	1217.779	0	0	744.0899	2319.054	620.5123
2	268.436	0	1123.346	755.6049	314.9482	0	406.564	0	0	142.9673	1042.992	159.5967
3	285.2725	0	1603.771	735.455	310.8747	0	710.5313	0	0	126.188	982.7766	155.3787
4	423.2834	0	1624.049	754.406	316.4169	0	501.8283	0	0	130.1962	1071.91	345.3597
5	256.9673	0	1072.425	749.3542	323.8392	0	738.1771	0	0	124.8174	2623.191	162.2997
Av Inv Italy												
1	586.515	0	0	0	997.1935	0	876.1308	0	0	0	1187.286	0
2	588.7139	0	0	0	992.0409	0	1051.202	0	0	0	1223.054	0
3	582.2044	0	0	0	1016.025	0	975.4332	0	0	0	1671.044	0
4	568.4278	0	0	0	945.7602	0	871.8801	0	0	0	1193.537	0
5	579.8093	0	0	0	991.3624	0	880.7493	0	0	0	1167.64	0
Av Inv France												
1	1044.602	267.9809	0	0	616.8774	434.5395	1961.093	0	0	348.03	779.1989	175.3488
2	1052.308	553.5749	0	0	620.0572	432.6894	1890.193	0	0	443.5368	873.752	170.0463
3	1039.093	243.8583	0	0	611.2534	428.5695	1918.011	0	0	342.9101	772.6621	318.4005
4	1055.142	131.0327	0	0	596.9837	426.8529	1907.319	0	0	336.8774	840.0654	657.049
5	1050.929	151.5668	0	0	607.7411	422.8556	1916.951	0	0	390.0218	772.0926	559.2861
Av Inv Ede												
1								2284.373	2372.155			
2								2099.041	2171.057			
3	0	0	0	0	0	0	0	1864.428	1842.384	0	0	0
4	0	0	0	0	0	0	0	2056.839	2135.943	0	0	0
5								2368.207	2866.719			
Av Inv Czech												
1	353.5831	0	0	0	178.2834	0	534.4714	0	0	453.9428	299.3297	485.9891
2	346.455	0	0	0	178.2098	0	526.4142	0	0	433.594	300.9237	541.6839
3	355.3624	0	0	0	203.1362	0	525.8665	0	0	408.7166	303.9673	454.9046
4	360.6866	0	0	0	181.9646	0	535.4387	0	0	419.4441	303.248	537.4986
5	350.2561	0	0	0	222.2888	0	540.7875	0	0	643.4905	306.1798	548.1199
Av Inv Arceniega												
1	308.3215	0	0	0	608.7439	583.7711	406.6376	0	0	516.6267	229.7357	325.5886
2	307.733	0	0	0	613.8692	608.97	408.0681	0	0	497.673	224.2425	321.7411
3	303.4033	0	0	0	628.1744	607.97	401.4523	0	0	500.9319	237.545	323.1744
4	303.4659	0	0	0	605.9101	595.079	400.6594	0	0	548.5777	243.4414	324.4632
5	304.6158	0	0	0	664.8093	656.2098	416.1035	0	0	546.5313	238.6785	327.4741

Table 10: Average Inventory for full global information based production and flexible maintenance period

Replication	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
Average Inventory at Koblenz												
1	17416.66	4391.046	45.55313	71.0218	12945.1	6773.706	19218.62	121.0463	283.6839	12717.03	12034.61	5784.719
2	11002.93	4266.379	79.99455	6.978202	16001.11	5871.768	12262.72	83.77112	202.0218	16117.23	25498.02	5719.256
3	11119.41	3668.403	54.22888	15.10627	17139.34	5691.308	16371.88	438.6703	319.5858	15009.45	12485.74	5727.589
4	16230.5	4178.902	122.327	6.978202	13660.18	6829.371	17088.74	144.7847	309.4332	12079.57	13051.77	5830.196
5	10149.64	3370.777	66.81199	8.583106	12368.5	6055.365	25152.08	170.0926	223.3569	18430.08	10705.19	30893.44
Average Inventory at UK												
1	1357.046	0	0	0	750.7493	743.3188	1374.676	0	0	1862.199	407.1063	832.4959
2	1407.008	0	0	0	773.4741	736.1853	1518.21	0	0	1787.441	361.7738	866.0654
3	1397.376	0	0	0	767.9946	821.6376	1331.608	0	0	1824.736	395.2044	842.3869
4	1374.88	0	0	0	766.0845	725.5695	1361.12	0	0	1815.839	365.1199	845.1771
5	1389.158	0	0	0	762.7112	730.9537	1389.074	0	0	1774.902	411.6512	846.7112
Average Inventory at Russia												
1	844.3433	0	0	0	461.7384	807.0327	332.8992	0	0	1219.556	188.3978	157.5831
2	876.673	0	0	0	430.5804	861.9918	365.0518	0	0	1000.556	210.7629	183.5259
3	724.9292	0	0	0	457.3188	994.5886	381.5722	0	0	1141.613	203.0054	181.6567
4	754.3896	0	0	0	409.1907	722.4196	344.6948	0	0	1035.616	190.3406	147.9183
5	1197.589	0	0	0	352.891	846.0354	312.1798	0	0	1168.763	220.6703	156.2289
Av Inv Neiderbipp												
1	123.158	0	1454.267	1399.308	341.2398	0	232.7084	0	0	1717.264	361.8747	268.0599
2	143.8093	0	1098.371	755.6049	319.7875	0	238.455	0	0	129.8883	338.5777	167.9891
3	136.2371	0	1278.54	737.0245	312.0518	0	248.9537	0	0	128.7166	317.6322	154.7902
4	139.376	0	1749.995	754.406	319.5559	0	227.564	0	0	129.4986	312.5422	163.2207
5	134.2316	0	1245.292	749.3542	326.0627	0	224.842	0	0	132.0545	317.1199	164.654
Av Inv Italy												
1	607.7929	0	0	0	1150.708	0	1037.54	0	0	0	1613.351	0
2	605.2016	0	0	0	1155.463	0	1089.85	0	0	0	1541.749	0
3	605.1144	0	0	0	1172.09	0	1038.616	0	0	0	2040.005	0
4	603.0845	0	0	0	1140.18	0	1053.809	0	0	0	1681.777	0
5	607.0954	0	0	0	1150.076	0	1011.09	0	0	0	1599.112	0
Av Inv France												
1	1217.531	356.7875	0	0	671.6131	297.8638	2826.289	0	0	475.4196	903.406	127.8011
2	1223.561	373.0191	0	0	678.8147	290.1935	2862.749	0	0	466.4251	891.8229	126.3025
3	1217.703	333.5804	0	0	673.7384	296.7984	2864.782	0	0	524.1526	897.9482	127.4332
4	1239.73	311.5777	0	0	673.1035	301.4905	2947.466	0	0	466.2289	897.5477	125.2834
5	1232.351	331.7302	0	0	666.9891	290.4959	2856.223	0	0	448.7466	888.0654	125.7657
Av Inv Ede												
1								2346.76	1844.221			
2								2329.951	1782.022			
3								2717.049	1813.986			
4	0	0	0	0	0	0	0	2373.09	2513.763			
5								2279.924	2114.251			
Av Inv Czech												
1	372.4169	0	0	0	374.7166	0	447.4332	0	0	409.8229	266.7684	168.5995
2	365.0926	0	0	0	369.3733	0	449.1608	0	0	412.406	269.0817	172.1471
3	374.1962	0	0	0	360.2153	0	446.3297	0	0	403.8338	268.861	203.9074
4	379.2262	0	0	0	343.6213	0	446.7629	0	0	417.8747	267.7602	324.6921
5	369.3842	0	0	0	409.9591	0	448.2916	0	0	411.2943	269.1172	220.9973
Av Inv Arceniega												
1	339.4005	0	0	0	607.4687	600.2643	633.2888	0	0	698.4251	259.0654	429.7466
2	338.3869	0	0	0	645.0627	622.2698	652.842	0	0	699.6131	259.1526	430.9019
3	340.7166	0	0	0	621.406	624.2561	623.6649	0	0	688.5477	262.0518	428.2834
4	337.6185	0	0	0	606.7929	614.1608	624.5886	0	0	686.2997	260.1172	428.9346
5	337.1117	0	0	0	638.8147	643.9891	656.6131	0	0	687.2616	261.1689	428.6076

Table 11: Average CSL for the Baseline Model

Replication

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
Average CSL at Koblenz												
1	1	1			1	0.915548	1			1	0.999346	0.935074
2	1	1			1	0.980758	1			1	0.985915	0.999705
3	1	1			1	0.958784	1			1	1	0.933451
4	1	1			1	0.980164	1			1	1	0.953667
5	1	1			1	0.978382	1			1	1	0.93596
Average	1	1			1	0.962727	1			1	0.997052	0.951571
Average CSL at UK												
1	0.980527				0.977986	0.986547	0.956946			1	0.926149	0.880485
2	0.99135				0.98912	0.920741	0.931255			0.993258	0.832272	0.953017
3	0.965877				0.959895	0.921581	0.923828			0.985053	0.887813	0.802027
4	0.98727				0.976971	0.911087	0.957369			0.986019	0.872414	0.897082
5	0.982084				0.970955	0.938327	0.959101			1	0.900686	0.839495
Average	0.981422				0.974985	0.935657	0.9457			0.992866	0.883867	0.874421
Average CSL at Russia												
1	1				0.921911	0.950445	0.95552			1	0.953202	1
2	0.991115				0.903557	0.912437	0.981622			1	0.948403	1
3	0.988614				0.968148	0.93038	0.972433			1	0.977833	1
4	0.961048				0.867284	0.925127	0.975629			0.995179	0.95599	1
5	0.989286				0.901815	0.93257	0.965669			1	0.961071	1
Average	0.986012				0.912543	0.930192	0.970175			0.999036	0.9593	1
Av CSL Neiderbipp												
1	0.969388		0.976482	0.767877	0.992584		0.871935			0.882823	0.937374	0.9564
2	0.979366		0.807763	1	1		0.999104			1	0.986245	0.984985
3	0.995451		0.85054	1	1		0.991476			1	0.988177	0.987692
4	0.95503		0.919302	1	1		0.998205			1	0.986245	0.990881
5	0.984264		0.970311	1	1		0.990638			1	0.999785	0.967359
Average	0.9767		0.90488	0.953575	0.998517		0.970272			0.976565	0.979565	0.977464
Av CSL Italy												
1	1				0.975674		0.997479				1	
2	1				1		0.948632				0.978168	
3	0.9985				1		0.97543				1	
4	1				1		0.939042				0.99903	
5	1				1		0.974729				0.993122	
Average	0.9997				0.995135		0.967062				0.994064	
Av CSL France												
1	1	0.951016			0.972854	0.987981	1			0.986838	1	0.997543
2	1	0.961753			1	0.990566	1			0.990539	0.999692	1
3	1	0.966149			0.995724	0.966667	1			0.981186	1	0.968098
4	1	0.961768			1	0.964115	1			0.992903	1	0.998773
5	1	0.949065			1	0.990453	1			0.970706	1	0.951279
Average	1	0.95795			0.993716	0.979956	1			0.984434	0.999938	0.983139
Av CSL Ede												
1								0.96016	0.924183			
2								0.943766	0.967427			
3								0.932781	0.85403			
4								0.973794	0.863504			
5								0.965505	0.81061			
Average								0.955201	0.883951			
Av CSL Czech												
1	0.968636				0.921212		1			1	1	0.867897
2	0.997891				0.930642		0.998199			0.996747	1	0.927075
3	0.966965				0.915546		0.999651			0.990692	1	0.852432
4	0.95186				0.924149		1			1	1	0.871757
5	0.968245				0.952738		1			0.99469	1	0.806255
Average	0.97072				0.928857		0.99957			0.996426	1	0.865083
Av CSL Arceniega												
1	0.995845				0.992076	0.955228	1			0.99633	1	0.965799
2	0.992623				0.968861	0.897538	1			0.993495	1	1
3	0.98988				0.976347	0.954056	1			0.998772	0.999313	0.966313
4	0.992159				0.99124	0.94276	1			0.986191	0.986933	0.989171
5	0.995377				0.985488	0.914634	1			0.982645	0.981595	0.941583
Average	0.993177				0.982802	0.932843	1			0.991487	0.993568	0.972573

Table 12: Average CSL for the Baseline Model with weekly review of production plan

Replication	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
Average CSL at Koblenz												
1	1	1			1	0.915667	1			1	1	0.982145
2	1	1			1	0.969474	1			1	0.981131	0.995573
3	1	1			1	0.985747	1			1	1	0.964143
4	1	1			1	0.980164	1			1	1	0.914416
5	1	1			1	0.960803	1			1	0.999109	0.926073
Average	1	1			1	0.962371	1			1	0.996048	0.95647
Average CSL at UK												
1	0.980527				0.977986	0.986547	0.956946			1	0.926149	0.894419
2	0.99135				0.98912	0.920741	0.931255			0.993258	0.832272	0.953179
3	0.965877				0.959895	0.921581	0.923828			0.985053	0.886686	0.860548
4	0.98727				0.976971	0.911087	0.957369			0.986019	0.872414	0.863152
5	0.982084				0.970955	0.938327	0.959101			1	0.901349	0.836113
Average CSL at Russia												
1	1				0.921911	0.950445	0.95552			1	0.953202	1
2	0.991115				0.903557	0.912437	0.981622			1	0.948403	1
3	0.988614				0.968148	0.93038	0.972433			1	0.977833	1
4	0.961048				0.867284	0.925127	0.975629			0.995179	0.95599	1
5	0.989286				0.901815	0.93257	0.965669			1	0.961071	1
Av CSL Neiderbipp												
1	0.969388		0.976482	0.782781	0.992584		0.871935			0.882823	0.937374	0.952912
2	0.979366		0.807763	1	1		0.999104			1	0.986245	0.984985
3	0.995451		0.867621	1	1		0.991476			1	0.988177	0.987692
4	0.95503		0.917442	1	1		0.998205			1	0.986245	0.975684
5	0.984264		0.970311	1	1		0.990638			1	0.999785	0.961424
Av CSL Italy												
1	0.999167				0.975674		0.997479				0.998538	
2	1				1		0.948632				0.978168	
3	0.9985				1		0.97543				1	
4	1				1		0.939042				0.99903	
5	1				1		0.974729				0.993122	
Av CSL France												
1	1	0.951016			0.972854	0.987981	1			0.986838	1	0.986486
2	1	0.961753			1	0.990566	1			0.990539	0.999692	1
3	1	0.966149			0.995724	0.966667	1			0.981186	1	1
4	1	0.961768			1	0.964115	1			0.992903	1	0.997546
5	1	0.949065			1	0.990453	1			0.970706	1	0.951279
Av CSL Ede												
1								0.870856	0.92127			
2								0.943766	0.967427			
3								0.932781	0.913489			
4								0.988413	0.852701			
5								0.965505	0.807324			
Av CSL Czech												
1	0.968636				0.921212		1			1	1	0.865683
2	0.997891				0.930642		0.998199			0.996747	1	0.927075
3	0.966965				0.915546		0.999651			0.990692	1	0.897774
4	0.95186				0.924149		1			1	1	0.836916
5	0.968245				0.952738		1			0.99469	1	0.815408
Av CSL Arceniega												
1	0.995845				0.992076	0.954661	1			0.99633	1	0.971375
2	0.992623				0.968861	0.881687	1			0.993495	1	1
3	0.98988				0.976347	0.95831	1			0.998772	0.999313	0.964266
4	0.992159				0.99124	0.94276	1			0.986191	0.986933	0.959858
5	0.995377				0.985488	0.898185	1			0.982645	0.981595	0.941583

Table 13: Average CSL for the model with decentralised informational structure

Replication	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
Average CSL at Koblenz												
1	1	1			1	0.915908	1			1	1	1
2	1	1			1	0.968286	1			1	0.998098	1
3	1	1			1	0.953795	1			1	1	1
4	1	1			1	0.928733	1			1	1	1
5	1	1			1	0.978382	1			1	1	1
Average CSL at UK												
1	0.980527				0.977986	0.986547	0.956946			1	0.926149	0.915339
2	0.99135				0.98912	0.920741	0.931255			0.993258	0.836282	0.946537
3	0.965877				0.959895	0.921581	0.923828			0.985053	0.887813	0.843393
4	0.98727				0.976971	0.911087	0.957369			0.986019	0.872414	0.923696
5	0.982084				0.970955	0.947827	0.959101			1	0.900686	0.905333
Average CSL at Russia												
1	1				0.921911	0.950445	0.95552			1	0.953202	1
2	0.991115				0.903557	0.912437	0.981622			1	0.948403	1
3	0.988614				0.968148	0.93038	0.972433			1	0.977833	1
4	0.961048				0.867284	0.925127	0.975629			0.995179	0.95599	1
5	0.989286				0.901815	0.93257	0.965669			1	0.961071	1
Av CSL Neiderbipp												
1	0.969388		0.976482	0.91993	0.992584		0.871935			0.882823	0.937374	0.970352
2	0.979366		0.832409	1	1		0.999104			1	0.845261	0.984985
3	0.995451		0.925396	1	1		0.991476			1	0.988177	0.987692
4	0.95503		0.935581	1	1		0.998205			1	0.986245	0.993921
5	0.984264		0.970311	1	1		0.990638			1	0.999785	0.988131
Av CSL Italy												
1	1				0.975674		0.997479				0.998538	
2	1				1		0.948632				0.978168	
3	0.9985				1		0.97543				1	
4	1				1		0.939042				0.99903	
5	1				1		0.974729				0.993122	
Av CSL France												
1	1	0.951016			0.972854	0.987981	1			0.986838	1	0.998
2	1	0.961753			1	0.990566	1			0.990539	0.999692	1
3	1	0.966149			0.995724	0.966667	1			0.981186	1	1
4	1	0.961768			1	0.964115	1			0.992903	1	0.998773
5	1	0.949065			1	0.990453	1			0.970706	1	1
Av CSL Ede												
1								1	0.86			
2								0.939934	0.964142			
3								0.932781	0.932275			
4								0.988413	0.887083			
5								0.965505	0.820751			
Av CSL Czech												
1	0.968636				0.921212		1			1	1	0.884871
2	0.997891				0.930642		0.998199			0.996747	1	0.927075
3	0.966965				0.915546		0.999651			0.990692	1	0.953009
4	0.95186				0.924149		1			1	1	0.89103
5	0.968245				0.952738		1			0.99469	1	0.900076
Av CSL Arceniega												
1	0.995845				0.992076	0.955795	1			0.99633	1	1
2	0.992623				0.968861	0.882819	1			0.993495	1	1
3	0.98988				0.976347	0.952354	1			0.998772	0.999313	1
4	0.992159				0.99124	0.920657	1			0.986191	0.986933	1
5	0.995377				0.985488	0.928247	1			0.982645	0.981595	0.991415

Table 14: Average CSL for the model with adjustable safety stock policy

Replication	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
Average CSL at Koblenz												
1	1	1			1	0.915905	1			1	1	1
2	1	1			1	0.995605	1			1	0.966214	0.932271
3	1	1			1	0.980164	0.997642			1	0.99896	0.974768
4	0.99709	0.998397			1	0.960684	1			1	1	1
5	0.981025	1			1	0.96009	1			0.996419	1	1
Average CSL at UK												
1	0.999691				0.992142	0.947149	0.960279			0.980449	0.96835	0.992788
2	0.986931				0.968226	0.970103	0.947287			0.973767	0.955886	0.931673
3	0.973796				0.95596	0.921736	0.94996			0.97444	0.97995	0.9375
4	0.990713				0.980371	0.959826	0.945533			0.962957	0.984729	0.986576
5	0.980992				0.979753	0.967762	0.948838			0.973545	0.974784	0.973964
Average CSL at Russia												
1	1				0.959818	0.991105	0.943209			1	0.965517	1
2	1				0.930435	0.953046	0.973232			1	0.948403	1
3	1				0.967407	1	0.984019			0.997249	0.975369	1
4	0.989523				0.95679	0.965736	0.972433			0.995081	0.95599	1
5	1				0.973597	0.973282	0.972854			0.98506	0.956204	1
Av CSL Neiderbipp												
1	0.983236		0.925037	0.920882	0.979899		0.861444			0.930633	0.95938	0.959888
2	0.965365		0.887554	1	1		0.992832			1	0.998066	0.927928
3	0.99166		0.914343	1	1		0.981157			1	1	0.969231
4	0.97561		0.950465	1	1		0.997757			1	0.985386	0.987842
5	0.966168		0.915786	1	1		1			1	1	0.985163
Av CSL Italy												
1	0.994167				0.990134		0.965999				0.982241	
2	0.976678				1.001217		0.968379				0.961439	
3	0.974675				0.985066		0.968513				0.993612	
4	0.97813				0.989728		0.960276				0.969501	
5	1				1		0.972062				0.960382	
Av CSL France												
1	0.99484	0.984867			0.986678	0.997596	0.974775			1	0.996886	1
2	0.973976	0.93745			0.976967	1	1			0.995681	0.990028	0.948148
3	0.989868	0.979291			0.975226	1	1			0.994037	0.989102	1
4	0.993201	0.946635			0.993715	1	0.996598			0.994754	0.999009	1
5	0.98902	0.971747			0.970973	1	0.979768			0.998047	0.989177	1
Av CSL Ede												
1								1	0.943724			
2								0.985652	0.931193			
3								0.970313	0.855063			
4								0.998217	0.95209			
5								0.985049	0.861315			
Av CSL Czech												
1	0.998955				1		0.970166			0.985981	0.990358	0.977122
2	0.99631				1		0.989557			0.973972	0.971449	0.979829
3	0.994961				0.992469		0.978709			0.967132	0.970808	0.964551
4	0.998906				0.990196		0.966267			0.983046	0.956989	0.966642
5	0.993541				0.991354		0.970074			0.971091	0.996995	0.967201
Av CSL Arceniega												
1	0.995845				1	0.990082	1			1	0.998639	1
2	0.992623				0.994217	0.951033	1			0.998171	1	0.940583
3	0.98988				0.989926	0.978729	1			1	0.999313	1
4	0.992159				1	0.97138	1			0.99868	1	1
5	0.994914				0.989226	0.954056	1			1	0.994547	1

Table 15: Average CSL for the model with collaborative RDCs using pull based replenishment

Replication	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
Average CSL at Koblenz												
1	0.994937	1			1	0.987291	1			1	1	1
2	1	0.954594			1	0.985509	0.997553			1	0.961638	0.974915
3	1	1			1	0.980164	1			1	1	0.973735
4	1	1			1	0.984202	1			1	1	1
5	1	1			0.993591	0.978382	0.994681			1	1	1
Average CSL at UK												
1	0.979689				0.992329	1	0.980085			0.991926	0.99573	1
2	1				0.994326	1	0.972453			0.995921	0.999764	0.98789
3	0.998376				0.995627	1	0.986229			0.991592	1	0.99298
4	0.999638				1	1	0.985048			1	1	1
5	0.98773				0.977101	1	0.983604			0.997257	1	0.998938
Average CSL at Russia												
1	1				0.97119	0.991105	0.943209			1	0.96798	1
2	1				0.945455	0.993655	0.981622			1	0.948403	1
3	1				0.979259	1	0.984019			0.996954	0.975369	1
4	1				0.952932	0.968274	0.972433			0.995081	0.95599	1
5	1				0.959571	0.973282	0.972854			0.996363	0.956204	1
Av CSL Neiderbipp												
1	0.997085		0.994855	0.955446	1		0.992234			1	1	0.993722
2	1		0.958718	1	1		1			1	0.998925	0.984985
3	1		0.993971	1	1		1			1	1	0.969231
4	1		0.993721	1	1		1			1	1	0.987842
5	1		0.985727	1	1		1			1	1	0.985163
Av CSL Italy												
1	1				1		1				1	
2	1				1		1				0.995652	
3	1				1		1				1	
4	1				1		1				1	
5	1				1		1				0.994803	
Av CSL France												
1	0.995083	0.989247			1	1	1			1	1	1
2	1	0.843028			1	1	1			1	0.998664	1
3	1	0.996018			1	1	1			1	1	1
4	1	0.990044			1	1	1			1	1	1
5	1	1			1	1	1			1	1	1
Av CSL Ede												
1								0.92148	1			
2								0.955262	0.962452			
3								0.940269	0.865114			
4								0.997059	0.947769			
5								1	0.926479			
Av CSL Czech												
1	1				1		1			1	1	0.983026
2	1				1		0.99856			1	0.964861	0.998448
3	1				1		1			1	1	0.972795
4	1				1		1			1	0.998566	0.975537
5	1				1		1			1	0.992487	0.97254
Av CSL Arceniega												
1	0.989381				1	0.995183	1			0.998637	1	0.992193
2	0.993084				1	0.962921	1			0.999797	1	0.983184
3	0.98896				0.996715	0.980998	1			1	1	1
4	0.992159				1	0.993766	1			0.998782	1	1
5	0.995377				1	0.963131	1			0.988326	0.997273	1

Table 16: Average CSL for the model with collaborative RDCs using push based replenishment

Replication

Average CSL at Koblenz

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1	0.994937	0.947115			0.99269	0.987291	1			1	1	1
2	0.987363	0.850427			0.982061	0.969236	0.997553			1	0.993314	0.970046
3	1	0.919338			0.975174	0.946312	0.990089			1	1	0.977719
4	1	0.945513			1	0.984202	1			1	0.999049	1
5	1	1			1	0.978382	0.991933			1	0.981428	1

Average CSL at UK

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1	0.986371				0.991394	1	0.980085			0.991926	0.99573	1
2	1				0.994326	0.991124	0.972453			0.995921	0.993159	0.98789
3	0.991658				0.995627	1	0.984573			0.991592	1	0.996284
4	1				1	1	0.985048			1	1	1
5	0.992693				0.990297	1	0.9805			0.997257	1	0.988319

Average CSL at Russia

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1	1				0.97119	0.991105	0.943209			1	0.96798	1
2	1				0.945455	0.993655	0.981622			1	0.948403	1
3	1				0.979259	1	0.984019			0.996954	0.975369	1
4	1				0.952932	0.968274	0.972433			0.995081	0.95599	1
5	1				0.959571	0.973282	0.972854			0.996363	0.956204	1

Av CSL Neiderbipp

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1	1		1	0.98906	1		0.992234			1	1	0.993722
2	1		0.978435	1	1		1			1	1	0.984985
3	1		0.733484	1	1		1			1	1	0.975385
4	1		1	1	1		1			1	1	0.987842
5	1		0.985727	1	1		1			1	1	0.985163

Av CSL Italy

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1	1				1		1				1	
2	1				1		1				1	
3	1				1		1				1	
4	1				1		1				1	
5	1				1		1				1	

Av CSL France

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1	0.996358	0.859419			1	1	1			1	1	1
2	1	1			1	1	1			1	1	1
3	1	1			1	1	1			1	1	1
4	1	0.848666			1	1	1			1	1	1
5	1	1			0.996984	1	1			1	1	1

Av CSL Ede

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1								0.934314	0.892428			
2								0.998129	1			
3								0.987876	0.839752			
4								1	0.992579			
5								1	0.917371			

Av CSL Czech

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1	1				0.979487		1			1	1	0.983026
2	0.998946				1		0.99856			1	0.980966	0.998448
3	1				1		1			1	1	0.953009
4	1				1		1			1	0.998566	0.975537
5	1				1		1			1	0.992487	0.97254

Av CSL Arceniega

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1	0.989381				1	0.995183	0.995499			1	1	1
2	0.993084				1	0.984149	1			0.970525	1	0.983184
3	0.98896				1	0.980998	1			1	1	1
4	0.992159				1	0.993766	1			0.992994	1	1
5	0.995377				1	0.963131	1			0.995661	0.997273	1

Table 17 Average CSL for partial information based production

Replication	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
Average CSL at Koblenz												
1	1	1			1	0.99121	1			1	0.998098	1
2	1	1			1	0.999762	1			1	1	1
3	1	1			1	0.996199	0.999805			1	1	0.998377
4	0.998485	1			1	0.999762	0.996135			1	0.987847	0.997492
5	0.996811	1			1	0.999644	0.992944			1	1	1
Average CSL at UK												
1	0.998721				0.992329	1	0.987188			1	1	1
2	0.998989				0.998465	1	0.972453			1	1	1
3	0.996953				0.995627	1	0.986229			1	1	1
4	1				1	1	0.985048			0.999456	1	0.98821
5	0.991258				1	1	0.971417			0.997257	1	0.997719
Average CSL at Russia												
1	1				0.97119	0.991105	0.943209			1	0.96798	1
2	1				0.945455	0.993655	0.981622			1	0.948403	1
3	1				0.979259	1	0.984019			0.996954	0.975369	1
4	1				0.952932	0.968274	0.972433			0.995081	0.95599	1
5	1				0.959571	0.973282	0.972854			0.996363	0.956204	1
Av CSL Neiderbipp												
1	1		1	1	1		0.992234			1	0.99569	0.993722
2	1		0.988293	1	1		1			1	1	0.984985
3	1		0.995981	1	1		1			1	1	0.981538
4	1		0.990698	1	1		1			1	1	0.987842
5	1		0.985727	1	1		1			1	1	0.985163
	1		0.99214	1	1		0.998447			1	0.999138	0.98665
Av CSL Italy												
1	1				1		1				1	
2	1				1		1				1	
3	1				1		1				1	
4	1				1		1				1	
5	1				1		1				0.994803	
Av CSL France												
1	0.997997	1			1	1	1			1	1	1
2	1	1			1	1	1			1	1	1
3	1	0.990442			1	1	1			1	1	1
4	1	0.990044			1	1	1			1	1	1
5	1	1			1	1	1			1	0.994482	1
Av CSL Ede												
1								1	1			
2								1	1			
3								1	1			
4								1	1			
5								1	0.998873			
Av CSL Czech												
1	1				1		1			1	1	0.983026
2	1				1		1			1	1	0.999224
3	1				1		1			1	1	0.97939
4	1				1		1			1	0.998566	0.975537
5	1				1		1			1	0.996995	0.97254
Av CSL Arceniega												
1	0.995845				1	0.995183	1			1	1	1
2	0.987552				1	0.988678	1			0.999797	1	1
3	0.985741				1	0.98667	1			1	1	1
4	0.992159				1	0.990649	1			0.998782	1	0.993839
5	0.994914				1	0.980431	0.996795			0.994008	0.997273	1

Table 18 Average CSL for full global information based production with fixed maintenance

Replication	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
Average CSL at Koblenz												
1	1	1			1	0.99121	1			1	1	1
2	1	1			1	0.999762	1			1	1	1
3	1	1			1	0.996199	1			1	1	1
4	1	1			1	0.999762	1			1	1	1
5	1	1			1	0.999881	0.998103			1	1	1
Average CSL at UK												
1	1				1	1	0.987188			1	1	1
2	0.999483				1	1	0.982126			1	1	1
3	1				1	1	0.986996			1	1	0.994294
4	1				1	0.992214	0.988216			1	1	1
5	1				1	1	0.987581			1	1	1
Average CSL at Russia												
1	1				0.974223	1	0.961477			1	0.96798	1
2	1				0.946245	1	0.981622			1	0.948403	1
3	0.989691				0.981481	1	0.984019			1	0.977833	1
4	1				0.952932	1	0.975629			0.995179	0.95599	1
5	1				0.966172	1	0.976447			1	0.961071	1
Av CSL Neiderbipp												
1	1		1	0.993816	1		0.979292			0.972705	0.996057	0.995117
2	1		1	1	1		1			1	1	0.984985
3	1		0.995981	1	1		1			1	1	0.987692
4	1		1	1	1		1			1	1	0.993921
5	1		1	1	1		1			1	1	0.988131
Av CSL Italy												
1	1				1		1				1	
2	1				1		1				1	
3	1				1		1				1	
4	1				1		1				1	
5	1				1		1				0.995659	
Av CSL France												
1	1	1			1	1	1			1	1	1
2	1	1			1	1	1			1	1	1
3	1	0.990442			1	1	1			1	1	1
4	1	0.990044			1	1	1			1	1	1
5	1	1			1	1	1			1	1	1
Av CSL Ede												
1								1	1			
2								1	1			
3								1	1			
4								1	1			
5								1	1			
Av CSL Czech												
1	1				1		1			1	1	0.984502
2	1				1		1			1	1	0.983708
3	1				1		1			1	1	0.991756
4	1				1		1			1	1	0.981468
5	1				1		1			1	1	0.977117
Av CSL Arceniega												
1	0.995845				1	0.996316	1			1	1	1
2	0.992623				1	0.992358	1			0.999187	1	1
3	0.98988				1	0.987521	1			1	1	1
4	0.992159				1	0.993483	1			0.99868	1	1
5	0.995377				1	0.983551	1			1	1	1

Table 19: Average CSL for full global information based production with learning RDCs

Replication	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
Average CSL at Koblenz												
1	1	1			1	0.99121	0.995408			1	1	1
2	1	1			1	0.999762	1			1	1	1
3	0.9941	1			1	0.996199	0.997943			1	1	1
4	1	1			1	0.999762	0.995497			1	1	1
5	1	1			1	0.999881	0.996011			1	1	1
Average CSL at UK												
1	1				1	1	0.987188			1	1	0.995695
2	1				1	1	0.970611			1	1	0.999392
3	1				1	1	0.983485			0.993741	0.996621	0.992455
4	0.993567				1	0.987543	0.987902			1	0.997044	0.999105
5	1				1	1	0.977754			1	1	0.985487
Average CSL at Russia												
1	1				0.974223	0.991105	0.961477			1	0.96798	1
2	0.995497				0.937549	0.988579	0.981622			1	0.948403	1
3	0.971996				0.981481	0.940506	0.984019			0.985852	0.977833	1
4	0.93499				0.952932	1	0.975629			0.995179	0.95599	1
5	0.9925				0.966172	0.984733	0.976447			1	0.961071	1
Av CSL Neiderbipp												
1	1		1	1	1	#DIV/0!	1			0.988873	1	0.995117
2	1		1	1	1	#DIV/0!	1			1	1	0.984985
3	1		0.995981	1	1	#DIV/0!	1			1	1	0.987692
4	1		1	1	1	#DIV/0!	1			1	1	0.993921
5	1		1	1	1	#DIV/0!	1			1	1	0.988131
Av CSL Italy												
1	1				1		1				1	
2	1				1		0.982094				0.988314	
3	1				1		1				1	
4	1				1		1				1	
5	1				1		0.991174				0.980038	
Av CSL France												
1	1	1			1	1	1			1	1	1
2	1	1			1	1	1			1	1	1
3	1	1			1	1	1			1	1	1
4	1	0.99084			1	1	1			1	1	1
5	1	1			1	1	1			1	1	1
Av CSL Ede												
1								1	1			
2								1	1			
3								1	1			
4								1	0.996712			
5								1	1			
Av CSL Czech												
1	1				0.997669		1			1	1	0.984502
2	1				0.991718		1			1	1	0.983708
3	1				1		1			1	1	0.9918
4	1				1		1			1	1	0.981468
5	1				0.997118		1			1	1	0.977117
Av CSL Arceniega												
1	0.995845				1	0.995183	1			1	1	1
2	0.992623				1	0.988678	1			0.999187	1	1
3	0.98988				1	0.98667	1			1	1	1
4	0.992159				1	0.990649	1			0.99868	1	1
5	0.995377				1	0.980431	1			1	1	1

Table 20 Stockouts for baseline model

Replication

Total StockOuts at Koblenz

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1						1					1	2
2						1					1	1
3						1						3
4						1						3
5						1						2

Total StockOuts at UK

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1	4				4	2	5				13	8
2	3				5	3	8			2	12	10
3	6				7	4	8			2	13	11
4	3				8	5	8			2	16	9
5	4				5	6	5				12	12

Total StockOuts at Russia

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1					5	1	1				2	
2	2				4	1	1			0	1	0
3	1				4	2	2					
4	2				2	1	1			1	1	
5	2				5	1	2				1	

Total StockOuts at Neiderbipp

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1	4		3	10	4		14			16	11	9
2	5		4				1				2	1
3	3		5				3				2	1
4	8		4				1				2	2
5	4		3				1				1	2

Total StockOuts at Italy

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1					1		1					
2							3				2	
3	1						1					
4							3				1	
5							3				3	

Total StockOuts at France

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1		2			2	1				3		1
2		3				1				4	1	
3		4			1	1				4		2
4		2				1				3		1
5		4				1				5		2

Total StockOuts at Ede

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1								2	4			
2								2	3			
3								2	5			
4								2	4			
5								2	3			

Total StockOuts at Czech

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1	6				10							17
2	2				8		2			2		14
3	8				12		1			4		11
4	10				12							23
5	7				8					1		10

Total StockOuts at Arceniega

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1	1				2	4				1		2
2	1				4	3				3		
3	1				3	3				1	1	2
4	1				2	5				2	1	2
5	1				3	5				1	3	1

Table 21 Stockouts for baseline model with weekly production planning

Total StockOuts at Koblenz

Replication	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1						1						1
2						1					1	1
3						1					1	1
4						1						3
5						1					1	2

Total StockOuts at UK

Replication	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1	4				4	2	5				13	7
2	3				5	3	8			2	12	10
3	6				7	4	8			2	12	12
4	3				8	5	8			2	16	10
5	4				5	6	5				13	10

Total StockOuts at Russia

Replication	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1					5	1	1				2	
2	2				4	1	1				1	
3	1				4	2	2				1	
4	2				2	1	1			1	1	
5	2				5	1	2				1	

Total StockOuts at Neiderbipp

Replication	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1	4		3	9	4		14			16	12	8
2	5		4				1				2	1
3	3		6				3				2	1
4	8		6				2				3	3
5	4		3				1				1	2

Total StockOuts at Italy

Replication	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1	1				1		1				1	
2							3				2	
3	1						1					
4							3				1	
5							3				3	

Total StockOuts at France

Replication	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1		2			2	1				3		2
2		3				1				4	9	
3		4			1	1				4		
4		2				1					3	2
5		4				1				5		2

Total StockOuts at Ede

Replication	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1								2	4			
2								2	3			
3								2	4			
4								1	4			
5								2	4			

Total StockOuts at Czech

Replication	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1	6				10							17
2	2				8		2			2		14
3	8				12		1			4		11
4	10				12							21
5	7				8					1		10

Total StockOuts at Arceniega

Replication	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1	1				2	4				1		1
2	1				4	4				3		
3	1				3	3				1	1	1
4	1				2	5				2	1	3
5	1				3	5				1	3	1

Table 22 Stockouts for model with decentralised informational structure

Replication	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
Total StockOuts at Koblenz												
1						1						
2						1					1	
3						1						
4						1						
5						1						
Total StockOuts at UK												
1	4				4	2	5				13	9
2	3				5	3	8			2	12	11
3	6				7	4	8			2	13	12
4	3				8	5	8			2	16	13
5	4				5	5	5				12	13
Total StockOuts at Russia												
1					5	1	1				2	
2	2				4	1	1				1	
3	1				4	2	2				1	
4	2				2	1	1			1	1	
5	2				5	1	2				1	
Total StockOuts at Neiderbipp												
1	4		3	13	4		14			16	11	8
2	5		3				1				20	1
3	3		5				3				2	1
4	8		3				1				2	1
5	4		3				1				1	1
Total StockOuts at Italy												
1					1		1				1	
2							3				2	
3	1						1					
4							3				1	
5							3				3	
Total StockOuts at France												
1		2			2	1	0			3		1
2		3				1				4	1	
3		4			1	1				4		
4		2				1				3		1
5		4				1				5		
Total StockOuts at Ede												
1								0	4			
2								3	2			
3								2	3			
4								1	3			
5								2	3			
Total StockOuts at Czech												
1	6				10							17
2	2				8		2			2		14
3	8				12		1			4		12
4	10				12							21
5	7				8					1		14
Total StockOuts at Arceniega												
1	1				2	4				1		
2	1				4	4				3		
3	1				3	3				1	1	
4	1				2	4				2	1	
5	1				3	4				1	3	1

Table 23 Stockouts for model with adjustable safety stock policy

Replication

Total StockOuts at Koblenz

Replication	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1						1						
2						1					1	1
3						1	1				1	1
4	1					1						
5	1					1				1		

Total StockOuts at UK

Replication	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1	1				2	4	7			6	7	2
2	4				5	6	7			5	8	5
3	6				7	6	6			5	9	9
4	2				5	4	8			11	7	6
5	4				3	3	8			4	7	7

Total StockOuts at Russia

Replication	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1					4	1	1				1	
2					2	1	1				1	
3					4		1			1	1	
4	3				3	1	1			1	1	
5	4				1	1	1			2	1	

Total StockOuts at Neiderbipp

Replication	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1	4		13	32	7		26			27	15	16
2	6		13				2				2	1
3	2		13				3					1
4	6		11				1				2	1
5	7		10									1

Total StockOuts at Italy

Replication	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1	1				1		2				4	
2	5				3		5				5	
3	3				2		5				3	
4	5				3		5				5	
5							4				5	

Total StockOuts at France

Replication	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1	4	3			4	1	2				2	
2	5	7			5					2	3	1
3		5			3					2	2	
4	2	4			2		2			1	1	
5	3	5			3		3			1	2	

Total StockOuts at Ede

Replication	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1								0	1			
2								2	2			
3								2	3			
4								1	2			
5								1	3			

Total StockOuts at Czech

Replication	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1	1						3			6	2	3
2	1						3			5	4	2
3	2				2		3			4	4	2
4	1				1		5			3	5	4
5	3				1		3			4	1	2

Total StockOuts at Arceniega

Replication	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1						1					1	
2	1				2	1				2	1	1
3	1				1	2					1	
4	1					1					1	
5	2				1	2					2	

Table 24 Stockouts for model with pull based replenishment used by collaborative RDCs

Replication	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
Total StockOuts at Koblenz												
1	1	1				1						
2		1				1	1				2	1
3						1						1
4						1						
5					1	1	2					
Total StockOuts at UK												
1	2				1		2			1	1	
2					2		1			1	1	1
3	3				1		2			2		1
4	1						1					
5	4				4		2			1		2
Total StockOuts at Russia												
1					1	1	1				1	
2					1	1	1				1	
3					1		1			1	1	
4					1	1	1			1	1	
5					1	1	1			1	1	
Total StockOuts at Neiderbipp												
1	1		1	2			1					1
2			1								1	1
3			2									1
4			1									1
5			1									1
Total StockOuts at Italy												
1												
2											1	
3												
4												
5											2	
Total StockOuts at France												
1	2	1										
2		2									1	
3		1										
4		1										
5												
Total StockOuts at Ede												
1								1	0			
2								1	1			
3								2	2			
4								1	3			
5								0	4			
Total StockOuts at Czech												
1												1
2							1				2	1
3												1
4											1	1
5											1	1
Total StockOuts at Arceniega												
1	1					1				1		1
2	1					1				1		1
3	1				1	1						
4	1					1				1		
5	1					1				2	1	

Table 25: Stockouts for model with push based replenishment and collaborative RDCs

Total StockOuts at Koblenz

Replication	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1	1	1			2	1						
2	3	1			2	2	1				2	2
3		1			2	2	2					1
4		1					1			1		
5						1	3				2	

Total StockOuts at UK

Replication	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1	2				2		2			1	1	
2					2	1	1			1	1	1
3	3				1		2			2		2
4							1					
5	2				4		3			1		2

Total StockOuts at Russia

Replication	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1					1	1	1				1	
2					1	1	1				1	
3					1		1			1	1	
4					1	1	1			1	1	
5					1	1	1			1	1	

Total StockOuts at Neiderbipp

Replication	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1				1			1					1
2			1									1
3			2									1
4												1
5			1									1

Total StockOuts at Italy

Replication	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1												
2												
3												
4												
5											1	

Total StockOuts at France

Replication	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1	1	1										
2												
3												
4		1										
5					1							

Total StockOuts at Ede

Replication	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1								1	1			
2								1				
3								1	1			
4									1			
5									1			

Total StockOuts at Czech

Replication	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1					1							1
2	1						1				2	1
3												1
4											1	1
5											1	1

Total StockOuts at Arceniega

Replication	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1	1				1	1						
2	1					1				4		1
3	1					1						
4	1					1				2		
5	1					1				1	1	

Table 26: Stockouts for model with partial global information based production

Replication

Total StockOuts at Koblenz

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1						1					1	
2						1						
3						1	1					1
4	1					1	1				1	1
5	1					1	1					

Total StockOuts at UK

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1	1						1					
2	1				1		1					
3	2				1		2					
4							2				1	1
5	2						2				1	1

Total StockOuts at Russia

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1					1	1	1				1	
2					1	1	1				1	
3					1		1			1	1	
4												
5					1	1	1			1	1	

Total StockOuts at Neiderbipp

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1							1				1	1
2			1									1
3			1									1
4			1									1
5			1									1

Total StockOuts at Italy

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1												
2												
3												
4												
5											2	

Total StockOuts at France

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1	1											
2												
3		1										
4		1										
5											1	

Total StockOuts at Ede

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1												
2												
3												
4												
5									1			

Total StockOuts at Czech

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1												1
2												1
3												1
4											1	1
5											1	1

Total StockOuts at Arceniega

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1	1					1						
2	1					1				1		
3	1					1						
4	1					1				1		1
5	2					1	1			1	1	

Table 27: Stockouts for model with full global information based production and fixed/flexible maintenance period

Replication

Total StockOuts at Koblenz

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1						1						
2						1						
3						1						
4						1						
5						1	1					

Total StockOuts at UK

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1							1					
2	1						1					
3							1					2
4						1	1					
5							1					

Total StockOuts at Russia

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1					1		1				1	
2					1		1				1	
3	1				1		1				1	
4					1		1			1	1	
5					1		1				1	

Total StockOuts at Neiderbipp

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1				1			3			3	1	1
2												1
3			1									1
4												1
5												1

Total StockOuts at Italy

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1												
2												
3												
4												
5											1	

Total StockOuts at France

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1												
2												
3		1										
4		1										
5												

Total StockOuts at Ede

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1												
2												
3												
4												
5												

Total StockOuts at Czech

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1												1
2												1
3												1
4												1
5												1

Total StockOuts at Arceniega

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1	1					1						
2	1					1				1		
3	1					1						
4	1					1				1		
5	1					1						

Table 28. Stockouts for model with learning RDCs and full information based production

Replication

Total StockOuts at Koblenz

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1						1	1					
2						1						
3	1					1	1					
4						1	1					
5						1	1					

Total StockOuts at UK

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1							1					1
2							2					1
3							2			1	1	1
4	1					1	2				1	1
5							2					2

Total StockOuts at Russia

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1					1	1	1				1	
2	2				1	1	1				1	
3	1				1	1	1			4	1	
4	3				1		1			1	1	
5	2				1	1	1				1	

Total StockOuts at Neiderbipp

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1										2		1
2												1
3			1									1
4												1
5												1

Total StockOuts at Italy

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1												
2							2				2	
3												
4												
5							1				2	

Total StockOuts at France

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1												
2												
3												
4		1										
5												

Total StockOuts at Ede

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1												
2												
3												
4									1			
5												

Total StockOuts at Czech

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1					1							1
2					1							1
3												1
4												1
5					1							1

Total StockOuts at Arceniega

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
1	1					1						
2	1					1				1		
3	1					1						
4	1					1				1		
5	1					1						

Appendix F

Potential Applications

I will discuss the potential applications of the agent based model described in Chapter 4. This type of agent-based framework can be used to almost all supply network configurations, which deal in multiple products and categories, to understand their behaviour under different environmental dynamics and uncertainty. This applies to consumer goods manufacturing firms, pharmaceuticals with multiple drugs needing multiple packaging requirements, chemical factories with batch productions.

Although here the machine is assumed to be catering to heterogeneous products thus making it suitable for application to logistics and distribution industries where a single machine is used to pack a variety of items with very different demand patterns. In such cases, the above framework could be extended by assuming several factories with the above decision making and functioning stages supply to the distribution centre, which itself then acts as an assembly factory and assembles/packs different materials and dispatches them according to the central warehouse agent framework. This will also have implications in supply network structures that deal in only one end product, such as automobile supply chains. In the case of such structures, though the end product is same, a car, but there can be several specifications for the car requiring wide variety of different raw materials. So in that case, the factory agent framework described earlier would be applied to each individual supplier that manufactures several raw materials for more than one auto-manufacturer, thus requiring manufacturing of very different motor-parts or same motor parts with different specifications. So although the end product is one, there may be myriads of parts required for one car. And when this car is tailor-made to order of individual customer, the requirements for decentralised informational structure becomes necessary requiring use of the framework described above to intelligently decide which product to produce when and for how long and then integrate that decision with the network-wide inventory of finished goods and raw materials. This can be shown by the simple replication of a complex automobile supply network (Figure F1). As can be seen, from above, two car companies A and B supply to 4 markets and source auto-parts from 4 suppliers. Say, all the suppliers have the capability to manufacture any of the twelve automobile parts but the two companies procure only a few from each of the suppliers. Each of these parts will have different specifications based on the car size, type, model etc. So each supplier can be represented by the factory agent framework discussed before. Each supplier will make these different products in batches decided by the decision making stage of each supplier agent every day and supply in response to the end-customer demands. The central factory of each auto-company will monitor the sales, forecast and stock in each type of car and accordingly carry out assembly using the motor parts supplied by the different suppliers. In this case though, the assembly will be carried out totally based on demand and the central factory will more act like the central warehouse agent in the current agent based framework. The supplier factories are integrated to the central warehouse and supply customers with their specific orders when needed.

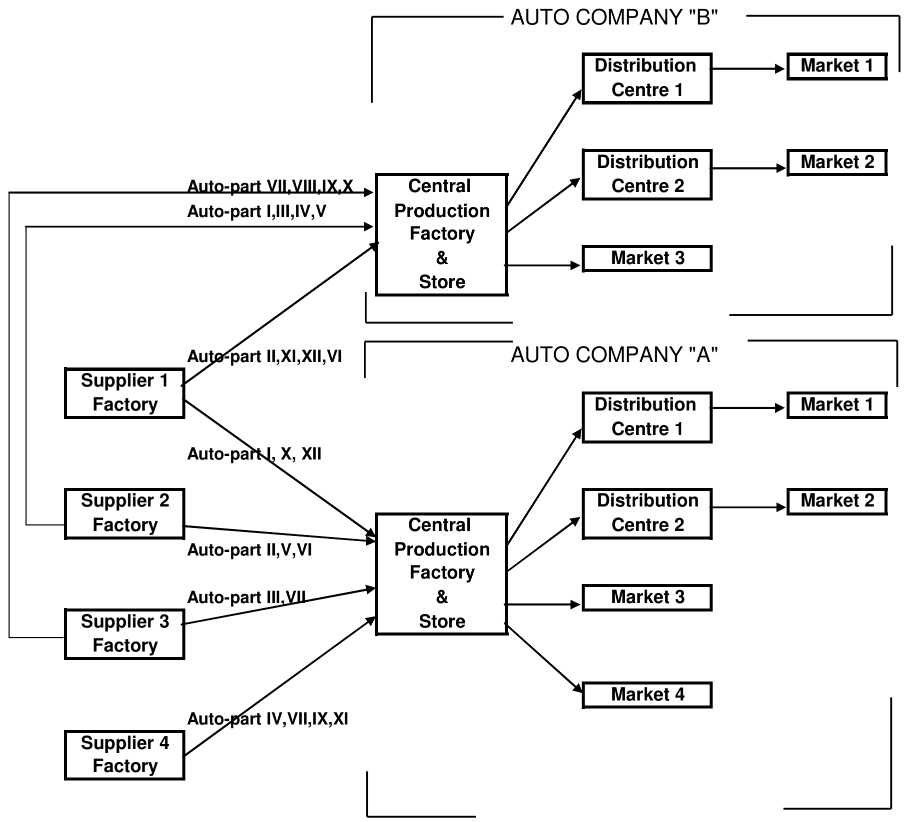


Figure F1: Application of the agent based framework to an auto supply chain

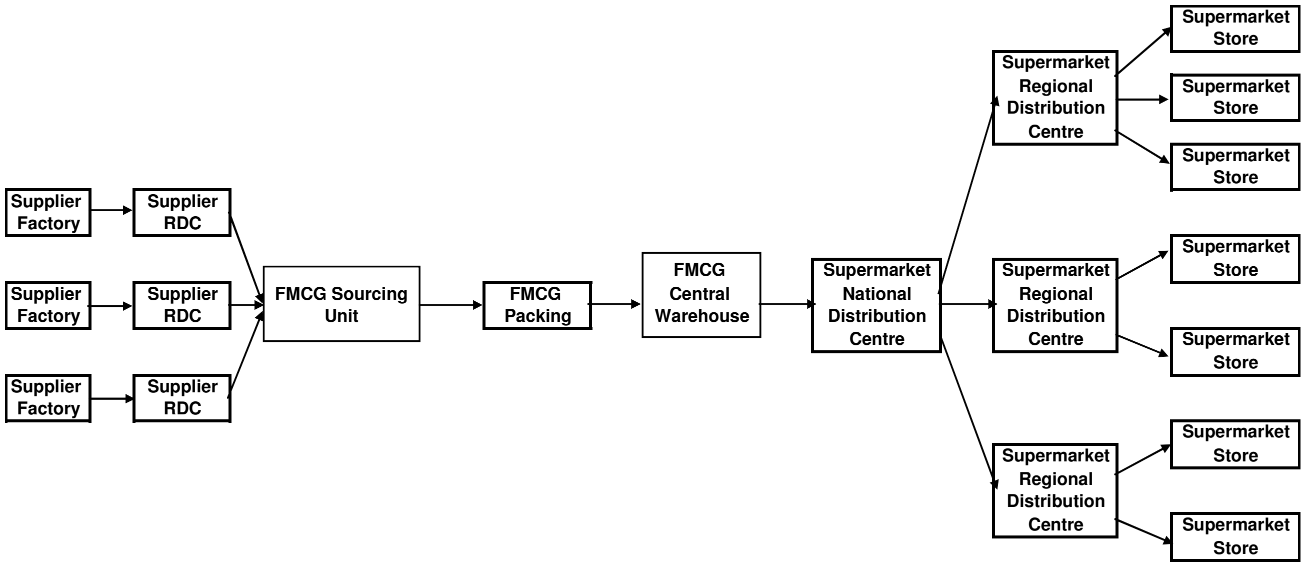


Figure F2: An FMCG supply chain starting from supplier to supermarket store

The agent based framework described above can also be used to study and improve the supply chain behaviour under uncertainty in a large FMCG (fast moving consumer goods) supply network. Since the FMCG company manufactures several categories of products which share common resources such as machines, distribution trucks, raw materials, the framework described in this chapter can be of immense use. Each supplier factory, the FMCG sourcing and packing units can be represented by factory agents. The supplier RDCs each can be represented by the central warehouse agent coupled to the FMCG sourcing unit. The FMCG sourcing and packing units together act to improve local and global objectives based on central warehouse and network inventory information. The regional distribution centres, sourcing unit pull materials from the supermarket national distribution centre and the supplier RDCs based on need. Stock and sales data at each supermarket store at certain time interval (multiple times in a single day) are communicated to all the elements of the supply chain. Based on the end-demand changes resulting in stock covers, the supplier factories and the FMCG sourcing unit change production schedules. Thus the agent based framework with sets of intelligent rules and control procedures can be used in this type of supply network structures as well.

The two supply network structures represent very different types of products. The one represented in figure F2 can be for any heavy engineering product such as aircraft engine or whole aircraft, excavator etc. The supply chain in figure F2 can be for any type of fast moving consumer goods, food, health-care, beauty products, laundry, baby products, batteries, even pharmaceuticals and chemicals (paper, paints etc) also can be included in this type of structure.

So the agent based framework described in this chapter can be used in any type of supply network structure to study the behaviour and understand best strategies for improving resilience, although this might require adjusting certain variables and parameters in each individual case.