The Effect of Uncertainties
on
Multi-Echelon Serial Supply Chains

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CERTIFICATE of APPROVAL

This is to certify that the thesis entitled, "**The effect of uncertainties on multi-echelon serial supply chains**" being submitted by **Sanjita Jaipuria** for the award of the degree of Doctor of Philosophy (Mechanical Engineering) of NIT Rourkela, is a record of bonafide research work carried out by her under my supervision and guidance. Miss Sanjita Jaipuria has worked for more than three years on the above problem at the Department of Mechanical Engineering, National Institute of Technology, Rourkela and this has reached the standard fulfilling the requirements and the regulation relating to the degree. The contents of this thesis, in full or part, have not been submitted to any other university or institution for the award of any degree or diploma.

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This Thesis Dedicated to Maa Sambaleswari

And My Sweet Family

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ABSTRACT

Uncertainties are the major concerns in supply chain because existence of uncertainties degrades the performance of supply chain. Hence, business executives need to seriously focus towards controlling the effect of uncertainty on supply chain performance. In this study, a four echelon serial supply chain employed with reorder-point order-up-to level inventory replenishment (s, S) policy is modeled using system dynamics approach. Manufacturing systems adopting make-to-stock (MTS) and assemble-to-stock (ATS) manufacturing policy and operating under uncertain environment are modelled through system dynamics approach. A serial two-stage MTS manufacturing system is modelled through system dynamics approach and the behaviour is studied under the influence of uncertainty in demand, lead time, supplier's acquisition rate, processing time and delay due to machine failure. Two different improved demand forecasting models are proposed to enhance the forecasting accuracy and reduce the bullwhip effect (BWE) and net-stock amplification (NSAmp). The first proposed model is the integrated approach of autoregressive integrated moving average (ARIMA) and generalized autoregressive conditional heteroskedasticity (GARCH) model denoted as ARIMA-GARCH to overcome the problem related to heteroskedastic nature of demand series. Second proposed model is the integrated approach of discrete wavelet transformation (DWT) and intelligence technique such as artificial neural network (ANN), adaptive neuro-fuzzy inference system (ANFIS), least square support vector machine (LSSVM) and multi-gene genetic programming (MGGP) to deal with non-linear, non-stationary demand series.

Simulation study of multi-echelon supply chain indicates that target inventory significantly influence the BWE and it can be reduced through keeping target inventory at low level when there is low uncertainty in demand and lead time. From the analysis of manufacturing supply chain, it is observed that backlog at manufacturer's end is significantly influenced by uncertainty in processing time and delay due to machine failure. The backup strategy adopted in manufacturing supply chain reveals that performance of manufacturing system is highly affected when uncertainty in supplier's acquisition rate increases. The study proves that maintaining high service level at the bottom echelon is required to achieve high service level at the upper echelon of a supply chain. From the forecasting study, it is found that performance of the ARIMA-GARCH model outperforms the ARIMA model. Further, it is proved through case-study examples

that intelligent models outperform the ARIMA-GARCH and ARIMA model. Further, the robustness of the intelligence models is tested for evaluating their performance for different varieties of (R, S) policies.

The proposed system dynamic model helps to analyse the impact of uncertainties in multi-echelon serial supply chain in an efficient manner and generate various scenarios to enable the managers to take appropriate decisions. Backup supply strategy is quite efficient in reducing stock-out situation at manufacturer's end. With the help of ARIMA-GARCH model, an organisation can easily predict the change in demand and properly estimate the safety-stock level and order quantity. Similarly, raw material/product demand can be accurately estimated through adoption of proposed hybrid forecasting techniques to reduce BWE and NSAmp. However, the proposed models consider a single retailer, distributor, wholesaler and manufacturer confined to a single product only. The proposed model can be further improved with multiple retailers, distributors, wholesalers and manufacturers dealing with multiple products. Although proposed forecasting models effectively reduce BWE and NSAmp but tested with (R, S) inventory control policy only.

Keywords: Make-to-stock; Assemble-to-stock; Back-up supply strategy; Bullwhip effect (BWE); Discrete wavelet transformation; Net-stock amplification; System dynamics.

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GLOSSARY

ACF	Autocorrelation fuction
ADF	Augmented Dickey–Fuller test
AI	Artificial intelligence
AIC	Akaike information criterion
ANN	Artificial neural network
ANFIS	Adaptive neuro-fuzzy inference system
ANOVA	Analysis of variance
AR	Autoregressive
ARCH	Autoregressive conditional heteroskedasticity
ARMA	Autoregressive moving average
ARIMA	Auto-regressive integrated moving average
ATS	Assemble-to-stock
BIC	Bayesian information criterion
BWE	Bullwhip effect
DOE	Design of experiments
DWT	Discrete wavelet transformation
FFMLP	Feed-forward multilayer perceptron
GARCH	Generalized autoregressive conditional heteroskedasicity
GP	Genetic programming
LSSVM	Least square support vector machine
MA	Moving average
MF	Membership function
MGPP	Multi-gene Genetic Programming
MSE	Mean square error
MT	Metric ton
MTS	Make-to-stock
NSAmp	Net-stock amplification
PACF	Partial autocorrelation function
RM	Raw material
RMSE	Root mean square error
ROP	Reorder point
SC	Supply chain
SDM	System dynamics and modelling
SD	System dynamics
SVR	Support vector regression
WIP	Work in progress inventory
WT	Wavelet theory

CHAPTER 1

RESEARCH BACKGROUND

1.1 Introduction

International Center for Competitive Excellence in 1994 defines supply chain management as integration of business processes from end user through original suppliers providing products, services and information in order to add value for customer (Cooper et al., 1997). According to Monczka et al. (2011), the supply chain integrates all the activities related with the flows and transformation of goods from raw materials stage to end user needs. Integration of activities such as systems management, transportation, warehousing, operations and assembly, purchasing, production scheduling, order processing, inventory management and customer service is emphasized because they are closely linked each other and action on any activity influences the profitability of the supply chain (Silver et al., 1998). The fundamental issue involved is to reduce the overall supply chain cost and satisfactorily meet the demand from the customer so that generated revenue can be increased.

The supply chain cost includes (i) raw material and other acquisition costs (ii) inbound transportation costs (iii) facility investment costs (iv) direct and indirect manufacturing costs (v) direct and indirect distribution costs (vi) inventory-holding costs (vii) outbound transportation costs (Shapiro, 2007). Different approaches have been applied in managing integration and coordination of supply, demand and their relationship in order to satisfy customer requirements in an effective and profitable manner (Wong et al., 2005). In order to improve the performance of supply chain, supply chain management practices emphasize on (i) reducing inventory holding costs (ii) providing better medium for information sharing between partners (iii) improving customer satisfaction (iv) maintaining better trust between partners (v) providing efficient manufacturing strategies (vi) improving process integration (vii) increasing cash flow (viii) improving quality and profit margin (Monczka et al., 2011). The key issues that can possibly improve the performance of the supply chain are product differentiation (Beamon, 1999; Li and O'Brien, 2001), lead time management (Christopher, 2004), inventory and cost management (Ketzenberg et al., 2000), bullwhip effect (Lee et al., 1997a), information sharing and coordination (Lee et al., 1997b), distribution and logistics (Kärkkäinen et al., 2003). Li et al. (2006) have suggested that few dimensions of supply chain such as strategic supplier partnership, customer relationship, level of information sharing, and quality of information sharing can substantially improve the performance of supply chain analysing data from one hundred ninety six organizations using structural equation modelling. The performance of supply chain and typical issues to be addressed in various industrial sectors are reported in (i) automobile (Sánchez and Pérez, 2005) (ii) pharmaceutical (Pedroso and Nakano, 2009). (iii) apparel (Palpacuer et al, 2005) (iv) electronics industry (Berry et al., 1994) (v) agriculture/food processing industries (Cunningham, 2001, Fritz and Schiefer, 2008) (vi) toy (Wong et al., 2005) and (vii) aerospace industry (Sinha et al, 2004). Different industries and retail shops in India successfully implemented supply chain are Tata Motors, Procter and Gamble, Big Bazar, Amazon and Flipkart. To cite an example, different supply chain management practices adopted by Flipkart are (i) well distribution network (ii) customer service management (iii) inventory management (iv) fast delivery (v) information system (http://opepiimraipur.blogspot.in/2011/12/best-practices-at-flipkart.html).

In real practice, supply chain is associated with different uncertainties along the supply network. Many times uncertainties affect adversely on the supply chain activities leading to unable to meet the business goals. Three major sources of uncertainty such as supplier (late in delivery, insufficient quantity); manufacturing process (machine breakdown, transportation reliability) and customer demand (volume and mix) severely affect managing the supply chain (Petrovic et al., 1998, 1999; Petrovic, 2001; Hwarng and Xie, 2008). Therefore, it is vital that each of these uncertainties must be measured and addressed to identify their impact on customer service and improve the supply chain performance (Davis, 1993; Petrovic et al., 1998, 1999). For the smooth operation of manufacturing process, it is essential that right quantity and quality of raw material must be available at right time at manufacturer end. Uncertainties at supplier end may occur in terms of variation in supply quantity or delivery time. Delay in delivery or insufficient supply quantity causes stock-out situation of finished goods inventory at manufacturer end resulting in deterioration of service level. Different uncertainties associated with the manufacturer may be listed as occurrence of machine failure, uncertain time to repair the machine and variation in time to process raw materials. These uncertainties affect the desired production rate leading to stock-out of finished goods. Stock-out situation causes increase in backlog which ultimately increases shortage cost and decreases service level. Similarly, uncertainty in customer demand leads to stock-out situation at the supplier/manufacturer's end causing increase in backlog. Therefore, the performance of the supply chain should be analysed through the service level/fill rate. The service level is defined as the probability that customer orders in a given time interval will be completely delivered from on-hand stock (Equation 1.1) (Silver et al., 1998).

$$\text{Service level} = 1\text{-}\left(\frac{\text{Expected number of units out of stock annually}}{\text{Total annual demand}}\right) \quad (1.1)$$

One of the adverse effects of uncertainty is bullwhip effect (BWE). This is the phenomenon of amplification of order in upward direction of supply chain with respect to variation in demand (Forrester, 1961). This can be estimated using Equation 1.2. It leads to increase in various cost components such as manufacturing cost/purchasing cost, inventory holding cost, transportation cost, shipping and receiving cost etc. Thus, it causes increase in total cost, replenishment lead time, decrease in fill rate and profitability (Chopra et al., 2006).

$$\text{BWE} = \frac{\text{variance of order}}{\text{variance of demand}} \quad (1.2)$$

According to Bout and Lambrecht (2009), moderating BWE does not necessarily reflect the inventory fluctuations which influence associated inventory costs. Under the fluctuations in inventory, an organisation needs to maintain high safety stock to achieve desired service level. This incurs high holding cost. Hence, variation in net stock with respect to demand known as net-stock amplification (NSAmp) is treated as another major supply chain performance measures. This can be estimated using Equation (1.3).

$$\text{NSAmp} = \frac{\text{variance of net - stock}}{\text{variance of demand}} \quad (1.3)$$

According to Beamon (1999), total cost is treated as one of the important performance measure in supply chain modelling because total cost can address both customer demand and service level. Generally, the total cost incurred in an organisation can be estimated using Equation (1.4) (Silver et al., 1998).

$$\text{TC} = C_h + C_p + C_b + C_t + C_o \quad (1.4)$$

where,

$C_h = \text{Holding cost}$; $C_p = \text{Purchaisng cost}$; $C_b = \text{Backlorder cost}$ $C_t = \text{Transportaion}$ cost and $C_o = \text{ordering cost}$

The performance of a supply chain under uncertain environment can be analysed through estimating backlog, service level, bullwhip effect, net-stock amplification and total cost.

1.2 Need of research

From the above discussions, it can be concluded that existence of uncertainties is the major issues in supply chain because it affects the planning and decision activities in the supply chain. Existence of uncertainty influences the performance of both supplier and manufacturer to meet the customer demand. In this direction, a large number of models have been proposed in the literature to study and analyse the effect of uncertainty (Petrovic et al., 1998; Petrovic et al., 1999; Petrovic, 2001; Xie et al., 2006; Hwarng and Xie, 2008; Mahnam et al., 2009) considering fill rate and total cost as supply chain performance measures. The impact of bullwhip effect and net-stock amplification on supply chain have been analysed by many researcher to suggest guidelines for the practitioner (Hong and Ping, 2007; Geary et al., 2006; Chen et al., 2000a; Fransoo and Wouters, 2000; Disney et al., 2003a, 2003b; Lee et al., 1997a, Mason-Jones et al., 2000; Dejonckheere et al., 2003; Kim et al., 2006; Croson and Donohue, 2005; Chatfield et al., 2004; Bout and Lambrecht, 2009). Therefore, it is essential to study and analyse the influence of uncertainties on the supply chain performance to make a supply chain more effective and efficient. Few research questions, which are not dealt in the literature so far, have been identified and needs to be addressed.

1. How can the influence of uncertainty on supply chain be studied in an efficient and effective manner?
2. How does the manufacturing system, an important subsystem of a supply chain, behave under the uncertain environment?
3. What type of strategy and policy should be adopted to mitigate the effect of uncertainty?
4. How can the adverse effect of uncertainty (bullwhip effect and net-stock amplification) be reduced to improve the performance of a supply chain?

To address the above research questions, simulation, statistical and artificial intelligence approaches have been used as major modelling tools in this research work to achieve the following objectives of the study.

1.3 Research objectives

The important theme of this research is to propose efficient modelling tools based on simulation, statistical and artificial intelligence approaches to analyse the effect of uncertainty on supply chain performance. Based on the above research questions, four basic objectives of the study are explored from the literature gap found through exhaustive literature review (Chapter 2).

1. To study and analyse the performance of multi-echelon serial supply chain under uncertain environment using system dynamics approach.

2. To study and analyse the performance of manufacturing supply chain under the influence of uncertainty.
3. To propose a back-up supply strategy to reduce the adverse effect of supply uncertainty in make-to-stock manufacturing supply chain.
4. To reduce the BWE and NSAmp amplification through improved forecasting approaches.

Each research objective is a step towards addressing a research question (Section 1.2). The mapping between research objective, research question and the sources of literature is shown in Appendix 1.

1.4 Organisation of thesis

To meet the above objectives, the thesis is organized into seven chapters including this chapter. A brief outline of each chapter is given as follows:

- **Chapter 2: Literature review**

  The purpose of this chapter is to review related literature so as to provide background information on the issues to be considered in the thesis and emphasize the relevance of the present study. Literature review provides a summary of the base knowledge already available in supply chain management. An exploratory approach is adopted for identifying and examining a diverse range of issues in supply chain management practices. This chapter highlights the different practices in supply chain management such as risk management, supplier management, inventory management, managing uncertainty and managing bullwhip effect. Finally, the chapter is concluded by summarizing the supply chain management practices, implication in industries and possible literature gap so that relevance of the present study can be emphasized.

- **Chapter 3: Performance analysis of multi-echelon serial supply chain under uncertainty**

  This chapter analyses the performance of four echelon serial supply chain employed with reorder-point order-up-to level replenishment policy ((s, S) policy). The considered supply chain is modelled through system dynamics approach and the performance is analysed through BWE and total cost considering uncertainty in demand, lead time and the inventory decision parameter the target inventory. The effect of uncertainty and the target inventory is systematically analysed through the design of experiments (DOE) approach. The optimal parameter settings to reduce the bullwhip effect and total cost are determined. Further, optimal parameter settings are obtained to simultaneously reduce the bullwhip and total cost through grey relational analysis.

- **Chapter 4: Performance analysis of manufacturing system under uncertainty**

  The supply chain with make-to-stock (MTS) and assemble-to-stock (ATS) manufacturing system is considered in this chapter to analyse the performance of manufacturing supply chain under uncertain environment. A single machine, single product MTS manufacturing system is modelled through the system dynamics approach. Six different scenarios are generated based on the uncertainties in raw material supply lead time, processing time and machine availability to simulate the MTS system and performance is analysed through estimating the backlog. A DOE approach is applied to analyse the influence of considered uncertainties on the performance of MTS manufacturing system in a systematic manner.

  Similarly, an ATS manufacturing system with three machines confined to assembling a single product is modelled through the system dynamics approach. There are fifteen experimental scenarios are generated using the response surface methodology (RSM) considering uncertainty in lead time, assembly time and delay due to machine failure. The model is simulated for 365days based on the generated scenarios and performance are measured in termed of backlog and work-in-progress (WIP) inventory. The influence of uncertainties on the backlog and WIP is analysed. Further, empirical relationship is developed between the uncertainties and performance parameters through regression analysis. To obtain optimal parameter settings both in MTS and ATS systems, a newly proposed meta-heuristic known as cuckoo search is applied.

- **Chapter 5: Managing supply uncertainty in a make-to-stock manufacturing system**

  This chapter considers a MTS manufacturing system consisting of two machines confined to a single product. The system is modelled and simulated through the system dynamics approach to analyse the effect of increasing uncertainty in raw material supply, lead time, supplier acquisition rate, production rate and machine availability. The behaviour is studied through measuring the impact of uncertainty on backlog at manufacturer's end, raw material shortage, WIP level and backlog at supplier's end. Further, a backup supply strategy is proposed to manage the supply uncertainty. Through a comparative study, the superiority of adopting a backup supply strategy is discussed. It is observed that it is desirable to maintain high service level at the upper stream (raw material supplier) to maintain high service level at bottom echelon (manufacturer end).

- **Chapter 6: Improved forecasting methods to deal with bullwhip effect and net-stock amplification**

  This chapter proposes two improved models to enhance the forecasting accuracy to reduce the BWE and NSAmp when (R, S) policy is adopted for inventory replenishment. The first model is an integrated approach of autoregressive integrated moving average (ARIMA) and generalized autoregressive conditional heteroskedasticity (GARCH) process denoted as ARIMA-GARCH to deals with heteroskedastic demand series. The second model proposed is the integrated approach of the discrete wavelet transformation (DWT) and artificial intelligence (AI) models such as artificial neural network (ANN), adaptive neuro-fuzzy inference system (ANFIS), least square support vector machine (LSSVM) and multi-gene genetic programming (MGGP). Four different intelligence models are denoted as DWT-ANN, DWT-ANFIS, DWT-LSSVM and DWT-MGGP. These models are validated through an example data taken from the open literature. The performance of the proposed models such as ARIMA-GARCH, DWT-ANN, DWT-ANFIS, DWT-LSSVM and DWT-MGGP are tested with data from three case-study examples. The performance is analysed through estimating order using the predicted demand from the proposed model applying base-stock policy. The BWE and NSAmp are estimated. From the analysis, it is found that BWE and NSAmp estimated using ARIMA-GARCH model is comparatively less to the ARIMA model. Further analysis reveals that the intelligence models outperform both the ARIMA and ARIMA-GARCH models. Further, the performance of the intelligent models is analysed in different (R, S) policies.

- **Chapter 7: Executive summary and conclusions**

  This chapter presents the summary of the results, recommendations and scope for future work in the direction of studies on effect of uncertainty on supply chain performance. It also discusses the specific contributions made in this research work and the limitations there in. This chapter concludes the work covered in the thesis with implications of the findings and general discussions on the area of research.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

The current chapter highlights various issues involved in managing supply chain and improving its performance. Although the concept of supply chain appeared in the literature in the mid-1980s, review of literature begins with research articles published after 1985 with maximum attention paid to last twenty years. Table 2.1 provides the source and number of citations from each source. The majority of the citations are found in peer reviewed journals (95%), two journals namely "European Journal of Operational Research" and "International Journal of Production Economics" together accounts for 34.6% of the total citations.

Table 2.1 Summary of publications referred

Source	Citation
Applied Mathematical Modelling	3
Applied Mathematics and Computation	1
Benchmarking: An International Journal	1
Computers and Industrial Engineering	1
Computers and Operations Research	1
Computers in Industry	2
Engineering Costs and Production Economics	1
European Journal of Operational Research	19
Expert Systems with Applications	2
Fuzzy Sets and Systems	2
IIE Transactions,	1
Informs Transaction on Education	1
Integrated Manufacturing Systems	1
Integrated manufacturing systems	2
International Journal of Advanced Manufacturing Technology	2
International Journal of Business Insights and Transformation	1
International Journal of Logistics: Research and Applications	1
International Journal of Operations and Production Management,	2
International Journal of Physical Distribution and Logistics Management	3
International Journal of Production Economics	17
International Journal of Production Research	4
International Journal of Services and Operations Management	2
International Transactions in Operational Research	1
Journal of Food Engineering	1
Journal of Modelling in Management	1
Journal of Operations Management	2

Journal of Productivity Analysis	1
Journal of Supply Chain Management	3
Journal of the Franklin Institute	1
Journal of the Operational Research Society	1
Logistics Information Management	1
Management Science	6
Naval Research Logistics	1
Omega	3
Operations Research	1
Production and Inventory Management Journal	1
Simulation Modelling Practice and Theory	2
Sloan Management Review	3
Supply Chain Management: An International Journal	4
System Engineering-Theory and Practice	1
Books	5
Conference	1
Total	110

The literature is classified into an assortment of sections dealing with specific issues associated with supply chain management as illustrated in Figure 2.1. Next sections provide brief discussion on these issues. Finally, the chapter is concluded by summarizing the advancement taken place in supply chain and possible literature gap so that relevance of the present study can be emphasized.

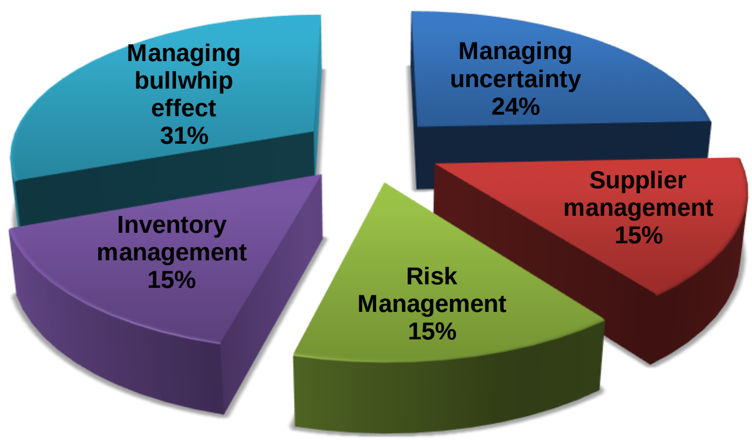

Figure 2.1 Percentage of paper surveyed

2.2 Supply chain risk management

Supply chain risk management (SCRM) deals with management of supply chain risks through coordination or collaboration among the supply chain partners so as to ensure profitability and continuity (Brindley, 2004). The risk in supply chain originates from two sources - supply and demand. Other risk such as environment, political, process and security are also equally important. However, supply chain risk can be mitigated through, demand management, product management and information management (Blos et al., 2009; Tang, 2006a). Issues of supply chain risk management can be addressed in two dimensions such as supply chain risk which includes operational risks or disruption risks and the mitigation approach. Operational risks are referred as the inheritance of uncertainties such as uncertainty in customer demand, supply and cost whereas disruption risks are the major distractions caused by natural and man-made disasters such as earthquakes, floods, hurricanes, terrorist's attacks or economics crises such as currency evaluation or strikes. In the past, many researchers have highlighted the importance of risk management in supply chain and proposed models and methods for assessment and mitigation. Blos et al. (2009) have suggested three important practices in supply chain risk management implementation such as (i) better supply chain communication (ii) supply chain risk management and business continuity management training program and (iii) creation of chief risk officer to reduce disruption of supply chain risk. Giunipero and Eltantawy (2004) have discussed the four situational factors such as purchasers' perceived experience, degree of product technology, security needs and relative importance of supplier for determining the level of risk management in supply chain. Wu et al., (2006) have proposed an inbound risk analysis methodology to classify, manage and assess the risk. They classified the risk factors based on the supplier oriented risk factors and applied analytical hierarchy process (AHP) to determine the weight for risk factor. A purchasing organisation can be able to focus on the supplier quality issues, make improvement in supplier performance and prevent the supply disruption through adopting a proactive approach for risk assessment (Zsidisin et al., 2004). Supply risk can be identified through analysing the effect of purchased item and services on profitability, market factors, and supplier characteristics. The risk can be managed through understanding the characteristics of supply risk and implementing different strategies (Zsidisin, 2003). Uncertainties and supply risk in a supply chain can be reduced through different approaches such as risk assessment, contingency plans, risk management process improvement and buffer strategies (Zsidisin et al., 2000). Zsidisin and Ellram (2003) have proposed agency theory to manage supplier behaviours in order to reduce supply risk and the impact of unfavourable events. Tuncel and Alpan (2010) have applied failure mode, effects and criticality analysis (FMECA) technique to examine the disruption factors in supply chain network. They determined the different uncertainties and risk mitigation action through integrating risk management procedures into design, planning, and performance evaluation process using Petrinet simulation approach. Lockamy and McCormack (2010) have suggested that suppliers associated with high probability of risk have significant impact on the organisation's revenue. Hence, it is essential to analyse the risk associated with supplier of outsourced material. Wu and Olson (2008) have proposed three different models such as chance constrained programming, data envelopment analysis and multi-objective programming to evaluate supply chain risk and different approaches to trade-off among expected costs, quality acceptance levels and on-time delivery distributions. Further, it is suggested that these tools can be alternatively used to evaluate and improve supplier selection decisions in an uncertain environment. Neiger et al. (2009) have proposed value-focused process engineering methodology for process-based supply chain risk identification in order to increase value to supply chain members and supply chain as a whole. Ellis et al. (2010) have examined the importance of buyers' perceptions on supply disruption risk and found out that product and market situational factors impact on the perceptions of risk. Goh et al. (2007) have proposed a stochastic model to mitigate the risk in supply, demand, exchange and disruption to solve the multi-stage global supply chain network problem. Tang (2006b) has proposed two different strategies to mitigate supply chain disruption such as supply alliance network, lead time reduction and recovery planning systems.

2.3 Supplier Management

Supplier management is one of the important activities in supply chain management. As good supplier management system helps in achieving competitive advantage, organisations are paying increasing attention towards it. Supplier selection is the process of finding the right suppliers those are able to provide right quality products/services at the right price at right time and in right quantities to the buyer. Different criteria such as supplier, product performance, service performance and cost are considered to evaluate suppliers of a firm (Burton, 1988; Çebi and Bayraktar, 2003). Supplier selection is one of the critical activities for establishing an effective supply chain. It is a hard problem since it involves a multi-criteria decision making problem with several conflicting criteria (Boran et al., 2009).

Many authors have highlighted the importance of supplier assessment and proposed different techniques for assessment. Ghodsypour and O'Brien (2001) have proposed a decision support system based on integrated approach of analytical hierarchy process

(AHP) and linear programming to handle both tangible and intangible factors for selecting best suppliers to place optimum order quantities among them such that the total value of purchasing can be maximized. Çebi and Bayraktar (2003) have suggested an integrated approach of lexicographic goal programming and AHP model for supplier selection for a food industry in Turkey considering quality, delivery, cost and utility as the conflicting objectives. A combined approach of scoring method and fuzzy expert systems is proposed for supplier assessment considering different criteria such as product quality, product construction, product safety, quality system, engineering, production and planning control (PPC) and research and development by Kwong et al. (2002). Chan and Kumar (2007) have proposed a fuzzy extended analytic hierarchy process (FEAHP) to tackle different decision criteria like cost, quality, service performance and supplier's profile including the risk factors involved in the selection of global supplier. Samantra et al. (2012) have suggested supplier evaluation model through coupling grey relational concept with rough set theory for appropriate supplier selection from among a group of feasible suppliers when the decision making criteria are uncertain, imprecise and vague in nature. Mahapatra (2011) have proposed a fuzzy approach for supplier evaluation to deal with impreciseness, uncertainty and vagueness in decision criteria, Mishra et al. (2012) have proposed a technique based on fuzzy set theory and VIseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) method. Demirtas and Üstün (2008) have proposed an integrated approach of analytic network process (ANP) and multi-objective mixed integer linear programming (MOMILP) for supplier evaluation in order to maximize the total value of purchasing and minimize the budget and defect rate considering both tangible and intangible supplier selection criteria. Razmi et al. (2009) have proposed a hybrid approach of fuzzy analytic network process model to evaluate the potential suppliers and select the suitable one with respect to the vendor related factors. An integrated approach of multi-attribute utility theory and linear programming is proposed for rating and choosing the best suppliers and defining the optimum order quantities among selected ones in order to maximize total additive utility (Sanayei et al., 2008). Weber et al. (1998) have applied combined approach of multi-objective programming and data envelop analysis for vendor selection and negotiation with the vendors who do not get selected. Bayazit, (2006) has applied ANP model to measure the supplier performance. Petroni and Braglia (2000) have proposed supplier evaluation model based on principal component analysis and validated though considering real-world data set of suppliers of a medium-sized firm operating in the bottling machinery industry. A multi-objective mixed integer programming approach is proposed to simultaneously determine the number of vendors to allocate order quantities in a multiple-product, multiple-supplier competitive sourcing environment (Dahel, 2003). Soner (2011) has developed an integrated methodology using two-stage stochastic programming model and fuzzy technique for order preference similar to ideal solution (TOPSIS) method to solve the supplier selection problem in case of multi-product, multi-period and multi-sourcing environment where the demand is uncertain in nature.

2.4 Inventory management

According to Davis (1993), inventory acts as a safeguard against the different uncertainties existing in the supply chain. Properly controlled inventory helps the executives to efficiently meet the customers' demands to smooth the production plans and reduce the operational costs such as purchase cost, order/setup cost, holding cost and stock-out cost (Tersine, 1994). Four commonly used inventory control system are (a) order-point, order-quantity (s, Q) system, (b) order-point, order-up-to-level (s, S) system, (c) periodic-review, order-up-to-level (R, S) system and (d) (R, s, S) system falling under two categories of periodic and continuous review inventory control system (Silver et al., 1998). The fundamental trade-off that managers come across during inventory decision activity is between responsiveness and efficiency. The supply chain responsiveness towards the customer can be improved through gradually increasing the inventory leading to increase in inventory holding cost (Chopra et al., 2006). A large body of literature exist in supply chain highlighting different issues involved in managing inventory and suggested models and methods to overcome these issues.

Aardal et al. (1989) have studied the relationship between shortage cost and service level in a continuous review inventory system where order point and lot sizes are computed simultaneously. De Bodt and Graves (1985) have analysed the continuous review inventory control policy to minimize expected average cost for multi-stage inventory system where demand of the end item assumed as stochastic in nature. Lee (2011) has analysed service level under multi-period inventory control dealing a single product with multiple (two) prices. Lee et al. (2006) have studied a periodic review inventory model considering a retailer replenishing inventory from a supplier to satisfy stochastic demands from customers. Capkun et al. (2009) have analysed the relationship between the inventory performance and financial performance of a manufacturing company. It is proved that raw material inventory is highly correlated with financial performance whereas work-in-process inventory and finished product inventory are highly correlated to gross profit and operating profit respectively. Ioannidis (2011) has examined a Markovian single-stage system producing a single item to satisfy demand of two different customer classes. The study proposes simple threshold type heuristic policy for coordinating production and order admission decisions in the system for joint control of inventories and backorders. Cachon and Fisher (2000) have analysed the effect of information sharing system considering a supply chain with of n number of identical retailer that face stationary stochastic consumer demand with a known distribution. Tiacci and Saetta (2009) have applied a design of experiments (DOE) approach to evaluate impact of interaction of demand forecasting and stock control policies considering multiple suppliers, multiple warehouses, multiple items and time-varying demands with seasonality. Zeng and Hayya (1999) have assessed the probability of no stock-out situation during lead time and the fill rate in the context of continuous inventory systems. Zhang and Bell (2007) have addressed the simultaneous determination of price and inventory replenishment in a newsvendor setting when the firm faces demand from two or more market segments. Gel et al. (2010) have analysed the impact of inventory execution error considering reorder-point order quantity ((Q, r) policy) inventory control policy on inventory related cost and risk. Axsäter and Juntti (1996) have evaluated the impact of lead time on different inventory policies in multi-echelon inventory system. Axsäter (1997) has proposed a method to compute shortage cost for a two-level inventory system (one warehouse and N retailers) employed with continuous review echelon stock (R, Q) policy.

2.5 Managing uncertainty in supply chain

Three different sources of uncertainty such as supplier (late in delivery, insufficient quantity), manufacturing process (machine breakdown, transportation reliability) and customer (volume and mix) exist supply chain. It is essential that impact of each of these on supply chain performance should be assessed (Davis, 1993). In the past, various researchers have attempted to study the behaviour of supply chain under uncertain environment. Petrovic et al. (1998) have applied fuzzy concept to represent the uncertainty in customer demand and supply reliability. In order to analyse the performance of a serial supply chain under uncertain environment, they have developed a simulation model for a serial supply chain consisting of multiple facilities. Each facility includes a raw material inventory, production unit, in-process inventory and adopted periodic review, order-up-to policy for inventory replenishment. They have determined the optimum order-up-to level through simulation to minimise the total cost and increase the fill rate. It is proved that negative impact of unreliable suppliers can be compensated by increasing stock level in the supply chain. Further, the proposed model is improved by incorporating uncertainty in supply deliveries along the supply chain with two control strategies - decentralised control of each inventory and partially coordination in the inventories (Petrovic et al., 1999). It is concluded that application of partial coordination leads to greater holding costs and smaller shortage cost for the end-product. Further, the same model is tested and analysed under the influence of uncertainty in customer demand. From the analysis, it is observed that increase in uncertainty increases the variation in stock level and orders quantity placed by the entity (Petrovic, 2001). Xie et al. (2006) have determined the optimal review period and order-up-to level value to minimize the total cost and maximize the fill rate under stochastic demand. Xu and Zhai (2010) have considered single period, two stage supply chain consisting of a manufacturer and retailer to analyse the benefits of coordination among them when uncertainty exist in demand. Through the fuzzy modelling approach, it has been proved that supply chain profit can be maximized when there is coordination between the retailer and manufacturer. Wang and Shu (2005) have considered uncertainty in demand, processing time and supply delivery using fuzzy logic approach. A genetic algorithm approach based on fuzzy supply chain model is proposed to determine the order-up-to levels at all stock-keeping units to minimize the supply chain inventory investment and fulfil the targeted fill rate of the finished product. Weng et al. (2003) have evaluated effect of supplier-buyer coordination on supply chain performance when uncertainty exists both in demand and delivery time. The importance of coordination of various entities of supply chain has been highlighted by Dolgui et al. (2002) and Xiao et al. (2008). A dual sourcing technique i.e. splitting the order to sources of supply is proposed by Ramasesh (1991) to reduce the holding cost.

Simulation modelling approaches have been found to be convenient tool for analysing the behaviour of supply chain under uncertain environment. It has been extensively used to focus on inventory decisions, policy formulation, demand amplification and supply chain design. De Souza et al. (2000) have examined the supply chain dynamics under different causes such as shortage, capacity constraint, information delay, coordination, supply delay, demand signalling and order batching by modifying the classical beer distribution game. Hwarng and Xie (2008) have studied the influence of dynamic factors such as demand pattern, ordering policy, lead time and information sharing on the behaviour of a supply chain considering classical beer distribution game model by estimating the system chaos using Lyapunov exponent at all level. Ge et al. (2004) have analysed the influence of factors like information delay, demand forecasting and information sharing on multi-echelon system using system dynamics and modelling, through a case study of supermarket supply chain in UK. Shukla et al. (2009) have investigated the impact of capacity constraint on a four stage supply chain using beer distribution game. Georgiadis et al. (2005) have proposed a system dynamics approach for analysing a multi-echelon food chain. Kumar and Nigmatullin, (2011) have modelled a food supply chain for a non-perishable product adopting system dynamics approach to study the behaviour under demand and lead time variability.

Williams (1984) has adopted queuing theory approach to analyse one stage production system under uncertain environment (stochastic nature of demand and manufacturing time). The paper also outlines the quantity of production and capacity allocation under manufacturing to stock (MTS) and manufacturing to order (MTO) policies. Bera and Sharma (1999) have proposed an analytical model for measuring production uncertainty under the different stochastic distributions. Soman et al. (2004) have addressed the scheduling and sequencing in a hybrid MTO-MTS food processing environment under the influence of stochastic demand. Accurate forecasting of demand and achieving high service level are important under MTS situation whereas order execution time is important in MTO situation (Soman et al., 2006). Helo (2000) has modelled a two echelon supply chain with multiple product manufacturing system using MTO production policy based on system dynamics approach to study the relationship between capacity utilization with production costs, lead time and the capability to respond to changes. Özbayrak et al. (2007) have modelled the MTO manufacturing supply chain system through the system dynamics to measure the performance in terms of backlog using eight different scenarios. Chakraborty et al. (2008) have proposed guidelines on lot sizing decisions considering the effect of process deterioration, machine breakdown and repairs (corrective and preventive). Groenevelt et al. (1992a) have analysed the effect of exponentially distributed machine failure time on lot sizing decision for classical EMQ (economic manufacturing quantity) model. In another study, lot sizing decisions under constant machine failure rate and randomly distributed repair time are proposed to avoid lost sales (Groenevelt et al. 1992b). Campuzano et al. (2010) have used the system dynamics modelling approach for a two stage supply chain with single item, multi-period supply representing demand and order by fuzzy membership functions for production planning decision purpose.

2.6 Managing bullwhip effect

One of the adverse effects of uncertainties is bullwhip effect (BWE). The concept of amplification of order in upward direction of supply chain is termed as BWE and it is one of the major issues in the supply chain as first identified by Forrester (1961). Further, this phenomenon is analysed by Sterman (1989) through beer distribution game at Massachusetts Institute of Technology. BWE leads to increase in total cost of supply chain and decrease fill rate and profitability (Chopra et al., 2006). Hence, it is one of the major parameter to analyse the performance of a supply chain. According to Lee et al. (1997a), there are five major causes of BWE within the supply chain. These are listed as (i) demand forecasting, (ii) order batching, (iii) price fluctuations, (iv) supply shortages and (v) non-zero lead-time. BWE can be reduced through moderating these causes.

Dobos (2011) has analysed the behaviour of BWE in a two stages centralized and decentralized supply chain considering a quadratic cost function. Sodhi et al. (2011) have analysed effect of operational deviations like misplaced orders, batching and lag in sharing demand forecast due to BWE considering auto-correlated demand. Li and Liu (2013) have addressed the BWE control problem in respect to different supply chain system uncertainties such as demand, production process, supply chain structure, inventory policy implementation and vendor order placement lead time and proposed inventory control policy for suppression of BWE to improve supply chain stability. Fransoo and Wouters (2000) have estimated the BWE in a food supply chain under different situations like individual product for specific sales, aggregated products for individual sales and aggregated products for aggregated sales. Agrawal et al. (2009) have analysed the impact of information sharing and lead time on BWE and on-hand inventory considering a two echelon serial supply chain consisting of warehouse and retailer employed with adaptive base-stock inventory policy. The retailer predicts demand through autoregressive (AR (1)) process. From the study, it has been proved that lead time reduction is more beneficial in comparison to sharing of information to reduce the bullwhip effect. Makui and Madadi (2007) have estimated BWE for two cases of supply chain (centralised and decentralised case) using Lyapunov exponent. Lee et al. (1997a; 1997b) have applied statistical approach to quantify the BWE. Disney and Towil (2003b) have quantified the BWE using discrete control theory for Deziel and Eilon - Automatic Pipeline Inventory and Order Based Production Control System (DE-APIOPBCS) model.

Dejonckheere et al. (2003) quantify the BWE employing order-up-to policy from a control engineering perspective using z-transforms and proved that order-up-to level policy is always associated with BWE whatever forecasting techniques are adopted. Kim et al. (2006) have extended the work of Dejonckheere et al. (2003) and Chen et al. (2000a) incorporating stochastic lead and information sharing to quantify bullwhip effect.

Geary et al. (2003) have proposed different approaches to measure the BWE using mathematical and simulation approaches. Kelepouris et al. (2008) have used simulation approach to examine the impact of replenishment parameters and information sharing on the BWE. Wangphanich et al. (2010) have proposed simulation approach based on system dynamics modelling and an adaptive network-based fuzzy inference system for quantifying and reducing BWE in a multi-product, multi-stage supply chain. Using system dynamic approach, Hussain and Drake (2011) have analysed the effect of order batching on BWE for a multi-echelon supply chain with information sharing and analysed the relationship between order batching and demand amplification. Sterman (2000) first proposed system dynamics and modelling (SDM) approach to develop a model for four level supply chains popularly known beer distribution game model to analyse the BWE. O'donnell et al. (2006) have used beer distribution model and computational intelligent technique to obtain the optimal ordering policy for supply chain members to reduce the BWE and cost in a supply chain. Fan et al. (2010) have used SDM approach to study the causes for BWE in military weapons maintenance supply system.

Improper forecasting is one of the reasons for BWE. Therefore, various time series models have been proposed to reduce the BWE through controlling the different supply chain parameters. Luong (2007) has examined the effect of autoregressive coefficient and lead time on BWE for a two stage supply chain (one supplier and one retailer) where retailer employs base-stock policy for inventory management using first order autoregressive model AR(1). Further, the model is modified for the higher order autoregressive model AR (p) (Luong and Phien, 2007). Chen et al. (2000a) have analysed BWE for a simple two stage supply chain based on lead time and information sharing considering single retailer and a manufacturer where retailer demand is predicted through moving average (MA) time series model. It is found that BWE increases with increasing in lead time at lower level of information sharing. Further, Chen et al. (2000b) have analysed the same model and obtained similar results employing exponential smoothing forecasting technique for retailer's demand forecasting. Duc et al. (2008a) have considered two stage supply chain (one supplier and a retailer). The retailer employs base-stock policy and demand is predicted through ARMA (1, 1) demand process. Under this model setting, they have analysed the BWE considering the autoregressive coefficient and the moving average parameter. From analysis, it has been found that BWE does not exist always within the supply chain. It occurs only when the autoregressive coefficient is higher than the moving average coefficient. It is not always true that BWE increases with increase in lead time. Further, the same model is considered to analyse the effect of lead time on BWE considering two case - forecasting retailer's demand using AR (1) and ARMA (1, 1) forecasting model (Duc et al., 2008b). It is proved that BWE increases either increase in mean demand or standard deviation of lead time occurs. Duc et al. (2010) have examined the effect of existence of a third-party warehouse on the BWE in a supply chain assuming retailers use the demand process AR (1) model and downstream member(s) implement the base stock policy for replenishment. From the analysis, it is found that third-party warehouse has no effect on BWE. Hong and Ping (2007) have studied the influence of different forecasting techniques MA, exponential weighted moving average (EWMA) and mean square error-optimal (MSE-optimal) for two stage supply chain employed with order-up-to policy on BWE. It is proved that MA model performs better than MSE-optimal model when lead time is short. Jakšič and Rusjan, (2008) have analysed the effect of different replenishment policies ((R, $\hat{D}$), (R, γO), (R, S), (R, βIP) and (R, $\gamma O, \beta IP$)) on the bullwhip effect assuming the retailer demand is forecasted through simple exponential smoothing. Bandyopadhyay and Bhattacharya (2013) have derived generalized expression to quantify BWE for five different replenishment policies like, (R, $\hat{D}$), (R, γO), (R, S), (R, βIP) and (R, $\gamma O, \beta IP$) using ARMA (p, d) considering fixed lead time. They have also studied the BWE under the influence of changing demand process parameters. Gilbert (2005) has proposed generalized expression for quantifying the BWE representing the demand with ARIMA time series process for a multistage supply chain. It is proved that BWE is high when the lead time is long and demand is auto-correlated. It has also been reported that BWE depends only on the total of lead times; not on number of stages in a multistage supply chains. Further, the model is extended by Gilbert (2006). Bout and Lambrecht (2009) have tested the different demand forecasting methods like MA, exponential smoothing (ES) and minimum mean square error (MMSE) for order-up-to policy in a two stage supply chain to quantify BWE and NSAmp value.

2.7 Summary

This chapter highlights different issues involved in supply chain management and approaches to manage these issues. For the sake of simplicity, the surveyed literature is classified into five main areas. In section 2.2, the importance of risk management in supply chain is dealt. Section 2.3 describes existing methods for supplier assessment. Section 2.4 discusses the different issues involved in managing inventory. It emphasizes on various approaches to improve the responsiveness of the supply chain and reduce different inventory related costs. Section 2.5 deals with studies on behaviour of supply chain under the influence of various uncertainties. It also discusses various ways and methods to analyse the supply chain uncertainty in order to improve its performance. One of the adverse effects of uncertainty is bullwhip effect which is major area of research in supply chain management. It accounts for 31% of the literature studied in this thesis. Section 2.6 deals with various methods to manage the bullwhip effect. Critical review of literature suggests that existence of uncertainty is one of the major concerns for managing supply chain in an efficient manner. Therefore, avenue exists for research to study the effect of uncertainty on the performance of a multi-echelon supply chain operating with various inventory replenishment policies. The influence of uncertainty must also be evaluated in various manufacturing policies. Plenty of scope exists for research to develop forecasting techniques that can address bullwhip effect in an effective manner. In this direction, the present work explains the effect of uncertainties on supply chain performance and different approaches to manage the uncertainty. In the next section (Chapter 3), the performance of multi-echelon serial supply chain under uncertainty in lead time and demand is presented.

CHAPTER 3

PERFORMANCE ANALYSIS OF MULTI-ECHELON SERIAL SUPPLY CHAIN UNDER UNCERTAIN ENVIRONMENT

3.1 Introduction

Although there are contrasting views on definition of supply chain management, many researchers agree to view supply chain management as various managerial activities to manage supply chain so as to produce and distribute right quantities of products/goods to the right location and at right time in order to minimize system-wide cost and satisfy service level requirement (Cooper and Ellram, 1993; La and Masters, 1994; Lambert et al., 1998; Monczka et al., 2011; Christopher, 1992). However, many a time, it becomes difficult to manage supply chain as there are various uncertainties inherent in it (Simchi-Levi et al., 2003). In the past, numerous researchers have proposed integrated approach of fuzzy logic and simulation modelling to analyse the impact of uncertainty on the performance of supply chain considering multiple echelon with periodic-review, order-up-to level replenishment policy. The performance of supply chain under the influence of uncertainty in demand, supplier reliability and supply deliveries is analysed and determined the optimum order-up-to level i.e. the target inventory level to reduce the total cost and increase the fill rate (Petrovic et al, 1998; 1999; Petrovic, 2001; Xie et al., 2006).

One of the adverse effects of uncertainty is bullwhip effect (BWE). In section 2.6 (in Chapter 2) the concept and its adverse effect has been discussed. BWE is one of the major issues in supply chain management as it adversely affects the supply chain performance through increasing various costs and decreasing service level. According to Bout and Lambrecht (2009), reduction of BWE not necessarily reduces the inventory holding cost because reduction of BWE smoothen the order resulting in reduction of ordering cost/switching cost. Fluctuation of inventory can be managed with increasing safety stock resulting in increase of holding cost. Therefore, both BWE and total cost are two important measures to analyse the performance of supply chain under uncertain environment. In reorder point order-up-to level ((s, S) policy) inventory replenishment policy, target inventory plays an important role in order quantity decision. Therefore, impact of target inventory along with uncertainties in demand and lead time on BWE and total cost need to be analysed. Many approaches have been proposed by different authors to analyse and reduce the BWE. Lee et al. (1997a), Lee et al. (1997b) and Chen et al., (2000a) have adopted statistical approach to quantify the BWE. Disney and Towil (2003) and Dejonckheere et al. (2003) have applied control theory approach to quantify BWE. Kim et al. (2006) have analysed the effect of variation in lead time and demand on BWE for four level serial supply chains. The complexity of study of a system through mathematical modelling can be reduced through simulation modelling approach. To study and analyse the BWE in a realistic manner, many researchers have proposed simulation modelling approaches. System dynamics and modelling (SDM) is one of the powerful computer-aided approaches that facilitate a set of conceptual tools to understand the structure and dynamics of a complex system. Earlier, many authors have applied SDM approach for modelling and simulation of supply chain to study and analyse the behaviour (Hwarng and Xie, 2008; Özbayrak et al., 2007; Minegishi and Thiel, 2000; Kumar and Nigmatullin, 2011; Georgiadis, 2005; Ge et al., 2004; Helo, 2000; Owens et al., 2002; Vlachos et al., 2007; Lee and Chung, 2012). Sterman (2000) has proposed classical beer distribution game model to analyse the BWE considering order decision based on anchoring and adjustment algorithm. Further, the classical beer distribution game model is adopted by many others to analyse the behaviour of supply chain under the influence of dynamic factors (Hwarng and Xie, 2008; O'donnell et al., 2006; Coppini et al., 2010).

This chapter studies the behaviour of a multi-echelon serial supply chain consisting of a retailer, distributor, wholesaler and factory employed with (s, S) inventory replenishment policy operating under uncertain environment. The system dynamics approach has been adopted to model the system. Each echelon of the supply chain is associated with order processing and receiving delay called lead time that varies with normally distributed pattern. Although SDM approach enables to study the behaviour of a supply chain in a realistic manner under the influence of different uncertainties, it is difficult to determine the impact of factors in more systematic fashion. The design of experiments (DOE) is used to efficiently obtain relevant information with less number of experimental runs. The well-known full factorial design is one of the DOE tool used in different area of research to design experimental runs to analyse the influence of factors on the system response (Bingol et al., 2010; Seki et al., 2006; Veličković et al., 2013). In this study, a full factorial experimental design is used to generate different simulation scenario considering uncertainty in demand and lead time and the inventory decision parameter i.e. the target inventory. Although DOE is one of the most widely used statistical tool, its use is limited to optimize a single performance measure (response). When multiple responses are desired to be simultaneously optimized in a DOE paradigm, the multiple responses are converted into an equivalent single response using multi-attribute decision making approaches such as analytical hierarchy process (AHP) (Ghodsypour and O'Brien, 1998), desirability function approach (DFA) (Datta et al., 2006), utility theory (Walia et al., 2006) and grey relational analysis (Ranganathan and Senthilvelan, 2011; Çaydaş and Hasçalık, 2008; Kuo et al. 2008; 2011). Therefore, the multi-response optimization technique such as grey relational analysis is combined with DOE approach to analyse the effect of uncertainties on combined objective of total cost and BWE.

3.2 Methodology

From the above section, it is found that system dynamics is one of the useful simulation modelling approaches through which a complex system can be studied in a realistic manner. To study the behavior of a multi-echelon serial supply chain under the influence of uncertainty, system dynamics approach has been adopted in the present study. A brief introduction of system dynamics is given in Section 3.2.1. The performance characteristics of a multi-echelon serial supply chain can be measures by BWE and total cost. In order to analyses both the characteristics of the supply chain, grey-relational analysis is adopted to convert multiple performance characteristics into an equivalent characteristic. Grey-relational approach is presented in Section 3.2.2.

3.2.1 The system dynamics approach

System dynamics, initially termed as Industrial Dynamics, is a computer-aided approach for analyzing and solving complex problem with a focus on policy analysis and design (Forrester, 1961). The system dynamics is a method which involves the study how a system can defend against or make benefit from the shocks which fall upon it. System dynamics is a part of system theory and an approach to understand the structure and dynamic behavior of the complex system influenced by different parameters over time (Coyle, 1977). It is a rigorous modelling method that facilitates to build formal computer simulations of complex systems and use them to design more effective policies. It is a perspective and set of conceptual tools that enable us to understand the structure and dynamics of a complex system (Sterman, 2000).

The system dynamics extensively use elements such as feedback loops, stocks and flows to study the behavior of complex system. There are two types of flows: physical flows and information flows. Physical flow is conserved flow as it reduces or increases the value of the level variable whereas information flows are not conserved flow. One rate variable is subdivided into various auxiliary variables. Stocks and levels are used interchangeably used in system dynamics; similarly as flows and rates. The level/stock variable represents the accumulations and it holds the current state of the system. Levels do not change instantaneously; it changes gradually over a period of time. Flow/rate represents the instantaneous flow rates and it causes to increase or decrease the stock in every unit of time (Mohapatra et al., 1994). The different elements used in system dynamics are shown in Figure 3.1. In order to combine the multiple performance measures into single equivalent parameter grey relational analysis can be used.

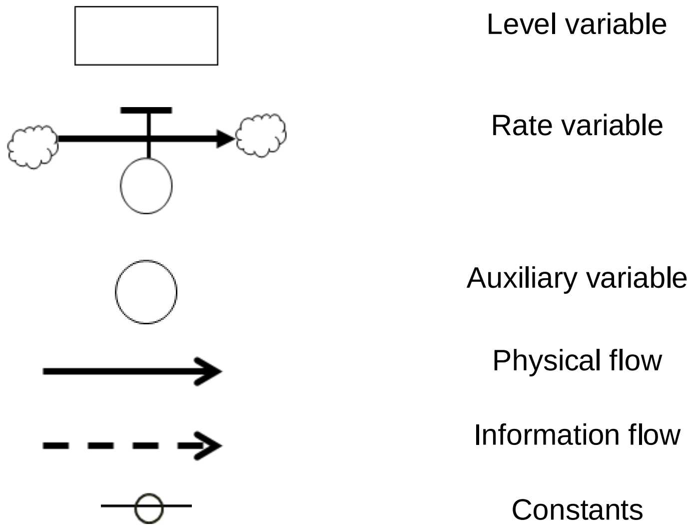

Figure 3.1. Different elements of system dynamics

3.2.2 Grey relational analysis

Multi-attribute decision making (MADM) or multi-criteria decision analysis (MCDA) is one of the sub-discipline of operations research which helps decision maker for solving decision and planning problem involving with multiple criterion. MADM helps the decision maker to select the best from the existing alternatives or options considering multiple attribute, goals or criteria, which are frequently in conflict with each other. It is a difficult problem to make trade-off between these conflicting attributes and make decision. Through the following paragraph, the MADM method - grey relational analysis (GRA) is briefly introduced. It has been successfully applied in solving a variety of MADM problems. GRA is based on the grey system theory. According to concept grey system theory, the situation with no information is defined as black and those with perfect information as white. However, neither of the idealized situations occurs in real world problem. In fact, the situations between these extremes can be defined as grey, hazy or fuzzy. Hence, a grey system means a system in which part of information is known and part of information in unknown. GRA reduce the original MADM problem into a single attribute decision making problem through combining the entire range of performance attribute considered for every alternative. Hence, the alternatives with multiple attributes can be easily compared after the GRA process.

The method consists of four steps such as (1) grey relational generating (2) reference sequence definition (3) grey relational coefficient calculation (4) grey relational grade calculation as discussed below.

a. Grey relational generating

When the measurement unit are different for different responses, it is necessary to convert all responses into same scale through the process of normalization (Huang and Liao, 2003). If there are m experimental scenarios and n responses, the i^{th} scenario can be expressed as $Y_i = (y_{i1,} y_{i2} \ldots y_{ij}, \ldots, y_{in})$ where y_{ij} is the performance value of response j at scenario i. The term Y_i can be translated into the comparability sequence $X_i = (x_{i1}, x_{i2} \ldots x_{ij}, \ldots, x_{in})$ using of one of Equation 3.1-Equation 3.3 where $\overline{y_j} = \mathrm{Max}\{y_{ij}, i = 1,2,\ldots,m\}$ and $\underline{y_j} = \mathrm{Min}\{y_{ij}, i = 1,2,\ldots,m\}$. Equation 3.1 and Equation 3.2 are used for larger-the-better and smaller-the-better type of response respectively. Equation 3.3 is used for nominal-the-better i.e. closer-to-the-desired-value, y_i^*. Through the grey relational generating procedure, the values of the responses will be scaled into [0, 1].

$$x_{ij} = \frac{y_{ij} - \underline{y_j}}{\overline{y_j} - \underline{y_j}} \tag{3.1}$$

$$x_{ij} = \frac{\overline{y_j} - y_{ij}}{\overline{y_j} - \underline{y_j}} \tag{3.2}$$

$$x_{ij} = 1 - \frac{\left|y_{ij} - y_j^*\right|}{\mathrm{Max}\left\{\overline{y_j} - y_j^*, y_j^* - \underline{y_j}\right\}} \tag{3.3}$$

where, i = 1, 2, 3, . . ., m; j = 1, 2,3, . . . ,n

b. Reference sequence definition

After the grey relational generating procedure, the response values are scaled into [0, 1]. If the grey relational generating value x_{ij} (j^{th} response value of i^{th} experimental scenario) is equal to 1 or nearer to 1 then the performance of the i^{th} scenario is best among the response j. If all the values are closest to or equal to 1 then the scenarios are considered as best choice. The aim is to find the experimental scenario whose comparability sequence is the closest to reference sequence x_0 as $(x_{01}, x_{02}, \ldots, x_{0j}, \ldots, x_{0n}) = (1,1,\ldots,1,\ldots,1)$.

c. Grey relational coefficient calculation

The grey relational coefficient is used to define the closeness between x_{ij} and x_{0j} i.e. how much x_{ij} is closer to 1. The grey relational coefficient can be calculated by using the Equation 3.4 where $\gamma(x_{0j}, x_{ij})$ is the grey relational coefficient between x_{0j} and x_{ij}.

$$\gamma(x_{0j}, x_{ij}) = \frac{(\Delta_{min} + \xi \Delta_{max})}{(\Delta_{ij} + \xi \Delta_{max})} \quad i = 1,2,\ldots,m \quad j = 1,2,\ldots,n \tag{3.4}$$

where ξ is known as distinguishing coefficient lies in between 0 to 1.

$$\Delta_{ij} = |x_{0j} - x_{ij}|$$

$$\Delta_{min} = \mathrm{Min}\{\Delta_{ij}, i = 1,2,\ldots,m; j = 1,2,\ldots,n\}$$

$$\Delta_{max} = \mathrm{Max}\{\Delta_{ij,} i = 1,2,\ldots,m; j = 1,2,\ldots,n\}$$

d. Grey relational grade calculation

Grey relational grade characterizes the degree of correlation between reference sequence x_{0j} and x_{ij}.It can be calculated using Equation 3.5 where $\Gamma(X_{0j}, X_{ij})$ is the grey relational grade between X_0 and X_i, and w_j is the weight of response j which depends on the judgement of the decision makers.

$$\Gamma(X_0, X_i) = \sum_{j=1}^{n} w_j \gamma(x_{0j}, x_{ij}); \quad i = 1,2,\ldots,m \quad j = 1,2,\ldots n \tag{3.5}$$

where,

$$\sum_{j=1}^{n} w_j = 1$$

Now, grey relational grade value can be treated as an equivalent response for multiple responses and possible best solutions can be obtained using DOE approach.

3.3 A model of multi-echelon serial supply chain

In a multi-echelon serial supply chain, the distinct entities/facilities (e.g. retailer, distributor, wholesaler and manufacturer) are linked to each other in a serial fashion to satisfy the demand from end customer. To study the performance of a serial supply chain under the influence of uncertain environment, demand data for an automotive component (gaskets for a two-wheeler) is collected from a retail shop located at the Eastern part of India from the year 2009-2011. The mean demand observed by the retail shop is 20 units per a day. To satisfy its demand, it depends on a local distributor and similarly, the distributor depends on the wholesaler in another city and wholesaler to a manufacturer located in another state. Delay is associated between the two adjacent entities and it is sum of the time taken to process the order and receive the order. A single period delay is involved between retailer and distributor. Similarly, two time period delay between distributor and wholesalers and three time period delay between wholesaler and factory. The raw material is supplied by external supplier to the factory for the production requirement. The manufacturer produces it at a constant rate of 25 units per period. The general structure for the considered supply chain is shown in Figure 3.2. The purchasing cost of the component for the wholesaler is Rs10 whereas it is Rs15 and Rs20 respectively for the distributor and retailer. Transportation charge is 15% of the value of the items purchased. The ordering cost is Rs. 100 and independent of ordering quantity.

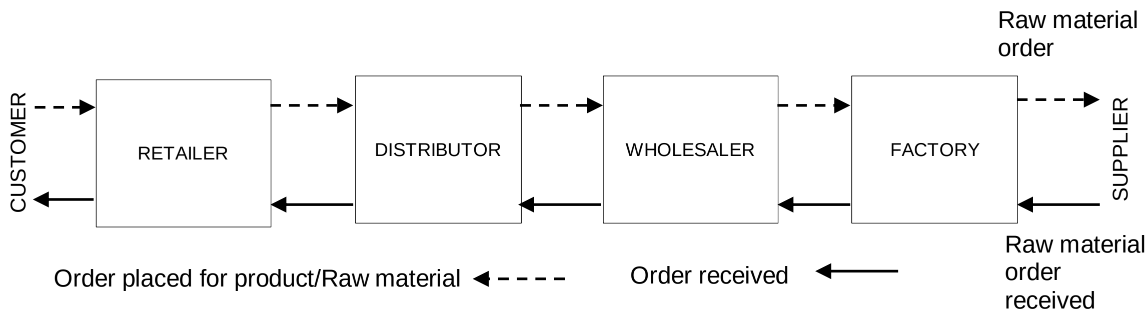

Figure 3.2 Block diagram of multi-echelon serial supply chain model

Inventory carrying cost is 13% of the value of items held by inventory for a period. The calculation for transportation cost, ordering cost, inventory holding cost and backorder cost is similar to all levels. The sales rate or the dispatch quantity from one echelon to other depends on the availability of stock and quantity of order placed i.e. $\mathrm{Min}(Q_t, INV_t)$ where Q_t denotes the amount of order placed by i^{th} echelon to $(i+1)^{th}$ echelon and INV_t represent available stock at echelon $(i+1)^{th}$ in period t. The continuous review policy is implemented by each stage for the replenishment of inventory. According this policy, when inventory position IP_t (Equation 3.6) become less than or equal to the reorder point (ROP) then an order quantity Q_t is placed by the echelon. The replenishment quantity Q_t is estimated through the Equation 3.7 where S represents the target inventory level and s is the ROP (Silver et al., 1998; Dejonckheere et al., 2003; Campuzano et al., 2010).

$$IP_t = \text{on hand stock} + \text{order in transit} - \text{backorder} \quad (3.6)$$

$$Q_t = \begin{cases} S - IP_t, \text{If } IP_t \le s \\ 0, \text{if } IP_t > s \end{cases} \quad (3.7)$$

There are different amount of safety stock is maintained at each stage. The value of safety stock and reorder point (ROP) s is calculated using Equation 3.8 and Equation 3.9 respectively (Silver et al., 1998). The unfilled quantity is considered as backorder and it incurs penalty to the echelon which is 25% of the value of the products backordered per period.

$$\text{Safety Stock(SS)} = z \times \sqrt{\left(\mu_{LT} \times \sigma_d^2 + \mu_d^2 \times \sigma_{LT}^2\right)} \quad (3.8)$$

$$s = SS + \mu_{LT} \times \mu_d \quad (3.9)$$

where, z represents service level, μ_{LT} is the mean value of lead time, μ_d is the mean demand, σ_{LT} is the standard deviation of lead time and σ_d represents the standard deviation of demand.

The performance of a supply chain can be measured through the two parameters-BWE and total cost throughout the supply chain. The amplification of orders with respect to the demand is known as BWE. It can be calculated using Equation 1.2 (in Chapter 1). Total cost includes all the expenses to bring a product from the supplier end to buyer end. It includes purchasing cost, ordering cost, inventory holding cost, backorder cost and transportation cost. Purchasing cost is the amount paid to supplier for purchasing. Ordering cost includes all the expenses to place an order. Transportation cost is the shipping charge to bring the product/material from the one echelon to other. Inventory holding cost includes all the expenses to hold a unit of product for a period. Backorder is the extra penalty to be borne by the echelon if there is some unfilled demand/order. Total cost (TC_i) can be calculated from Equation 3.10 and Equation 3.11.

$$TC_i = C_h + C_p + C_b + C_t + C_o \quad (3.10)$$

$$TC\_SC = \sum_{i=1}^{3} TC_i \quad (3.11)$$

where,

$$C_h = 0.13 \times \text{Average\_inventory} \times \text{unit price of product}$$

$$C_p = \text{unit price of product} \times Q_t$$

$$C_b = 0.25 \times \text{back order quantity}$$

$$C_t = 0.15 \times Q_t \times \text{unit price of product}$$

$$C_o = \text{Rs.}100/\text{order}$$

where C_h denotes the holding cost, similarly C_p: purchase cost, C_b: backorder cost, C_t: transportation cost, C_o: ordering cost, TC_i: total cost of echelon i (i=1, 2, and 3), TC_SC: total cost of supply chain.

To study and analyse the behavior of above described multi-echelon serial supply chain model in realistic and systematic manner under the influence of uncertainty environment, the model is modelled through system dynamics approach and behavior is studied using DOE approach.

3.4 The simulation procedure

The system dynamics approach is one of the useful approach for simulation modelling as discussed in section 3.2.1. Hence, the four echelon serial supply chain model as shown in Figure 3.2 is modelled through system dynamics approach using the software STELLA 0.5 as shown in Figure 3.3. Various notations used in system dynamics model are given as follows:

Notations:

i. R – Retailer
ii. D – Distributor
iii. W – Wholesaler
iv. F – Factory/Manufacturer
v. INV – Inventory
vi. R INV – Amount of inventory available at Retailer at a particular period.
vii. demand – demand generated from the customer
viii. R ROP – retailer’s Reorder Point
ix. R target INV – Retailers Target Inventory similarly
x. Order placed by R – amount of order placed by Retailer
xi. R projected on hand INV – Retailer’s projected on – hand inventory.
xii. Customer demand – demand from the customer.
xiii. Sales rate – amount product sales to the customer.
xiv. Total demand at R – sum of customer demand and backlog quantity at retailer end.
xv. Dispatch to R – quantity dispatch from the distributor to retailer against the order placed.
xvi. R order received – Retailer’s order received.

xvii. R backorder per period – unsatisfied demand to the lower level at period t.

xviii. R backorder acquisition – accumulation of backorder

xix. Total backorder – total backorder at period t to satisfied.

All these notations are similar in case of distributor (D), wholesaler (W) and factory (F).

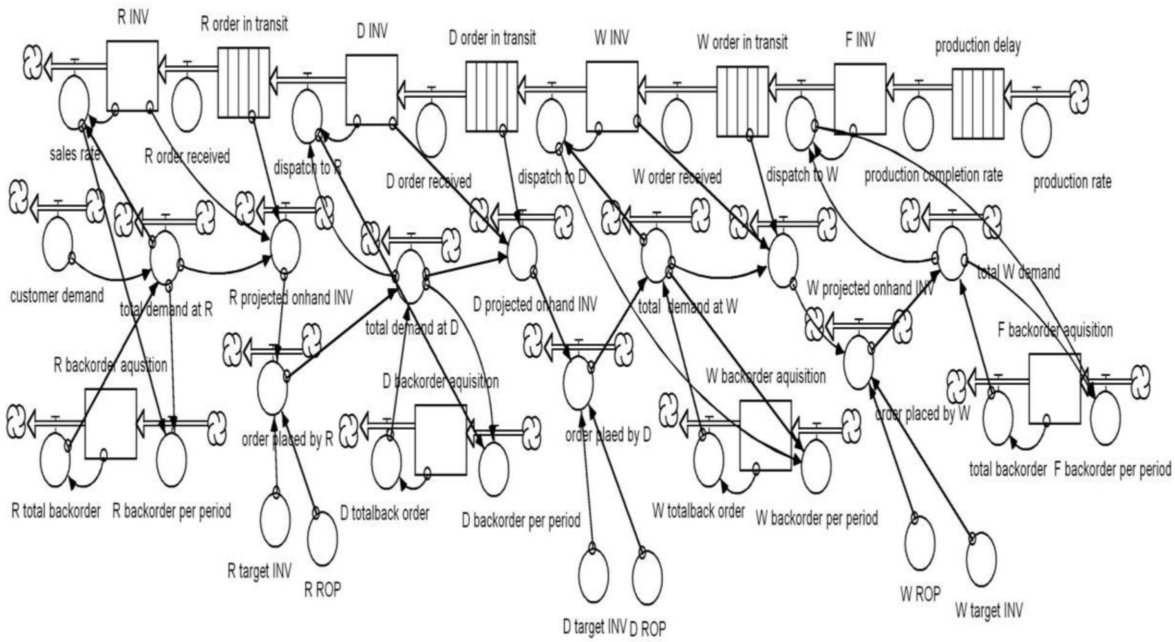

Figure 3.3 The system dynamics model for multi-echelon serial supply chain

There are certain assumptions are made for the modelling and simulation purpose of the considered a multi-echelon serial supply chain, these are as follows:

Assumptions:

1. Once order placed, it cannot be cancelled and received shipment cannot be returned.
2. Once order placed by lower echelon, it cannot be discarded by upper echelon.
3. The unit variable cost of the product does not depend on the replenishment quantity i.e. there is no discount in either the unit purchase cost or transportation cost.
4. Cost factors do not change with time.
5. At time period t, the backorder from t-1 period is given higher priority than the demand at t.
6. Each echelon has to maintain 99% service level.

Initial condition for the model:

For the simulation purpose following are the initial conditions taken for the planned model.

1. Inventory position at each echelon is equal i.e. 100 units.
2. Initially there is no backlog.
3. Initially there is no outstanding order from the lower echelon.
4. There is no order in transit.

The equation for stock-flow diagram (Figure 3.3) is shown in Appendix 2. There are various sources of uncertainties which adversely influence on the performance of supply chain. Among them, uncertainty in demand and supply lead time is two major parameters having impact of the performance of a supply chain. The target inventory plays major role in ordering decision activity in (s, S) inventory replenishment policy. Hence, in this study, in addition to uncertainty in demand and lead time, the modelling parameter - target inventory is taken as one of the important parameter to examine the behaviour of considered multi-echelon serial supply chain employed with (s, S) policy. DOE approach is one of the best approaches to determine the experimental setup to carry out the experiment or to simulate the models. It also helps in determining the behaviour of different influencing factor of the system (Montogomory, 2001). Therefore, to examine the influence of uncertainty in demand, lead time and target inventory on supply chain performance, different simulation setup are designed to simulate the system dynamics model (Figure 3.3) based on full factorial design. Increase in rate of uncertainty for the considered parameter is presented through increasing the standard deviation of the parameter. In the experimental settings to generate simulation scenarios, each parameter is considered in three levels - low (L), medium (M) and high (H). Levels values are based on the variation in parameters. For representing the increasing uncertainty in lead time between retailer and distributor, the standard deviation of 0.1, 0.2 and 0.3 is taken representing low, medium and high level of variation respectively as summarized in Table 3.1. This is same for distributor, wholesaler and manufacturer case.

Table 3.1 Parameters and their levels

Factors (Parameters)	Echelons	LEVELS					
		Low (L)		Medium (M)		High (H)	
		mean	Standard Deviation	mean	Standard deviation	Mean	Standard Deviation
Lead Time (in days)	Retailer	1	0.1	1	0.2	1	0.3
	Distributor	2	0.2	2	0.4	2	0.6
	Wholesaler	3	0.3	3	0.6	3	0.9
	Factory	4	0.4	4	0.8	4	1.2
Demand (in units)		20	2	20	4	20	6
Target Inventory (in units)		ROP+1x demand		ROP+2xDemand		ROP+3xDemand	

Similarly, the parameter - target inventory at low level is sum of ROP and single period demand and medium and high level is set as summarized in Table 3.1. Mean demand is 20units and low, medium and high level of uncertainty is represented as standard deviation of 2, 4, and 6 respectively. There are three parameters - each at three levels. Hence, twenty seven numbers $\left(3^3 = 27 \;\; 3\,\text{levels and } 3\,\text{factors}\right)$ of experimental scenarios are generated based on full factorial design using software Minitab16. This is summarized in Table 3.2. Each row of this column represents the experimental scenario. Different model parameters are set according to these experimental scenarios and the model Figure 3.3 is simulated for 104 weeks (2-year) time period. At the end of each run, different parameters are estimated to study the behaviour of the considered supply chain. To analyse the warm-up period, the time series plot is plotted for the retailer's inventory as shown in Figure 3.4. From the figure, it can be observed that first 14-weeks are under transient phase. Hence, these periods are considered as warm-up period and discarded from the total simulation runs. The rest periods are considered as steady state period to estimate different parameters.

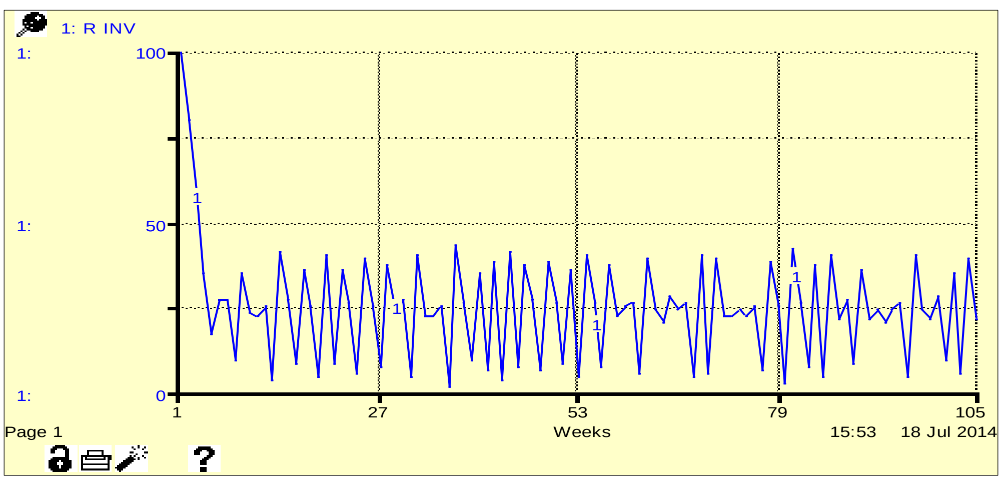

Figure 3.4 Time series plot for retailer inventory level

3.5 Results and discussions

The system dynamics model shown in Figure 3.3 is simulated for two-year time period. Based on the simulation scenarios, the mean and standard deviation of the order quantity placed by each echelon is estimated at the end of each simulation run considering steady period as summarized in Table 3.2. The variance of order quantity at each stage is estimated from each experimental run is plotted to visualize the amplification of order from one stage to others in Figure 3.5. From the Figure 3.5, it can be observed that variation in order increases from retailer to wholesaler end for the all experimental scenarios. This signifies the existence of BWE within supply chain whatever may be the scenario.

Table 3.2 Summary of estimated order quantity at different echelon

Experiment scenario number	Simulation scenario			Orders Values For Different Echelon					
				Retailer		Distributor		Wholesaler	
	Lead Time	Demand	Target Inventory	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation
1	L	L	L	19.75	14.70	19.62	14.89	19.73	15.07
2	L	L	M	19.72	25.08	19.96	25.46	20.51	25.66
3	L	L	H	19.71	31.38	20.25	32.65	21.15	41.88
4	L	M	L	20.06	15.12	19.94	15.47	20.08	15.55
5	L	M	M	20.01	25.31	20.26	25.77	20.83	27.22
6	L	M	H	19.99	31.71	20.55	33.15	21.48	44.86
7	L	H	L	20.41	15.96	20.33	18.56	20.59	18.46
8	L	H	M	20.34	25.75	20.61	26.13	21.20	29.53
9	L	H	H	20.53	31.91	20.53	39.72	21.13	40.14
10	M	L	L	19.77	14.61	19.65	15.07	19.80	15.33
11	M	L	M	19.74	25.10	19.99	25.52	20.56	26.51
12	M	L	H	19.73	31.41	20.27	34.05	21.22	44.55
13	M	M	L	20.07	15.09	19.97	17.69	20.17	17.58
14	M	M	M	20.02	25.32	20.30	26.66	20.91	27.39
15	M	M	H	20.00	31.73	20.56	34.36	21.53	45.53
16	M	H	L	20.52	31.89	20.71	31.52	21.24	31.56
17	M	H	M	20.35	25.76	20.63	26.17	21.23	28.09
18	M	H	H	20.54	31.92	21.13	37.50	33.84	66.43
19	H	L	L	19.79	14.27	19.69	14.20	19.87	14.33
20	H	L	M	19.76	25.07	19.66	24.97	20.21	25.16
21	H	L	H	19.75	31.44	20.31	34.00	20.86	36.35
22	H	M	L	20.09	15.57	20.01	16.29	20.22	16.17
23	H	M	M	20.04	25.37	20.34	26.63	20.95	28.35
24	H	M	H	20.02	31.75	20.60	32.01	26.57	56.25
25	H	H	L	20.44	16.36	20.38	18.61	20.63	18.51
26	H	H	M	20.37	25.78	20.68	27.98	21.37	31.36
27	H	H	H	20.56	31.95	20.58	38.82	33.78	65.83

Similarly, the mean and standard deviation of the inventory level at each echelon is estimated to present the inventory status as summarised in Table 3.3. The estimated mean inventory quantity is pictorially shown in Figure 3.6. It can be observed that inventory quantity held by each stage increases in upward direction as a result of variation in order. Similarly, from Figure 3.7 it can be observed that variation in inventory quantity increases in upward direction of the supply chain for all scenarios. In fact, Figure

3.6 and Figure 3.7 describe the fluctuation in inventory level due to variation in demand, lead time and change in target inventory quantity.

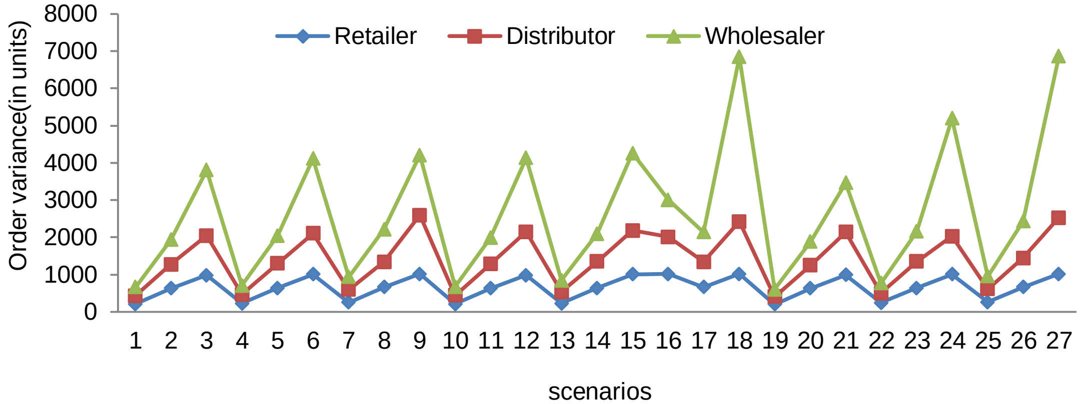

Figure 3.5 Order quantity variations at different echelon

Table 3.3 Summary of estimated inventory quantity

Experiment scenario number	Inventory level at each echelon					
	Retailer		Distributor		Wholesaler	
	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation
1	24.71	15.83	47.83	16.25	52.74	16.97
2	32.60	19.78	84.69	21.20	94.69	21.81
3	42.18	23.04	112.64	34.75	180.90	92.91
4	26.45	15.47	49.46	17.25	54.58	19.41
5	34.29	19.20	85.06	21.35	93.99	23.98
6	43.38	22.77	113.63	35.19	190.58	98.22
7	28.58	16.06	51.58	19.90	67.61	23.46
8	36.19	19.43	86.57	21.83	100.18	36.81
9	45.88	22.65	103.12	40.84	146.13	87.54
10	26.10	15.60	48.96	18.15	57.18	21.19
11	34.06	19.15	85.55	24.24	97.75	27.79
12	43.76	22.54	111.15	36.67	172.56	90.35
13	27.35	16.32	50.33	20.37	63.00	23.36
14	34.97	18.88	86.71	24.83	105.54	33.02
15	44.13	22.51	112.15	36.89	185.00	93.64
16	45.13	22.87	78.03	34.59	99.58	42.31
17	36.92	19.17	88.43	23.15	108.17	42.23
18	46.73	22.48	110.71	39.51	213.83	118.70
19	26.74	15.38	52.04	20.52	58.11	21.60
20	33.90	18.31	53.23	25.55	96.59	29.18
21	44.94	22.53	112.67	38.05	127.85	68.49
22	27.28	16.51	52.44	21.90	62.25	25.25
23	35.88	18.73	89.24	25.38	103.65	37.52
24	45.52	22.48	116.89	34.05	215.56	124.04
25	29.42	16.12	54.86	24.31	67.83	27.09
26	37.99	19.19	89.63	29.24	113.76	44.92
27	47.80	22.63	110.61	42.52	211.95	116.59

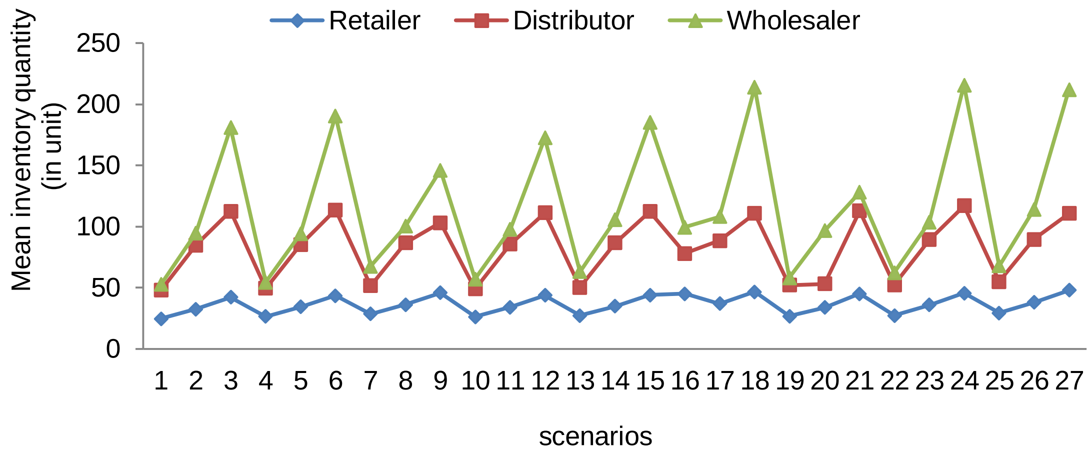

Figure 3.6 Estimated mean inventory level at different echelon

Figure 3.7 Variance of inventory level at different echelon

The supply chain performance measures such as BWE and total cost are estimated from each simulation run by applying the Equation 1.1 (in Chapter 1) and Equation 3.10-Equation 3.11 respectively as summarized in Table 3.4. Unlike, variation in order and inventory quantity, the total cost incurred at each stage increases in reverse direction i.e. from wholesaler to the retailer as observed Figure 3.8. This is due to the fact that retailer is subjected to high backorder quantities, high unit price, and frequency of placing orders. Figure 3.9 depicts backorder per period for each echelon. Comparatively, backorder quantity is more in case of retailer than rest of other echelons.

Table 3.4 Estimated total cost and bullwhip effect at each simulation run

Experiment number	Lead time	demand	Target inventory	Total cost of retailer	Total cost of distributor	Total cost of wholesaler	Total cost of supply chain	Bullwhip effect
1	L	L	L	58347.50	44814.83	32580.63	135742.95	1.02
2	L	L	M	54946.50	44204.90	31930.10	131081.50	0.99
3	L	L	H	53911.55	45039.56	33897.05	132848.16	1.58
4	L	M	L	58996.15	45385.45	33044.20	137425.80	1.00
5	L	M	M	55600.90	44758.18	32085.88	132444.95	1.09
6	L	M	H	54659.15	45624.04	34505.00	134788.19	1.75
7	L	H	L	59860.80	45801.45	33766.58	139428.83	0.98
8	L	H	M	56336.60	45455.71	32543.68	134335.99	1.24
9	L	H	H	55841.15	44561.70	33192.03	133594.88	0.99
10	M	L	L	58182.10	44980.10	32793.78	135955.98	1.03
11	M	L	M	54851.30	44300.04	31990.95	131142.29	1.05
12	M	L	H	53894.15	44898.50	33560.45	132353.10	1.63
13	M	M	L	59034.60	45076.08	32783.90	136894.58	0.98
14	M	M	M	55525.05	44811.03	32579.70	132915.78	1.02
15	M	M	H	54633.50	45466.70	34549.00	134649.20	1.68
16	M	H	L	55838.10	44480.06	42528.80	142846.96	0.98
17	M	H	M	56284.00	45584.79	33078.25	134947.04	1.12
18	M	H	H	55862.00	46316.33	51810.85	153989.18	1.96
19	H	L	L	58491.65	45523.85	33190.48	137205.98	1.01
20	H	L	M	54831.90	43012.55	31665.13	129509.58	0.99
21	H	L	H	54040.10	45044.53	32747.20	131831.83	1.11
22	H	M	L	58986.05	45506.08	33391.05	137883.18	0.98
23	H	M	M	55487.80	45008.24	32492.00	132988.04	1.10
24	H	M	H	54663.10	45976.04	42260.35	142899.49	2.39
25	H	H	L	59557.00	46281.19	33966.55	139804.74	0.98
26	H	H	M	56332.15	45639.23	33043.08	135014.45	1.22
27	H	H	H	55995.15	45217.71	51428.48	152641.34	1.75

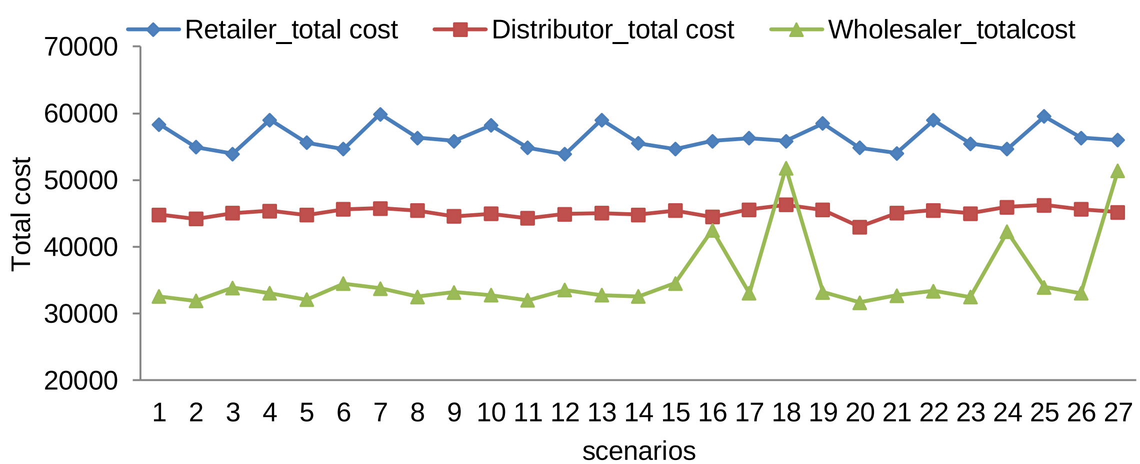

Figure 3.8 Estimated total cost at different echelon

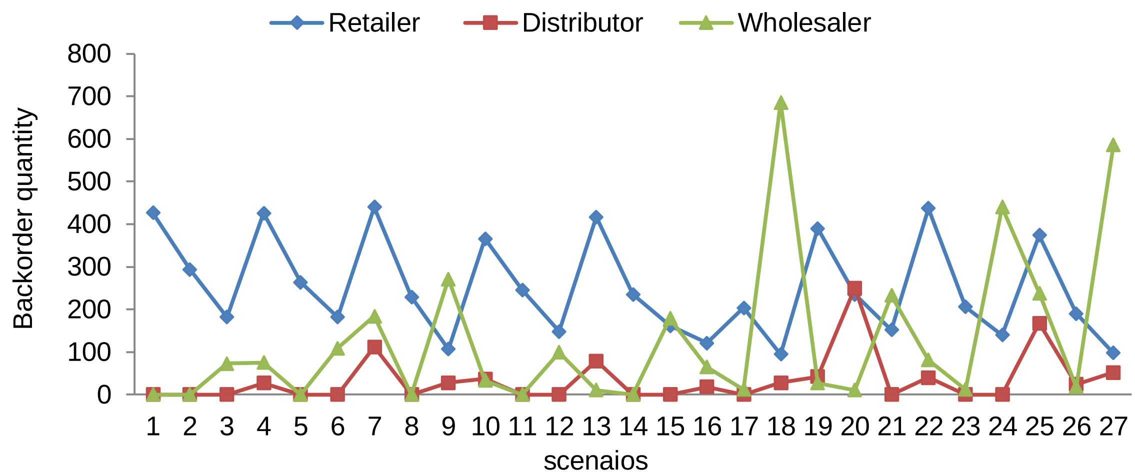

Figure 3.9 Estimated backlog at each echelon from the simulation runs

To measure the impact of increasing uncertainty in lead time and demand, and changes in target inventory level on total cost, analysis of variance (ANOVA) is performed for the estimated total cost at 5% significance level and the summary is described in Table 3.5. From this table, it can be observed that the p-Value for demand and target inventory is less than 0.05. This signifies that uncertainty in these two parameters (factors) significantly influence on total cost. Although no significant interaction effect is observed, influence of interaction effect of the factors such as demand and target inventory may impact moderately on total cost. The main and interaction plots are shown in Figure 3.10 and Figure 3.11 respectively. From the main effect plot (Figure 3.10), it can be concluded that total cost can be minimised through keeping medium target inventory level i.e. (ROP + two period demands) while there is low variation in demand and lead time.

Table 3.5 Summary of ANOVA for total cost

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Lead time	2	51174814	51174814	25587407	1.88	0.215
Demand	2	270314682	270314682	135157341	9.91	0.007
Target inventory	2	202673177	202673177	101336588	7.43	0.015
Lead time * Demand	4	81172908	81172908	20293227	1.49	0.293
Lead time * Target inventory	4	74797081	74797081	18699270	1.37	0.325
Demand * Target inventory	4	107084236	107084236	26771059	1.96	0.193
Error	8	109101531	109101531	13637691		
Total	26	896318429				
S = 3692.92 R-Sq = 87.83%						

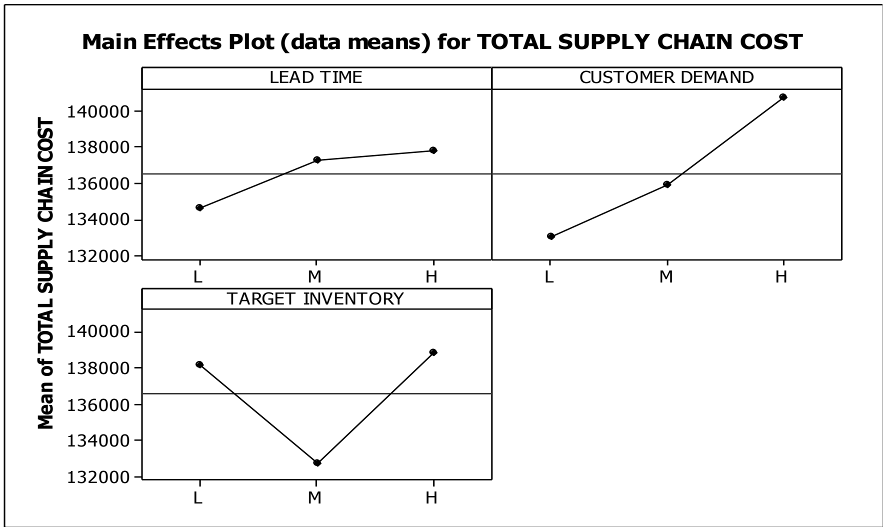

Figure 3.10 Individual effect of demand, lead time and target inventory on total cost

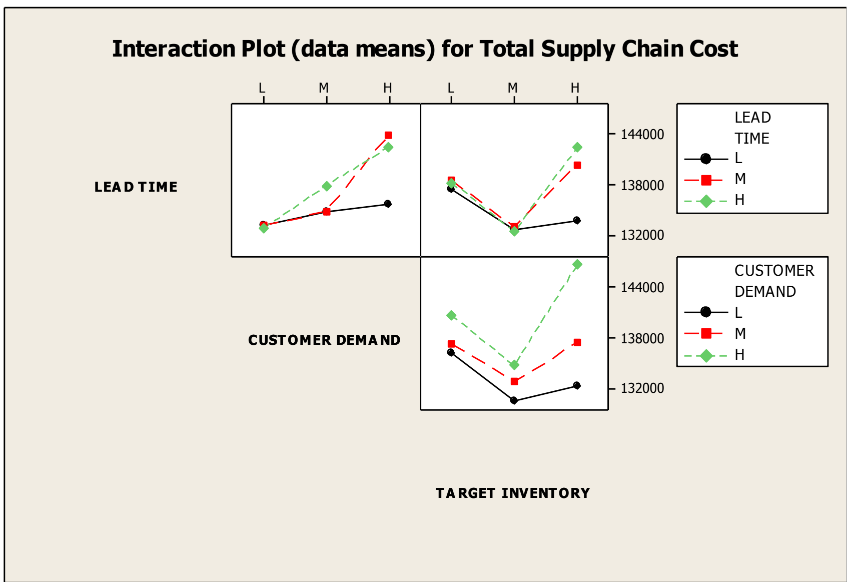

Figure 3.11 Effect of interaction of lead time, demand and target inventory on total cost

Similarly, ANOVA for the response parameter BWE has been performed at 5% significance level. The resulting ANOVA table is shown in Table 3.6. From the table, the estimated p-Value for target inventory is less than 0.05 which indicates that it has significant effect on BWE. No interaction has strong effect on BWE. The main effect and interaction effect of uncertainty in demand, lead time and the target inventory on BWE can be pictorially observed from the Figure 3.12 and Figure 3.13 respectively. From the ANOVA table and interaction plot, it can be observed that interaction of demand and target inventory has mild influence on BWE. From the main effect plot (Figure 3.12), it can be observed that BWE can be reduced when the lead time and demand vary with low value and target inventory is kept at low level i.e. ROP + single period demand.

Table 3.6. Summary of ANOVA for bullwhip effect

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Lead time	2	0.05413	0.05413	0.02707	0.40	0.680
Demand	2	0.13941	0.13941	0.06971	1.04	0.396
Target inventory	2	2.25955	2.25955	1.12977	16.94	0.001
Lead time * Demand	4	0.26981	0.26981	0.06745	1.01	0.457
Lead time *Target inventory	4	0.14761	0.14761	0.03690	0.55	0.704
Demand *Target inventory	4	0.32050	0.32050	0.08013	1.20	0.382
Error	8	0.53478	0.53478	0.06685		
Total	26	3.72580				
S = 0.258549 R-Sq = 85.65%						

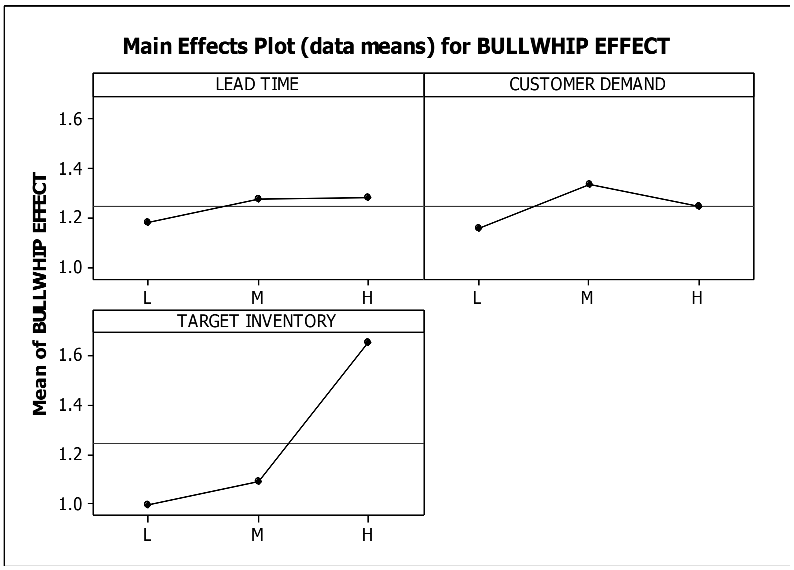

Figure 3.12 Individual effect of lead time, demand and target inventory on BWE

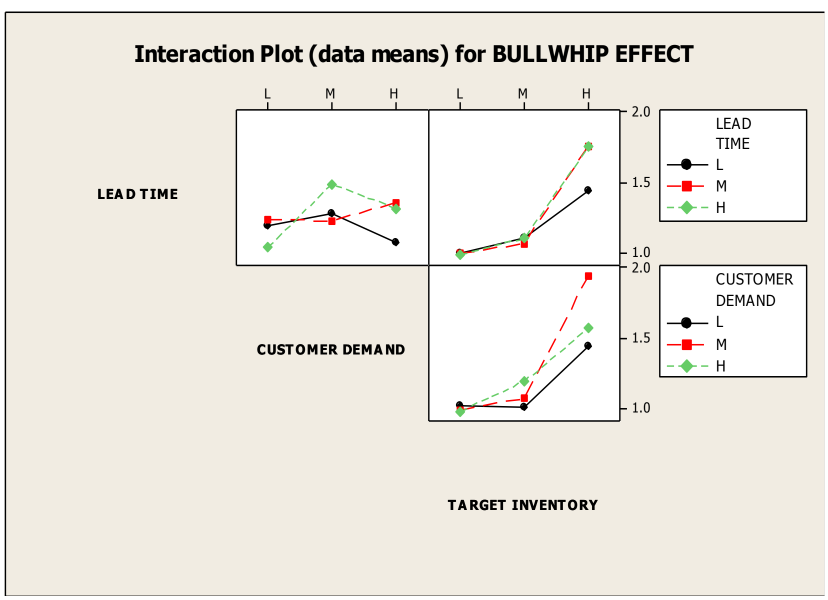

Figure 3.13 Interaction effect of lead time, demand and target inventory on BWE

From the above analysis, it is observed that uncertainty in demand and inventory decision parameter target inventory has significant effect on the total cost while the factor target inventory significantly influence to supress BWE. However, optimum settings for both the performance measures happen to be different. If it is desired to minimize both the performance measures simultaneously, then it is required to convert both the responses into an equivalent single response. To determine the optimal parameter settings to simultaneously reduce the BWE and total cost, grey relational analysis has been used in this study. The different steps for grey relational grade outlined in section 3.2.2 are followed to convert the BWE and total cost into an equivalent single response considering distinguishing coefficient as 0.5 and weighting both the responses equally. The summary of the grey relational grades analysis is described in Table 3.7.

Table 3.7 Summary of grey relational analysis

Experiment number	Grey relational generation		Grey relational coefficient		Grey relational grade
	Total Cost	BWE	Total Cost	BWE	
1	0.745368	0.970077	0.662571	0.943533	0.803052
2	0.935787	0.99019	0.886189	0.980757	0.933473
3	0.863619	0.577081	0.785691	0.541759	0.663725
4	0.676624	0.979968	0.607253	0.96148	0.784366
5	0.880091	0.922408	0.806567	0.865663	0.836115
6	0.78437	0.452426	0.698682	0.477293	0.587988
7	0.594801	0.998653	0.552361	0.997314	0.774838
8	0.802842	0.812308	0.717195	0.72707	0.722132
9	0.833116	0.987668	0.749753	0.97593	0.862842
10	0.736666	0.962594	0.655018	0.930396	0.792707
11	0.933304	0.947698	0.882306	0.905303	0.893804
12	0.883843	0.534912	0.811479	0.518088	0.664783
13	0.698324	0.998151	0.62369	0.996316	0.810003
14	0.860857	0.965359	0.782296	0.935206	0.858751
15	0.790047	0.505763	0.704269	0.502898	0.603584
16	0.455171	0.998118	0.478544	0.996251	0.737397
17	0.777881	0.897985	0.692404	0.830545	0.761474
18	1.37E-05	0.306388	0.333333	0.418897	0.376115
19	0.685604	0.976159	0.613948	0.954488	0.784218
20	1	0.991082	1	0.982477	0.991238
21	0.905137	0.90255	0.840527	0.836891	0.838709
22	0.65794	1	0.593779	1	0.796889
23	0.857906	0.911815	0.778699	0.850073	0.814386
24	0.453025	0	0.477563	0.333333	0.405448
25	0.579445	0.998557	0.543147	0.997122	0.770135
26	0.775127	0.830443	0.689773	0.746762	0.718268
27	0.055073	0.45255	0.346035	0.47735	0.411692

To identify the optimal parameter settings that minimises both total cost and BWE, ANOVA is performed at 5% significance level for the obtained grey relational grade (Table 3.8). The resultant ANOVA table is described in Table 3.8.

Table 3.8 Analysis of variance for grey relational grade

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Lead time	2	0.01531	0.01531	0.00765	0.66	0.543
Demand	2	0.08889	0.08889	0.04445	3.84	0.068
Target inventory	2	0.27349	0.27349	0.13674	11.80	0.004
Lead time*demand	4	0.05919	0.05919	0.01480	1.28	0.355
Lead time*target inventory	4	0.03290	0.03290	0.00823	0.71	0.607
Demand* target inventory	4	0.04296	0.04296	0.01074	0.93	0.494
Error	8	0.09267	0.09267	0.01158		
Total	26	0.60541				
S = 0.107627 R-Sq = 84.69%						

From the table, p-Value of target inventory is found to be less than 0.05. Hence, it is the most significant parameter for controlling both total cost and BWE. Next, significant influencing parameter on grey relational grade is uncertainty in demand. From the main effect plot shown Figure 3.14, it can be observed that best setting for reducing BWE and total cost is low variation in lead time and demand and medium level of target inventory. From the analysis, it can be concluded that the BWE and total cost can be simultaneously reduced when there is low variation in demand and lead time and target inventory level is kept at medium level (i.e. ROP + two periods demand from immediate lower echelon). From Table 3.8 and interaction plot (Figure 3.14), it can be observed that no strong interaction effect exists. But the interaction of lead time and demand has minor effect on simultaneous minimization of both the responses.

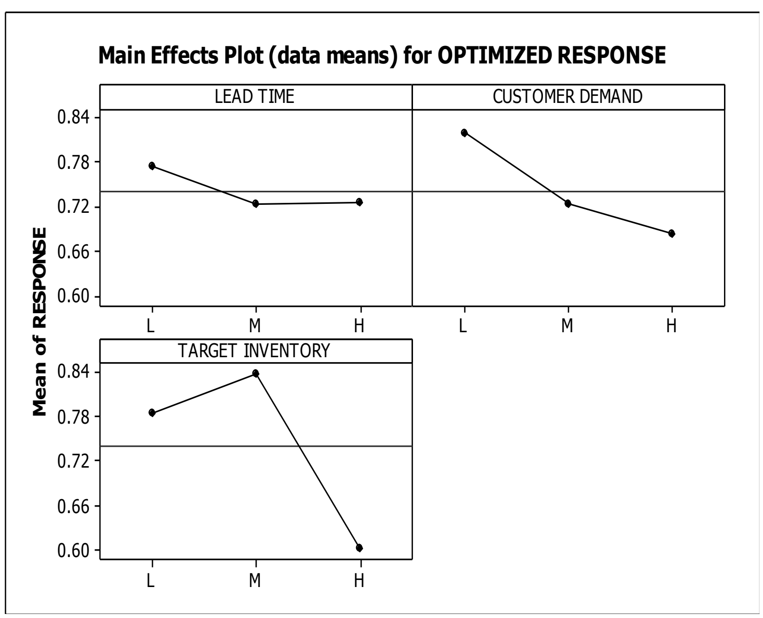

Figure 3.14 Individual effect of lead time, demand and target inventory on grey relational grade

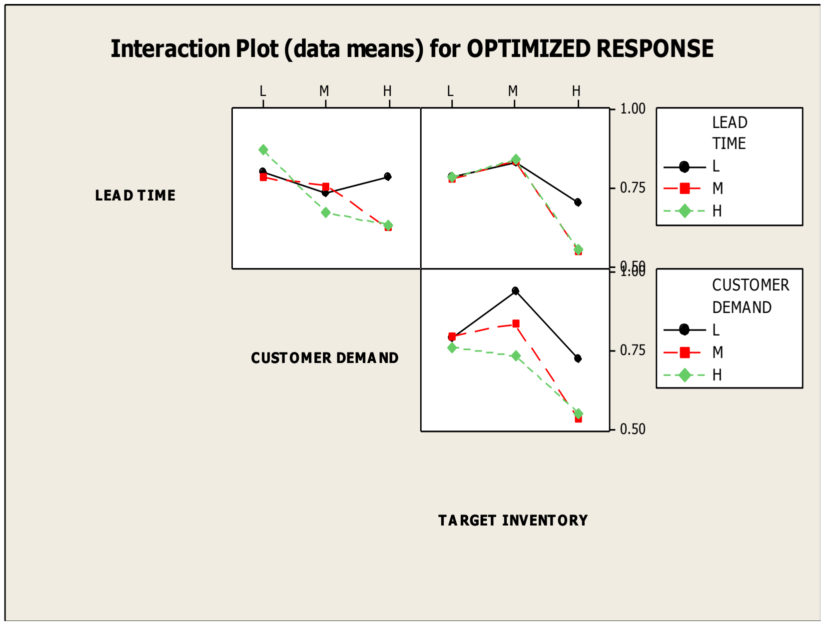

Figure 3.15 Interaction effect of factor lead time, demand and target inventory on grey relational grade

3.6 Summary

In this work, a four echelon serial supply chain employed with (s, S) policy is modelled through the system dynamics approach. Using full factorial design, different scenarios are generated and the model is simulated to estimate the impact of uncertainty in demand, lead time and the target inventory on BWE and total cost. Further, from the statistical analysis, it has been determined that target inventory level has significant effect on the BWE whereas total cost is affected due to increase in uncertainty in demand and increase in target inventory level along the supply chain. BWE can be minimised when there is low variation in demand and lead time and target inventory level is kept at low level (i.e. ROP + single period demand). Similarly, the total cost can be minimised while there is low variation in demand and lead time and target inventory kept at medium level (ROP + two periods demand). An integrated approach of DOE and grey relational analysis is adopted to minimise the BWE and total cost simultaneously. Both the performance parameters can be minimised if low variation in demand and lead time is encountered while target inventory is kept at medium level (i.e. ROP + two periods of demand). From the study, it can be concluded that target inventory decision is one of the most important parameter. Hence, proper decision for target inventory along the supply chain can help in moderating the BWE and total cost under uncertain environment. However, the methodology is quite generic and simulation of the supply chain in this work relates to the case study example. The managers can gain insight into real applications using the proposed methodology. In future, the study can be extended to include supply chain network with multiple suppliers and multiple products. The next chapter analyses the performance of manufacturing supply chain under uncertain environment.

CHAPTER 4

PERFORMANCE ANALYSIS OF MANUFACTURING SUPPLY CHAIN UNDER UNCERTAINTY

4.1 Introduction

In Chapter 3, performance of the multi-echelon serial supply chain employed with reorder-point order-up-to-level inventory policy is studied under the influence of uncertainty in demand and lead time and target inventory, an inventory decision parameter. Manufacturing system is one of the sub-systems of a supply chain in which different manufacturing policies such as (i) make-to-stock (MTS), (ii) make-to-order (MTO), (iii) assemble-to-stock (ATS) and (iv) assemble-to-order (ATO) are adopted to manufacture a product depending on its type. The classic structure of a manufacturing system encompasses raw material supplier(s), raw material stock(s), raw material processing unit(s) and finished goods inventory. In MTO or ATO manufacturing system, items are manufactured or assembled based on customer demand. In a MTS production system, a finished goods inventory is maintained to fulfil the market demand based on forecasted data or production capacity. Similarly, an ATS manufacturing system combines multiple components into a single product which is stocked in an inventory to satisfy the customer demand. Therefore, accurate demand forecasting in both MTS and ATS manufacturing policy is important to achieve high service level whereas order execution time is important in MTO situation (Silver et al., 1998). Existence of uncertainty in demand, supply of raw material, production process and machine repair time due to random occurrence of failure severely affect the finished goods stock and hence, service level gets affected. Previously, researchers highlight the effect of uncertainty on the manufacturing/production process (Bera and Sharma, 1999; Williams, 1984). However, behaviour of supply chain under the influence of various uncertainties has not been addressed adequately when MTS and ATS manufacturing system is adopted. Hence, in this chapter, an attempt has been made to analyse the behaviour of MTS and ATS manufacturing supply chain operating under the stochastic environment using system dynamics approach.

For this purpose, six different scenarios are generated considering uncertainties in raw material supply lead time, processing time, machine availability, market demand and raw material acquisition from the supplier. Based on these generated scenarios, the stochastic behaviour of the manufacturing supply chain is studied in terms of unfilled demand (total backlog). The impact of dynamic factors on system behaviour is studied using design of experiment (DOE) approach. Further, relationship between the backlog and uncertainty factors is determined for obtaining optimal setting for the system.

To study the behaviour of ATS manufacturing system under uncertain environment, a serial ATS system is modelled through the system dynamics approach. Different simulation scenarios are generated using response surface methodology (RSM) considering uncertainty in lead time for supply of components, assembly time and repair time due to occurrence of machine failure. The performance of the simulated model is measured in terms of backlog and work-in-progress inventory. Further, relationship between theses response parameters and uncertainty factors are determined to optimise the system.

4.2 Model description

In MTS and ATS manufacturing system, the demand is fulfilled from the finished goods inventory. Hence, maintaining high service level (or minimizing backlog situation) is one of the important parameter. The following paragraph describes the model for MTS and ATS manufacturing system to analyse the effect of uncertainty in manufacturing supply chain.

4.2.1 Model description for make-to-stock manufacturing system

A production system based on the make-to-stock (MTS) production policy considered here is confined to a single product. The basic structure of the production system is shown in Figure 4.1. The production system is a continuous production system having three-shift (8x3) working hours. Single raw material is required for its production operation supplied by a sole supplier. The supplier has limited capacity which is normally distributed with ~N (20, 1) units. Delay is allied between manufacturer and its raw material supplier. The delay includes order processing and material shipment delay i.e. raw material supply lead time is normally distributed ~N (4,1) days. The external customer demand is probabilistic in nature and it is normally distributed ~N (19, 1) units. The raw material inventory at manufacturer end is replenished through reorder point order-up-to level ((s, S) policy) inventory control policy where s is the reorder point (ROP) and S denotes the target inventory level. The safety stock quantity is estimated through Equation (3.8) (section 3.3, in Chapter 3) and based on this value, the ROP is estimated using Equation (3.9) (section 3.3, in Chapter 3). Generally, the target inventory level is a fixed quantity which is set by the executives of the firm and it can be estimated using Equation (4.1). The raw material order quantity (Q_t) placed by the manufacturer to the supplier is decided based on the Equation (3.7) (section 3.3, in Chapter 3).

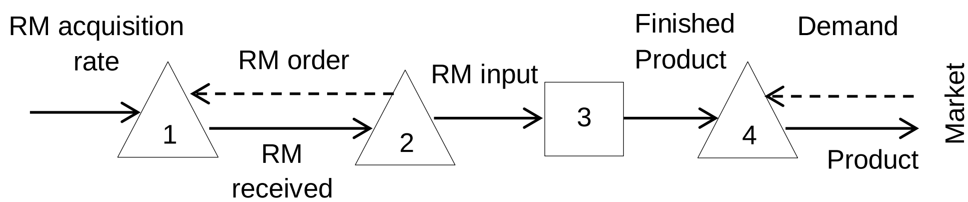

Figure 4.1. Block diagram of make-to-stock manufacturing system

1: Supplier's raw material inventory 2: Manufacturer's raw material inventory 3: Raw material processing unit 4: Finished goods inventory RM: Raw material.

$$\text{Target inventory}(S) = \text{ROP} + \text{single period demand} \tag{4.1}$$

To convert raw material into finished product, time taken by the machine is normally distributed with ~N (32, 4) hrs. The machine has limited capacity is 50 units/day. However, production runs at normal production rate is 40units/day and the rate may vary depending on backlog quantity. The desired production rate in a period depends on the backlog quantity generated from previous period given by Equation (4.2). Raw material input decision depends on the desired production rate and availability of raw material in the inventory as given by Equation (4.3). The external market demand for the product is fulfilled from the finished product inventory. The sales rate depends on the available finished goods stock and the current demand as described in Equation (4.4). While machine failure occurs, the raw material remaining at the processing unit is removed from the machine and taken as input. Time to machine failure and time to repair the machine follow exponential distribution. While machine failure occurs, the production delay is the sum of the delay to repair machine time and production delay.

$$\begin{aligned}&\text{Desired Production Rate} = \text{IF } (\text{Backlog} < 3) \text{THEN} (\text{Normal production rate}) \text{ELSE} \\ &\{(\text{IF}(\text{Backlog} > 3 \text{ AND Backlog} < 10) \text{ THEN } (\text{Normal production rate} + 15\% \times \\ &\text{Normal production rate}) \text{ELSE } (\text{Normal production rate} + 25\% \times \\ &\text{Normal production rate}))\}\end{aligned} \tag{4.2}$$

$$\text{RM\_Input for Production} = \text{Min}(\text{Desired Production Rate}, \text{RM\_INV}) \tag{4.3}$$

$$\text{Sales Rate} = \text{Min}(\text{Finished\_INV}, \text{Demand}) \tag{4.4}$$

4.2.2 Model description for assemble-to-stock manufacturing system

The model considered here is confined to single product, multiple shops and a continuous production system. The production system is a continuous production system having three-shift (24x7) working hours. The production process goes through a three assembly processes in a serial manner where each next process depends on the completion of previous process. Each assembling process starts with semi-finished product from previous stage and a new assembly component. Three different assembly components/raw materials are used to assemble the product. All three machines have equal in capacity and limited in nature. The maximum capacity of each machine is 200 lots whereas normal production rate is 150 lots. It is assumed that a lot contains 25 units. The time taken by each machine to assemble a lot is normally distributed with ~N (5, 0.167) days. Machine failure occurs exponentially with a failure rate of 0.0001. Three raw materials are supplied from three different external suppliers and each supplier has limited capacity which varies randomly. A random supply delay is associated between manufacturing unit and individual raw material supply unit. The lead time between manufacturer and suppliers to supply assembly components is normally distributed with ~N (5, 0.5) days. Customer demand is normally distributed with ~N (25, 0.5) lots per day and satisfied from the finished product inventory. Three raw material/assembly component inventories are maintained. Each raw material inventory is controlled through (s,S) inventory control policy i.e. reorder-point order-up-to level. The order quantity Q_t for each assembly component is decided using the Equation (3.7) (section 3.3, in Chapter 3). The occurrence of machine failure follows an exponential distribution and it takes random amount of time to repair the machine. The desired production rate depends on the product backlog quantity and the normal production rate that can be decided through Equation (4.5). Similarly, raw material/assembly component input decision depends on desired production rate and availability of assembly component in stock and decided through Equation (4.3). Similarly, the sales rate is decided through availability of product in finished good inventory and the external demand from the customer (Equation (4.4)). The schematic block diagram of the ATS manufacturing system is shown in Figure 4.2.

$$\begin{aligned}&\text{Desired Production Rate} = \text{IF } (\text{Backlog} <= 3) \text{THEN } (\text{Normal production rate}) \text{ELSE}\\&\{(\text{IF}(\text{Backlog} > 3 \text{ AND Backlog} <= 10) \text{ THEN } (\text{Normal production rate} + 20\% \times\\&\text{Normal production rate}) \text{ELSE } (\text{IF}(\text{Backlog} > 10 \text{ AND backlog} <= 20) \text{ THEN}\\&(\text{Normal production rate} + 25\% \times \text{Normal production rate}) \text{ELSE}\\&(\text{Normal production rate} + 30\% \times \text{Normal production rate}))\}\end{aligned} \tag{4.5}$$

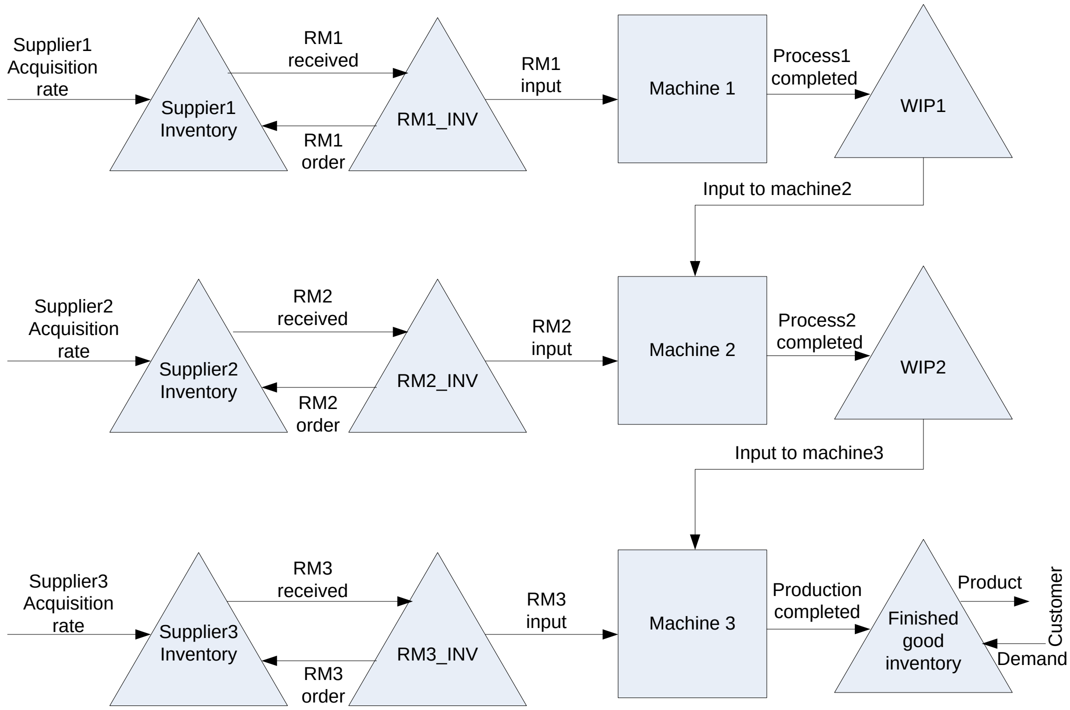

Figure 4.2 Block diagram for multi-shop assemble-to-stock manufacturing system

4.3 Cuckoo search algorithm

Nature inspired optimization techniques are being adopted these days for solving hard and complex optimization problems (Rajendran and Ziegler, 2004; Tasgetiren et al., 2007; Tasgetiren et al., 2011). Recently, a nature inspired algorithm based on the brood parasitism of cuckoo species is developed known cuckoo search algorithm is one of the efficient optimization techniques. Cuckoos are charming birds - not only because of the beautiful sounds they can make but also because of their aggressive reproduction strategy. The cuckoo species select recently spawned nests of other host bird (mostly other species) to lay their eggs and remove the existing eggs for increasing the hatching probability of their eggs. Alternatively, some of the birds fight for this parasitic behavior of cuckoos and discard the discovered stranger eggs or build their new nest in new locations. Based on this distinct life style and aggressive reproduction strategy of cuckoo species, a meta-heuristic algorithm has been developed by Yang (2011). This algorithm contains a population of nests or eggs. Different steps in cuckoo search are as follows:

Initialize the Cuckoo search algorithm parameters: The different parameters are number of nests (n), step size parameter (α), discovering probability (pa) and maximum number of analysis as stopping criteria.

1. Generate initial nest or eggs of host bird: Initial locations of the nests are determined by the set of values assigned to each decision variable randomly as:

$$nest_{i,j}^{(0)} = x_{j,min} + rand\left(x_{j,max} - x_{j,min}\right) \quad (4.8)$$

where, $nest_{i,j}^{(0)}$ determine the initial value of the j^th variable for the i^th nest, $x_{j,min}$ and $x_{j,max}$ are the minimum and maximum allowable values for the j^th variable, rand is the random number in the interval [0,1].

2. Generate new cuckoo by Lévy flights: In this step, all the nests except for the best one so far are replaced by new cuckoo eggs produced with levy fights from their position as:

$$nest_i^{(t+1)} = nest_i^{(t)} + \alpha \times S \times \left(nest_i^{(t)} - nest_{best}^{(t)}\right) \times r \quad (4.9)$$

where, $nest_i^t$ is the i^th nest current position, α is the step size parameter which is considered to be 0.1, S is the Lévy flight vector as in Mantegna's algorithm, r is a random number from a standard normal distribution and $nest_{best}^t$ is the position of the best nest so far.

3. Alien eggs discovery: The alien eggs discovery is performed for all of the eggs using the probability matrix for each component of each solution. Existing eggs are replaced considering quality by newly generated ones from their current position by random walks with step size such as:

$$S = rand(nests[permute1[i][j]] - nests[permute2[i][j]]) \quad (4.10)$$

$$nest^{(t+1)} = nest^{(t)} + step\_size \times P \quad (4.11)$$

$$p_{ij} = \begin{cases} 1 & \text{if } rand < pa \\ 0 & \text{if } rand \geq pa \end{cases} \quad (4.12)$$

where permute 1 and permute 2 are different rows permutation function applied to the nests matrix and P is the probability, pa in the range of [0,1].

4. Termination Criterion: The generation of new cuckoos and the discovery of the alien eggs steps are performed alternately until a termination criterion satisfied.

The cuckoo search is one of the popular meta-heuristic optimization technique used in different field of research for optimization the system parameters (Moravej and Akhlaghi, 2013; Yang and Deb, 2010; 2013; Chandrasekaran and Simon, 2012; Yildiz, 2013; Burnwal and Deb, 2013). The above described steps are coded using software MATLAB 2013 version.

4.4 Simulation procedure

To analyse the performance of MTS and ATS manufacturing systems, modelling based on system dynamics approach has been adopted. The system dynamics is one of the useful computer aided approaches helps in developing model and studying the behaviour of a system under the influence of various internal and external factor in a realistic manner (section 3.2.1, in chapter 3).

4.4.1 Simulation procedure for make-to-stock manufacturing system model

The model as described in Figure 4.1 is modelled through the system dynamics approach using the software STELLA 0.5 as shown in Figure 4.3. The figure describes the MTS production system without machine failure. The various symbols and notations used in the system dynamic models are defined in Table 4.1. Followings are the certain assumption made to model and simulate the considered MTS manufacturing system (Figure 4.3).

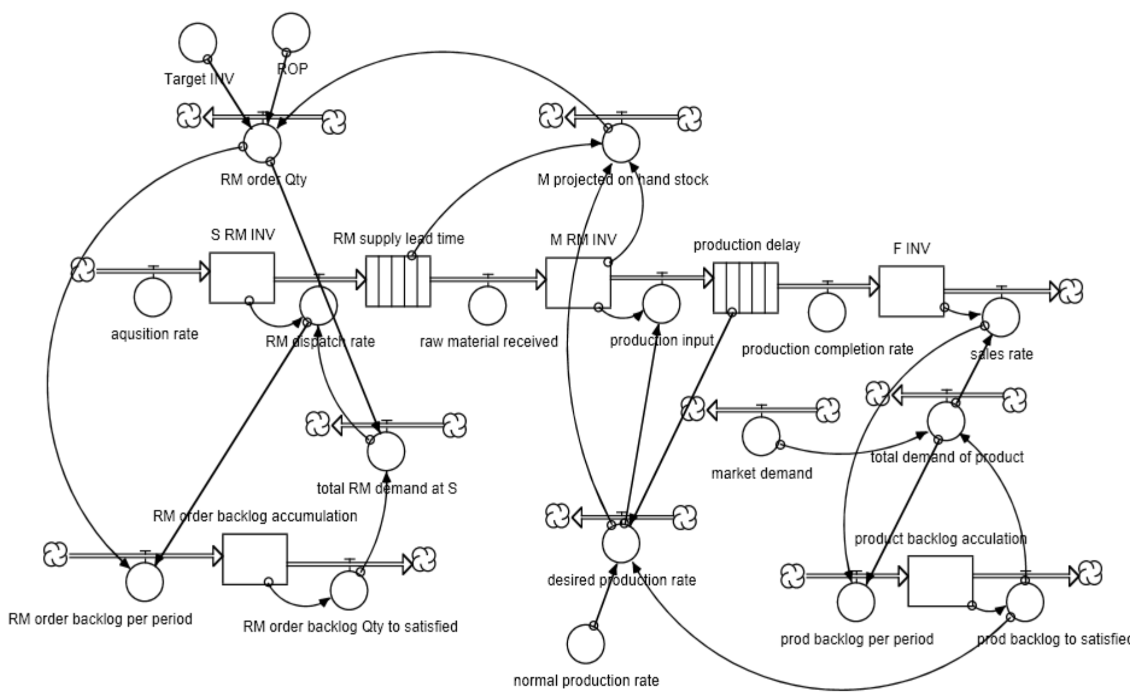

Figure 4.3 Make-to-stock manufacturing system without machine failure

Assumptions

1. Once the order for raw material is placed by the production unit, it cannot be discarded by the supplier and it cannot cancelled by the production unit.
2. Once order received at production end, it cannot be returned back.

3. The unmet demand is counted as backorder and immediately fulfilled when sufficient stock is available.
4. Backorders during previous periods are given higher priority than the current demand.
5. Machine setup time is not considered.
6. Production time is independent of raw material input for production.
7. During the occurrence of machine failure, the in-process material is removed from machine and later it is taken as fresh raw material to continue the production process.
8. No cost components are considered here.
9. The raw materials and finished goods are not perishable.

Table 4.1 Notations used in system dynamics model for MTS manufacturing system

1. M RM INV – Manufacturer's raw material inventory
2. M project on hand stock – Estimated projected on hand stock for raw material at manufacturer end
3. ROP – Reorder point for raw material inventory of manufacturer
4. Target INV – Raw material target inventory at manufacturer
5. RM order Qty –Quantity of raw material order by manufacturer
6. S RM INV – Supplier's raw material inventory
7. Acquisition rate – raw material acquisition rate for supplier
8. RM order backlog Qty to satisfied – Total backlog for raw material order that is to be satisfied by supplier
9. RM backlog accumulation – Accumulation for backlogged raw material
10. RM backlog per period – Amount of raw material backlog in current period
11. RM dispatch rate – Quantity of raw material dispatch from supplier to manufacturer
12. Raw material received – Raw material received at manufacturer end
13. RM supply lead time – Lead time between raw material supplier and manufacturer
14. Total RM demand at S – Total raw material demand at supplier end
15. Normal production rate – Normal production rate of manufacturing unit
16. Desired production rate – Total amount of product need to produce
17. Production input – Raw material input for production
18. Occurrence of failure – Occurrence of machine failure
19. Production delay – Time taken by machine to convert raw material into finished product
20. Production completion rate – Finished product produced per period
21. Delay due to machine failure –Delay in production completion due to machine failure
22. Leakage – Raw material remove from machine while machine get shut down
23. F INV – inventory for finished product
24. Sales rate – Amount of product sale in a period
25. Total demand of product – Total demand for product
26. Prod backlog per period – Unmet product demand quantity in current period

27.	Prod backlog acquisition – Accumulation product backlog quantity
28.	Prod backlog to satisfied – Amount of backlog product to be satisfied
29.	Market demand – external market demand

Different scenarios are considered to analyse the sustainability and behaviour of production system under the different dynamic factors. Six different scenarios have been generated for comparative study as described below:

i. Scenario 1: Base model

The production system without machine failure is simulated so that performance of the production system can be compared with the rest of the scenarios. Scenario 1 has been taken as the base model to compare the rest of the scenarios.

ii. Scenario 2: Variation in lead time

The time taken by supplier to deliver an order may vary from order to order. The variation in raw material supply lead time affects the raw material stock level at manufacturer's end and impacts on production process leading to influence on finished goods inventory. Scenario 2 describes the effect of increase in variation of raw material supply lead time on the manufacturer's performance.

iii. Scenario 3: Variation in production delay

The time taken to process a unit of raw material and converting it into finished product take some amount of time called production delay (processing time). The variation in processing time affects the finished goods inventory. In this scenario, the dynamic behaviour of the manufacturing unit is studied under the effect of increasing variation in production delay.

iv. Scenario 4: Delay due to machine failure

The occurrence of machine failure causes interruption in production process. It takes a random time to repair the machine and hence, random delay to restart the production process. Random delay in production operation affects the production rate and impacts on service level. Here, the performance of production system is studied under varying the delay due to machine failure.

v. Scenario 5: Variation in lead time and processing delay

Under this scenario, the performance of the manufacturer is studied under simultaneously increasing in the variation of both raw material supply lead time and processing delay.

vi. Scenario 6: Variation in lead time, processing delay and delay due to machine failure

This scenario describes the behaviour of the production system under the simultaneous increase in variation of all the three uncertainty factors - raw material supply lead time, processing delay and delay due to machine failure.

Initial conditions

1. There is no outstanding order for raw material.
2. There is no raw material in transit.
3. There is no raw material in processing.
4. There is no backlog for raw material and product.
5. S_RM_INV = 200 units, M_RM_INV = 100 units and F INV = 100 units. (S, M, F, RM and INV represent supplier, manufacturer, finished product, raw material and finished goods inventory respectively).The ROP value taken here is 135 units and target inventory level is set at 154 units.

The equations for the stock-flow diagram (Figure 4.3) are shown in Appendix 3. The initial condition for supplier's raw material inventory, manufacturer raw material inventory and finished goods inventory remains same for all scenarios. The other parameters of the model like ROP, target inventory, demand and acquisition rate also remain same for all scenario. The models are simulated for 365 days (1year) time period. The total unfilled demand (backlog) quantity is taken as the performance measure and estimated at the end of each simulation run.

4.4.2 Simulation procedure for assemble-to-stock manufacturing system model

In order to simulate the purposed ATS manufacturing system (Figure 4.2), it is modelled through system dynamics approach as shown in Figure 4.4. The different notations for the system dynamics model are described in Table 4.2. In order to simulate the model (Figure 4.4), certain assumptions and initial conditions are considered as described in the followings.

Assumptions

i. Once the order placed by manufacturing system, it cannot be discarded by the supplier nor gets it cancelled.
ii. Once the order for assembly components is received, it cannot be discarded.
iii. Each assembly component is essential to the production process.
iv. Backorders are allowed and is given higher priority than the current demand.
v. Product defects or assembly component defects has not been considered.
vi. No setup time is considered.
vii. No cost components are taken care of.

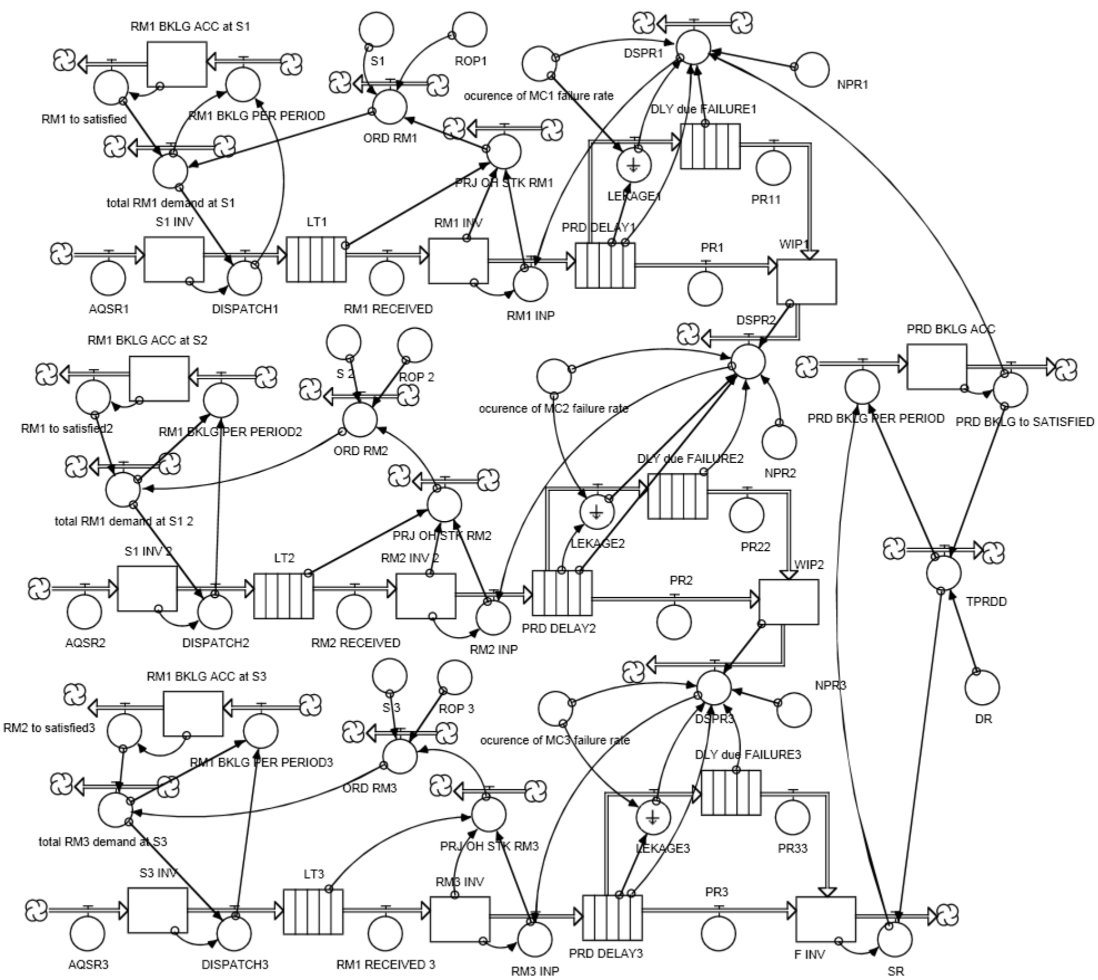

Figure 4.4 System dynamics model for assemble-to-stock manufacturing system

Table 4.2 Notations used in system dynamics model for ATS manufacturing system

1. RM1: raw material1
2. RM1 BKLG ACC at S1: Raw material1 backlog accumulations occur at supplier1.
3. RM1 to satisfy: raw material1 needed to be satisfied in next period.
4. RM1 BKLG PER PERIOD: raw material1 backlog occurs at each period
5. TOTAL RM1 Demand at S1: total raw material1 demand at supplier1
6. S1: target inventory for raw material1
7. ROP1: reorder-point for raw material1
8. ORD RM1: order quantity for raw material component1
9. PRJ OH STK RM1: projected on-hand stock for raw material1
10. DSPR1:desired production decision input for machine1
11. NPR1: normal production rate for machine1
12. ASQR1:acquisition rate for machine1
13. S1 INV: supplier1 raw material component inventory
14. Dispatch1: raw material1 dispatch from supplier1
15. LT1: raw material supply lead time between supplier1 and manufacturing unit
16. RM1 received: raw material1 received at manufacturer inventory
17. RM1 INP: raw material input to machine1

18. PRD delay1: assembly time taken by machine1
19. Lekage1: raw material remove after machine fails
20. Delay due failure1: delay due to the failure of machine1
21. PR1: normal production completion rate
22. PR11: production completion rate after machine failure of machine1
23. WIP1: work-in-process inventory1

Initial conditions

i. No raw material component in transit.
ii. No product backlog.
iii. No raw material component under process.
iv. No raw material component in WIP inventory.
v. No raw material backlog.
vi. S1_INV = 800 lots, S2_INV = 800 lots, S3_INV = 800 lots, RM1_INV = 800 lots, RM2_INV = 800 lots, RM3_INV = 800 lots, F_INV = 800 lots.

The equations for stock-flow diagram (Figure 4.3) are shown in Appendix 4. To analyse the performance of the ATS manufacturing system, three different uncertainties such as lead time, assembly time and delay due to repairing the machine when break down occurs are considered. To measure the influence of the uncertainty, the standard deviation of the uncertainties is varied. The uncertainty factors are considered with three levels (low, medium and high) as described in Table 4.3. A response surface methodology (RSM) approach is adopted to generate experimental scenarios and examine the relationship between performance measures and uncertainty factors (Zabeti et al., 2009; Kansal et al., 2005). Using the Box-Behnken design of RSM, different experimental scenarios are generated and the model is simulated for 364 days.

Table 4.3 Experimental setting for identified factors level

Factors	Level (in days)		
	Low (L)	Medium (M)	High (H)
Lead time (A)	0.5 (-1)	1 (0)	1.5 (1)
Assembly delay (B)	0.333 (-1)	0.667 (0)	1 (1)
Delay due to machine failure (C)	0.333 (-1)	0.667 (0)	1 (1)

The figures in the bracket indicate coded level for the factor

4.5 Performance analysis of manufacturing system

Following paragraphs contain the performance analysis for MTS and ATS manufacturing system under uncertain environment.

4.5.1 Performance analysis of make-to-stock system under uncertain environment

a. Scenario 1: Base model

This scenario has been considered as the benchmark to compare rest of the scenarios. Under this scenario, production system without machine failure (Figure 4.3) is simulated for 365 days when lead time is considered as ~N(4,1) days and the processing time as ~N(32,4) hrs. i.e. ~N (1.33, 0.167) days as described in Table 4.4. Backlog is estimated at the end of each simulation run. To identify the warm-up period, the finished goods inventory level is estimated and the time series plot is shown in Figure 4.5. From the figure, it can be observed that initial 80-periods are under transient phase. Hence, these periods are removed from the simulation runs considering as warm-up period and rest of the periods are considered as steady state. The estimated backlog is 379units considering only the steady state period (from Table 4.4).

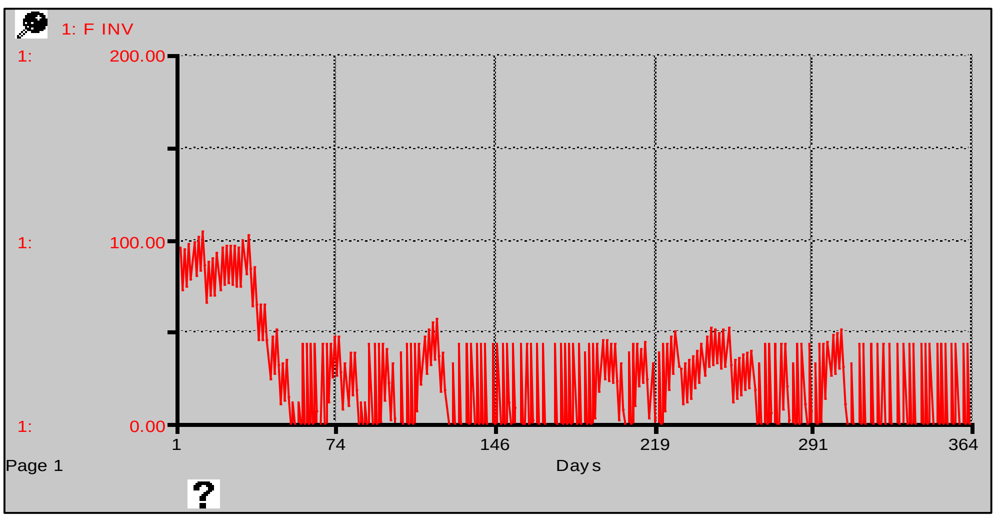

Figure 4.5 Time series plot for the finished goods inventory for MTS manufacturing system

Table 4.4 Estimated values for scenario 1

Factors		Total backlog (in units)	Total demand (in units)
Lead time (in days) (mean, std. dev.)	Processing (time in hours) (mean, std. dev.)		
(4, 1)	(32, 4)	379	5377

b. Scenario 2

The backlog quantities are estimated by simulating the base model through gradually increasing the standard deviation of raw material supply lead time at 10% from the base model keeping all other parameters constant. The results are summarized in the Table 4.5. From the table, it can be observed that backlog quantity increases as standard deviation (uncertainty) of supply lead time increases from the base value.

Table 4.5 Estimated backlog from scenario 1 and scenario 2

scenario	Standard deviation of supply lead Time (in days)	Total backlog (in units)	Total demand (in units)
Scenario 1	1	379	5377
Scenario 2	1.1	391	
	1.2	485	
	1.3	510	

c. Scenario 3

Under this scenario, the backlog quantities are estimated by simulating the base model by increasing the standard deviation of processing time at 10% keeping all other parameters to base model case and the results are summarized in Table 4.6. From the table, it can be observed that backlog increases with increase in uncertainty in processing time.

Table 4.6 Estimated values from scenario 1 and scenario 3

Scenario	Standard deviation of processing time (in days)	Total backlog (in units)	Total demand (in units)
Scenario 1	0.167	379	5377
Scenario 2	0.183	656	
	0.200	661	
	0.217	685	

d. Scenario 4

Under this scenario, uncertainty in repair time of machine if a machine fails is introduced in the base model (Figure 4.3) as shown in Figure 4.6. Equations for the stock-flow diagram are shown in Appendix 5. The mean failure rate of the machine is considered as 0.0001. Initially, mean repair time for machine is taken as 8 hours and then it is increased by 33% (4 hrs.) keeping all other parameters at the base model case. The estimated backlog quantities from the simulation runs are summarized in Table 4.7. From the table, it can be observed that the backlog quantity increases with increase in time taken to repair the machine.

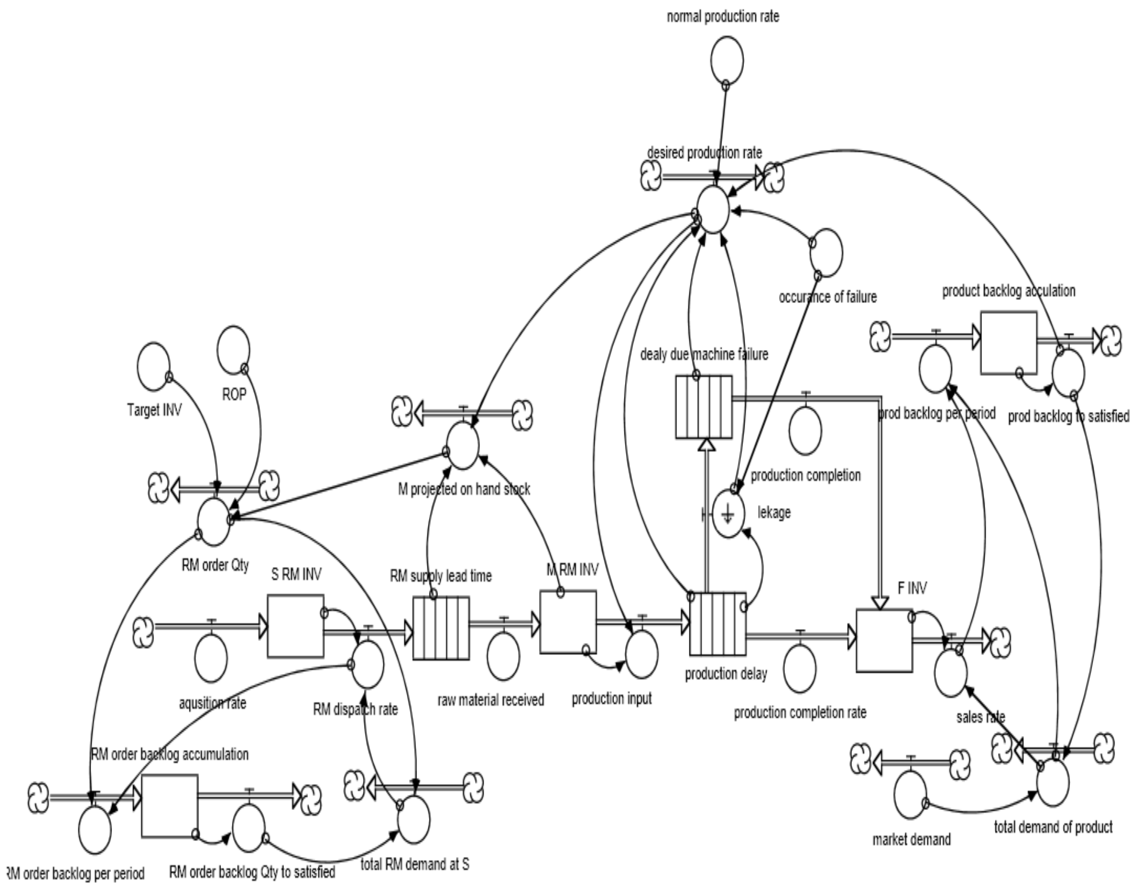

Figure 4.6 MTS manufacturing system with machine failure

Table 4.7 Estimated values for scenario 4

Mean repair time (in days)	Total backlog (in units)	Total demand (in units)
0.333 (8hrs)	1605	5377
0.5 (12hrs)	1851	5377
0.667 (16hrs)	2018	5377
0.833 (20hrs)	2307	5377

e. Scenario 5

Under this scenario, effect of uncertainties in raw material supply lead time and processing time on backlog is analysed. For this purpose, standard deviation in lead time and processing time is varied as shown in Table 4.8. The model shown in Figure 4.3 is simulated. From the table, it can be observed that backlog increases with increase in uncertainty in lead time and processing time.

Table 4.8 Estimated values from scenario 5

Scenario	Standard deviation of lead time (in days)	Standard deviation of processing time (in days)	Total backlog (in units)	Total demand (in units)
Scenario 1	1	0.167	379	5377
Scenario 2	1.1	0.183	677	
	1.2	0.2	709	
	1.3	0.217	733	

f. Scenario 6

In this scenario, simultaneous effect of uncertainty in lead time, processing time and repair time on backlog is analysed. For this purpose, the two levels of uncertainty are considered as shown Table 4.9.

Table 4.9 Levels of factors

Factors	Levels (standard deviation values in days)	
	Low	High
Lead time (LT)	1.1	1.3
Processing time (PT)	0.183	0.217
Repair time (delay due to machine failure) (DMF)	0.5	0.833

Using the factors and their levels, eight different experimental scenarios are generated through full factorial design as shown in Table 4.10. Parameters are set based on these scenarios and the system dynamics model (Figure 4.6) is simulated keeping rest of the parameter at their base level case. The estimated backlog from simulation runs is summarised in Table 4.10. From table, it can be observed that the backlog quantity estimated in experiment number 4 and 8 is much higher than other experimental runs. It signifies that high uncertainty in processing time and delay due to machine failure cause frequent stock-out situation at finished goods inventory leading to increase in backlog.

Table 4.10 Estimated values for different experimental scenarios for scenario 6

Exp. No.	Lead Time (in days)	Processing time (in days)	Repair time (in days)	Total backlog (in units)
1	1.1	0.183	0.500	2087
2	1.1	0.183	0.833	2174
3	1.1	0.217	0.500	2193
4	1.1	0.217	0.833	2563
5	1.3	0.183	0.500	2171
6	1.3	0.183	0.833	2258
7	1.3	0.217	0.500	2271
8	1.3	0.217	0.833	2642

To identify the influencing factor on backlog, an analysis of variance (ANOVA) is conducted (Table 4.11). From the table, it can be observed that uncertainty in lead time, processing time and delay due to machine failure have significant effect on backlog at significance level of 0.05. From the main effect plot shown Figure 4.7, it can be identified that backlog can be reduced when variation in lead time, processing time and machine repair time is minimized. Similarly, from Table 4.11, it can be observed that interactions of processing time and delay due to machine failure have strong effect on the backlog at significance level of 0.05. This can be observed from the interaction plot shown in Figure 4.8.

Table 4.11 Summary of analysis of variance for backlog

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Lead time	1	13203	13203	13203	105625	0.002
Processing time	1	119805	119805	119805	958441	0.001
Delay due to machine failure	1	104653	104653	104653	837225	0.001
Lead time× Processing time	1	15	15	15	121	0.058
Lead time× Delay due to machine failure	1	0	0	0	1	0.5
Processing time ×Delay due to machine failure	1	40186	40186	40186	321489	0.001
Error	1	0	0	0		
Total	7	277863				
S = 0.353553 R-Sq = 100.00% R-Sq(adj) = 100.00%						

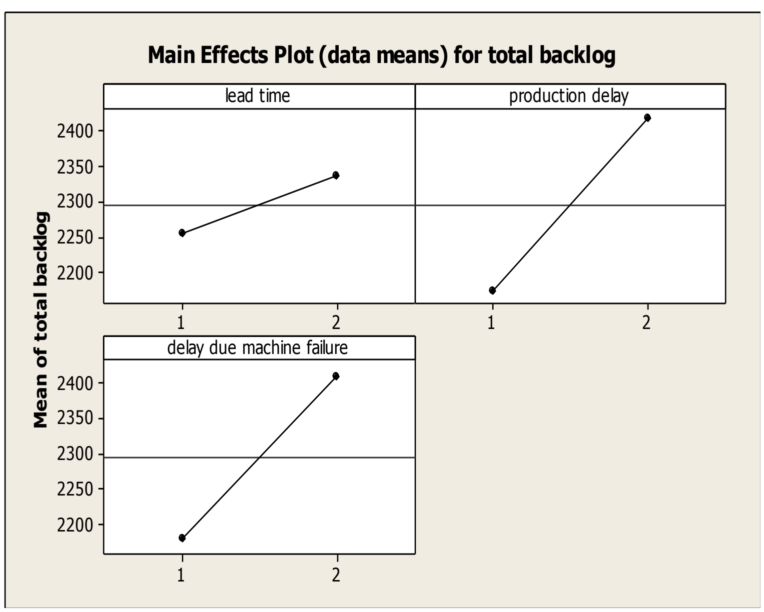

Figure 4.7 Main effect plot for backlog estimated from scenario 6

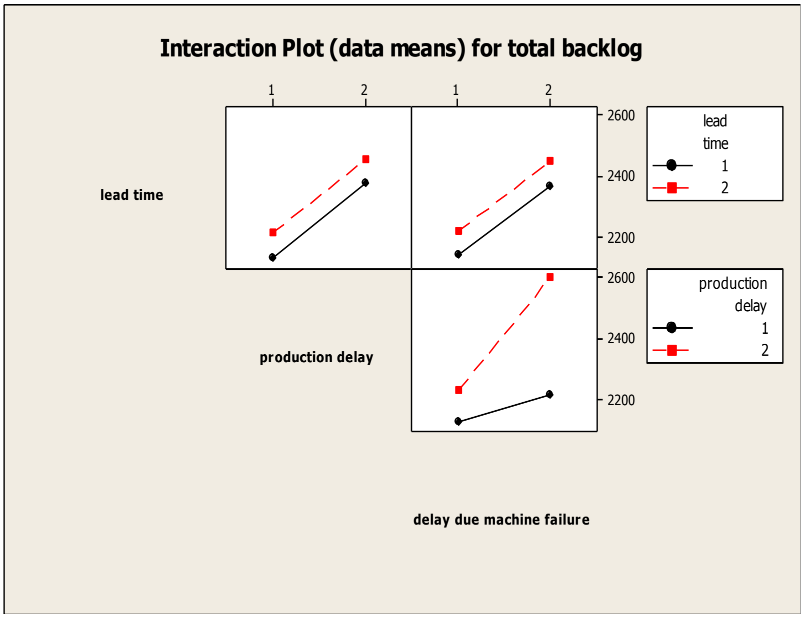

Figure 4.8 Interaction effect for estimated backlog from scenario 6

A generalized regression equation is developed to relate input factors with backlog are shown in Equation (4.13).

$$\text{Backlog} = 3059.51 + 563.011 \times \text{LT} - 8519.87 \times \text{PT} - 4330.02 \times \text{DMF} - 808.824 \times \text{LT} \times \text{PT} + 7.50751 \times \text{LT} \times \text{DMF} + 25039.7 \times \text{PT} \times \text{DMF} \tag{4.13}$$

To obtain the best minimum value for the backlog, the above derived equation is optimized through the cuckoo search algorithm. Based on the steps described in section 4.3, the parameter settings for optimization are number of nests, n=30, maximum iteration=1500, pa=0.89 and tolerance value=2087units (minimum backlog value shown in Table 4.10). Under these parameter settings, the optimal backlog obtained is 1968 units with optimal factorial values of LT=1.1, PT=0.183 and DMF=0.5957. The obtained optimal backlog (1968 units) is less than minimum value estimated from experimental scenarios (Table 4.10). The convergence curve for optimizing backlog through cuckoo search is shown in Figure 4.9. From the figure, it can be observed that optimal minimum value for backlog is obtained after 600 iterations.

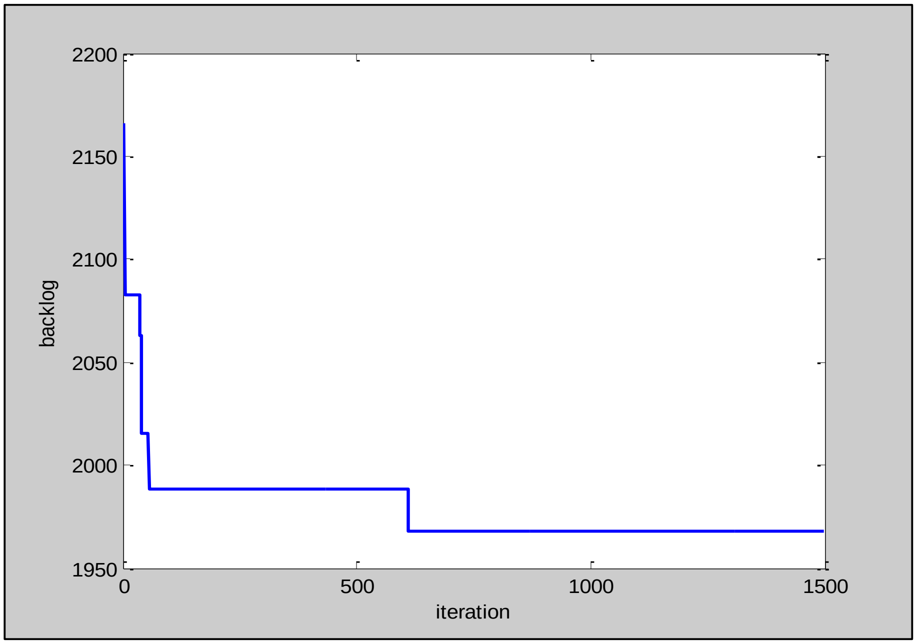

Figure 4.9 Convergence plot for optimized backlog for MTS manufacturing system

4.5.2 Performance analysis of assemble-to-stock manufacturing system under uncertain environment

To analyse the performance of ATS manufacturing system under the influence of uncertainty in lead time, assembly time and repair time, fifteen different experimental scenarios are generated using experimental setting shown in Table 4.3. The complete experimental runs are shown in Table 4.12. Figure 4.4 is simulated for 1-year (364days) time period. To analyse the warm-up period, the finished goods inventory is estimated and time series plot is shown in Figure 4.10. From the figure, it is identified that initial 90-periods are under transient phase. Hence, these periods are considered as warm-up period and eliminated from the total simulation time period. From the simulation runs, the estimated backlog and WIP values considering the steady state period are summarised in Table 4.12.

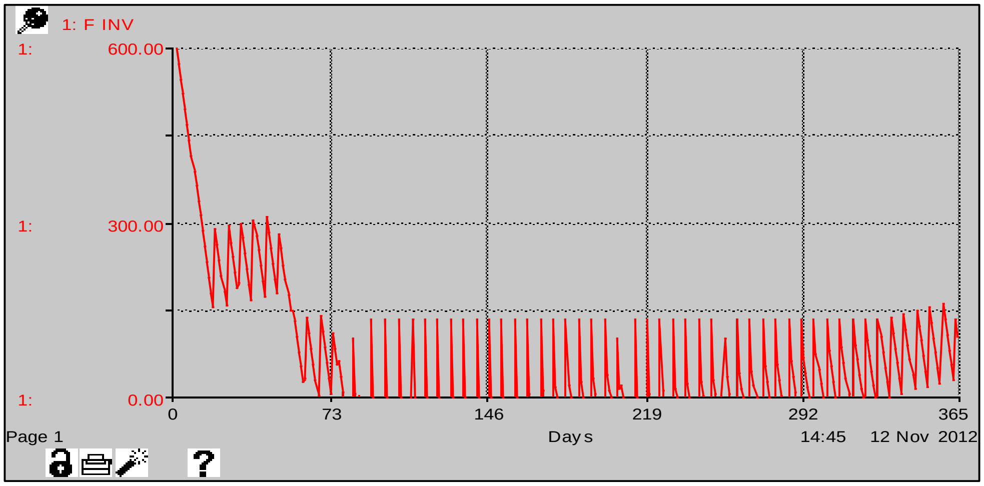

Figure 4.10 Time series plot for finished goods inventory

Table 4.12 Summary of the experimental scenarios generated for Box-Behnken design and estimated parameters

Design points	Lead time (A)	Assembly Time (B)	Delay due to machine failure (C)	Product Backlog (in lots)	WIP1 (in lots)	WIP2 (In lots)
	Coded in depended variable levels					
1	-1	-1	0	4491	447.369	184.404
2	1	-1	0	4691	458.369	223.404
3	-1	1	0	4857	481.895	313.549
4	1	1	0	4897	492.895	343.549
5	-1	0	-1	4706	432.193	216.288
6	1	0	-1	4816	452.193	206.288
7	-1	0	1	5047	539.087	196.736
8	1	0	1	5447	589.087	206.736
9	0	-1	-1	2711	278.004	179.468
10	0	1	-1	4681	493.433	364.672
11	0	-1	1	4564	509.933	181.319
12	0	1	1	4857	504.793	341.798
13	0	0	0	5047	524.227	208.172
14	0	0	0	5049	642.494	211.284
15	0	0	0	5016	472.866	310.878

The mathematical model obtained from the regression analysis for backlog is expressed in Equation (4.14). The coefficient of determination (R^2) obtained is 90.1% signifying best fitting of the model. From the ANOVA, it is found that uncertainty in assembly time (B), delay due to machine (C) and interaction of these two factors have significant effect on backlog. Figure 4.11 describe simultaneous effect of assembly time (B) and delay due to machine (C) on backlog.

$$\begin{aligned} \text{Back log} = & -574.055 - 1864.07 \times A + 10532.9 \times B + 6684.53 \times C + 960.833 \times A^2 \\ & - 5039.83 \times B^2 - 2612.26 \times C^2 - 239.88 \times A \times B + 434.783 \times A \times C - 3769.48 \times B \times C \end{aligned} \quad (4.14)$$

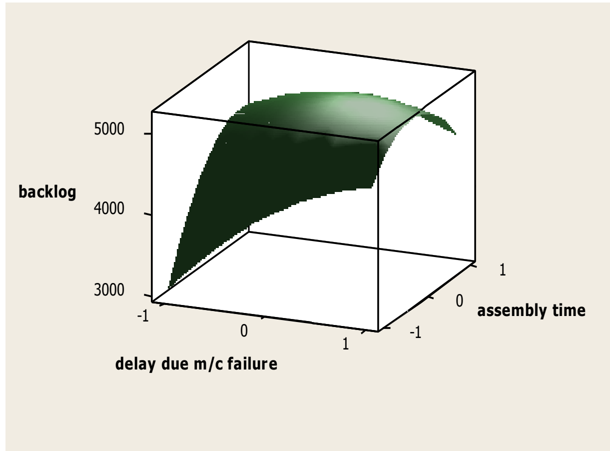

Figure 4.11 Surface plot of backlog vs. delay due machine failure and assembly time

Similarly, the estimated regression model for WIP1 is shown in Equation (4.15). The R^2 value obtained is 80.1% signifying good fitting of the model. From the ANOVA, it is found that factor C has significant effect on the WIP1 inventory at significance level of 0.05. Interactions do not have strong effect on the WIP1. Figure 4.12 indicates that WIP1 increases rapidly with increase in assembly time. However, it increases slowly with increase in delay due to machine failure.

$$\begin{aligned} \mathrm{WIP1} &= 546.529 + 11.500\times \mathrm{A} + 34.918\times \mathrm{B} + 60.885\times \mathrm{C} - 9.899\times \mathrm{A}^2 - 66.498\times \mathrm{B}^2 \\ &\quad - 33.490\times \mathrm{C}^2 + 7.5\times \mathrm{A}\times \mathrm{C} - 55.142\times \mathrm{B}\times \mathrm{C} \end{aligned} \tag{4.15}$$

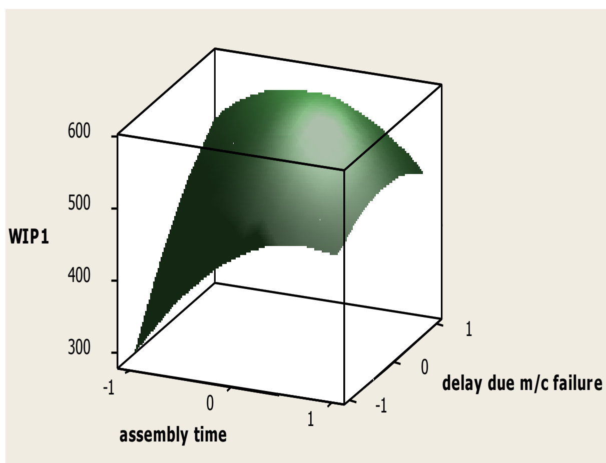

Figure 4.12 Surface plot of WIP1 vs. assembly time and delay due to machine failure

Similarly, the estimated regression model or WIP2 is shown in Equation (4.18) and estimated R^2 value is 86.5%. From ANOVA, it is found that factor B has significant effect on the WIP2 whereas no interaction has strong effect on WIP2. Increase in uncertainty in assembly time (B) leads to increase in WIP2 level as shown in surface plot Figure 4.13.

$$\text{WIP2} = 243.445 + 8.625\times \text{A} + 74.372\times \text{B} - 5.016\times \text{C} - 18.760\times \text{A}^2 + 41.542\times \text{B}^2 - 18.173\times \text{C}^2 - 2.250\times \text{A}\times \text{B} + 5.0\times \text{A}\times \text{C} - 6.181\times \text{B}\times \text{C} \quad (4.16)$$

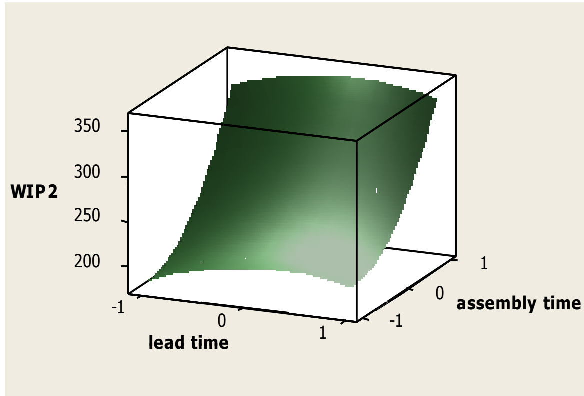

Figure 4.13 Surface plot of WIP2 vs. lead time and assembly time

4.6 Summary

The performance of MTS and ATS manufacturing system is analysed under the influence of uncertainty in lead time, processing time/assembly time and repair time. For this purpose, the MTS production system employed with (s, S) is modelled through system dynamics approach. The performance of the system is analysed in terms of backlog under the influence of considered uncertainties and found that increase in uncertainty in lead time, processing time and delay due to the machine failure have significant effect on backlog. However, simultaneous increase in production delay and delay due to machine failure exhibits higher influence on backlog. Further, the cuckoo search optimization technique is applied to determine the optimal parameter settings to reduce the backlog.

Similarly, an ATS manufacturing is modelled through system dynamics approach. Different scenarios are generated using RSM methodology considering uncertainty in lead time, assembly time and delay due to machine failure. The impact of uncertainties on backlog and WIP is investigated through RSM analysis. From the analysis, it is observed that assembly time and delay due to machine failure has significant effect on backlog whereas assembly time has significant effect on the WIP2 and delay due to machine failure has significant effect on the WIP1. Further, relationship between uncertainty and performance measures is derived and represented through empirical equation. These equations may help the practitioners in predicting performance measures when uncertainty in various model variables is known. The next chapter deals with study on managing uncertainties through adopting strategic plan.

CHAPTER 5

MANAGING SUPPLY UNCERTAINTY IN MANUFACTURING SUPPLY CHAIN

5.1 Introduction

Previously, many researchers have identified the significance of analysing the uncertainties in the context of supply chain management using various modelling approaches (Petrovic et al., 1998; 1999; Petrovic, 2001; Mahnam et al., 2009; Wang and Shu, 2005; Xie et al., 2006; Vorst and Beulens, 2002; Prater, 2005; Koh and Tan, 2005). The manufacturing unit is one of the important subsystems of a supply chain getting severely affected due to uncertainties associated along the supply chain typically when it operates on a MTS policy (Bera and Sharma, 1999; Williams, 1984; Silver et al., 1998). Studies have been carried out to propose mathematical models for economic manufacturing quantity (EMQ) considering random machine failure (Groenevelt et al., 1992a; Groenevelt et al., 1992b; Chakraborty et al., 2008). However, it is difficult to analyse mathematically even a simple two stage supply chain when many kinds of uncertainties act upon a system. Therefore, simulation approaches like system dynamics modelling is a viable method for analysing complex systems. Recently, researchers have applied this approach to analyse the behaviour of complex supply chains (Vlachos et al., 2007; de Souza et al., 2000; Ge et al., 2004; Owens et al., 2002; Hwarng and Xie , 2008; Campuzano et al., 2010; Hussain and Drake, 2011; Helo, 2010).

Helo (2010) has modelled a two level supply chain capable of manufacturing multiple products operating under make-to-order (MTO) policy using system dynamics approach to study the relationship between capacity utilization with lead time and demand variation. Özbayrak et al. (2007) have adopted system dynamics approach to analyse the behaviour of four level supply chains operating with MTO policy through different scenarios considering uncertainties in demand, production time, manufacturing reliability, supplier reliability and information sharing. Different strategic plans are considered to tackle different issues in supply chain. Huang et al. (2012) have studied the impact of backup strategy on supply disruption for a supply chain with one retailer and two independent suppliers (major and backup supplier) through the SDM approach. Georgiadis et al. (2005) have adopted system dynamics tool for proposing a framework to tackle the strategic issues in food supply chain. Ramasesh (1991) has proposed dual sourcing strategy to minimize the inventory holding cost under uncertain lead time.

However, limited number of studies focus on analysing the performance of two stage supply chain operating with MTS policy under the influence of various uncertainties in demand, raw material supply quantity, lead time, random occurrence of machine failure, processing time and repair time. Therefore, a simulation modelling framework is proposed in this chapter to analyse the performance measures of the MTS manufacturing system expressed in terms of system outputs such as work-in-progress (WIP) inventory, backlog and raw material shortage under the influence of various uncertainties like demand, lead time, processing time, delay due to machine failure, acquisition rate of the supplier and random occurrence of machine failure. The model is confined to a single product processed through two machines and raw materials supplied from an external suppliers. Further, a backup supply strategy is suggested to improve the service level at manufacturer end by enhancing the service level at the raw material supplier end under the uncertain environment.

5.2 Model description

In MTS manufacturing system, a finished goods stock is maintained in anticipation to meet the fluctuations in customer requirements. The schematic block diagram of a serial manufacturing supply chain confined to a single product is depicted in Figure 5.1. For the analysis purpose, a gear manufacturing process has been considered in this study. Gears are manufactured through hobbing process. The production system consists of two processes - hobbing and finishing. Two machines are involved in production process having equal and limited capacity. The production system is a continuous process (24×7hrs). Three types of inventories such as raw material (blanks), work-in-progress (WIP) and finished goods inventory are maintained in the production process. The demand for gears is probabilistic in nature and satisfied from finished goods inventory. The raw material (RM) is supplied from a single external supplier. The raw material inventory is replenished through reorder-point, order-up-to-level inventory control policy i.e. (s, S) inventory control policy. The replenishment quantity Q_t is decided based on the Equation 3.6 and Equation 3.7 (section 3.3, in Chapter 3).

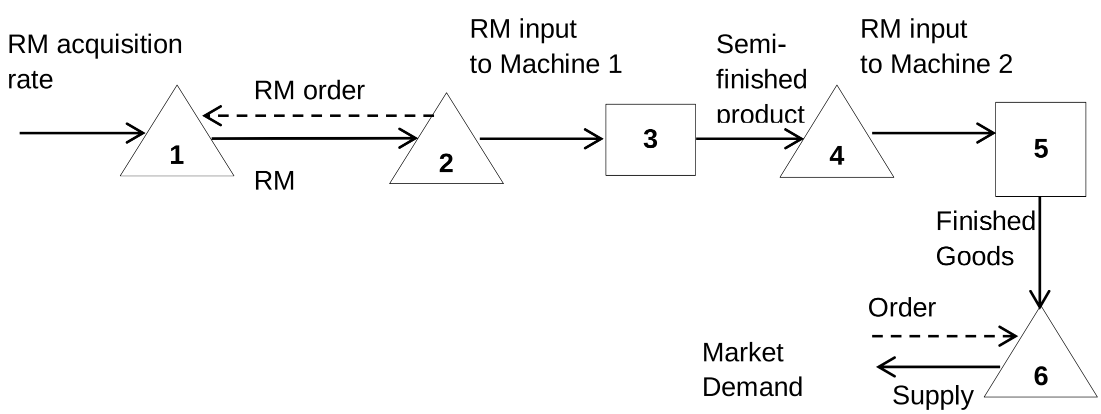

Figure 5.1 Serial manufacturing supply chain

1: Supplier’s raw material inventory
2: Manufacturer’s raw material inventory
3: Machine 1
4: WIP inventory
5: Machine 2
6: Finished goods inventory

RM: Raw material

The dotted lines represent flow of information for order and solid line represents the flow of raw material/goods.

Data related to demand, supply lead time, machine break down and repair time are collected from the past records of the manufacturer. Statistical analysis of data leads to (i) demand is normally distributed with ~N (27, 1) in lots per day (ii) supplier’s lead time is normally distributed with ~N(5,1) in days (iii) processing time in both the machines is equal and normally distributed with ~N (5,1) in days (iv) raw material acquisition rate of the supplier is normally distributed with ~N(26,1) lots per day (v) failure of machine occurs exponentially with a rate of 0.0001 failures per day (vi) repair time for each machine is exponentially distributed with ~Exp(20hrs).

The demand for gears is normally distributed with ~N (27, 1) lots per day is satisfied from the finished goods stock. Any unfilled demand is considered as backlog and fulfilled when sufficient stock becomes available. The total demand at time period t is sum of current demand and backlog from previous period (t-1). The sales rate at time period t depends on finished goods stock and total demand as described in Equation (5.1).

$$\text{Sales rate} = \text{Min}\left(\text{Finished\_INV}, \text{Total demand}\right) \tag{5.1}$$

The finished goods stock level depends on the production rate. There are two machines involved in the production process. Both the machines have equal processing time and normally distributed with ~N (5, 1) in days. The normal production rate of the machines is 150 lots and the maximum production rate is 200 lots. The production decision depends on backlog generated from previous periods. Hence, production rate get fluctuated between normal production rate and maximum production rate. If backlog from t-1 period is less than or equal to 5 lots then the production is run with normal production rate. While backlog is more than 5 lots and less than 10 lots, the production rate increases with 10%. Similarly, the production rate is increased by 20% or 30% based on the generated backlog from previous period as descried in Equation (5.2). The production process may get interrupted due to occurrence of failure. The machine failure occurs exponentially with a rate of 0.0001 failures per day. The repair time for each machine is exponentially distributed with ~Exp (20 hrs). The raw material input for production is decided based on the availability of raw material quantity and the desired production rate estimated through the Equation (5.3). The raw material inventory at the manufacturer end is replenished through reorder-point order-up-to level i.e. (s, S) policy. While the raw material inventory position falls below the re-order point (s) i.e. 200 lots, an order of Q_t is placed to the external supplier. The supplier has limited capacity and its acquisition rate is normally distributed with ~N (26, 1) lots per day.

$$\begin{aligned}&\text{Desired production rate} = \text{IF } (\text{Backlog} <= 5) \text{THEN} (\text{Normal production rate})\\&\text{ELSE } \{(\text{IF}(\text{Backlog} > 5 \text{ AND Backlog} < 10)\text{THEN} (\text{Normal production rate} + 10\% \times\\&\text{Normal production rate}) \text{ELSE } (\text{IF } (\text{Backlog} >= 10 \text{ AND Backlog} <= 25) \text{ THEN}\\&(\text{Normal production rate} + 20\% \times \text{Normal production rate}) \text{ELSE}\\&(\text{Normal production rate} + 30\% \times \text{Normal ptoduction rate})))\}\end{aligned} \tag{5.2}$$

$$\text{RM input for production} = \text{Min } (\text{Desired production rate, RM\_INV}) \tag{5.3}$$

5.3 The simulation procedure

The system shown in Figure 5.1 is modelled through system dynamics approach using the software STELLA 5.0 as shown in Figure 5.2. This figure describes the two stage MTS manufacturing supply chain without backup supply. Different notations for the system dynamics model are defined in Table 5.1. For modelling and simulation purpose, certain assumptions and initial conditions are considered as described below.

Assumptions:

1) Backorders are allowed. Backorder keeps higher priority than the current demand.
2) Occurrence of failure is not consecutive for same machine.
3) Both machines do not fail simultaneously.
4) Machine setup time is not considered.

Initial conditions:

1) No raw material under processing in machine 1 and machine 2.
2) No raw material order in transit.
3) No material in work-in-progress inventory.
4) No backlog at manufacturer's end.
5) No backlog at supplier's end.
6) No shortage of raw material at the manufacturing unit.
7) S INV = 600 lots, M RM INV = 600 lots, F INV = 700 lots, ROP = 200 lots, M RM TINV = 350 lots (S INV: supplier inventory, M RM INV: manufacturer raw material inventory; F INV: finished goods inventory; ROP: reorder-point, M RM: manufacturer raw material inventory and TINV: target inventory).

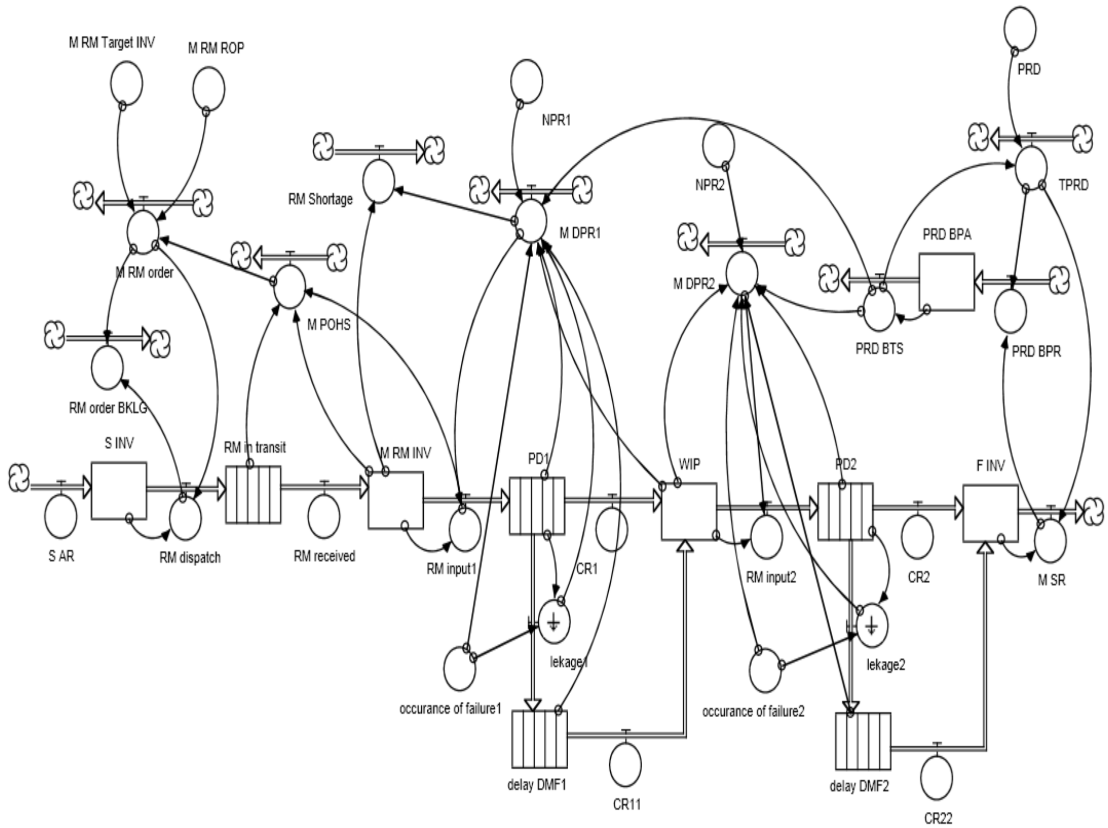

Figure 5.2 System dynamics model for serial manufacturing supply chain without backup supplier

Table 5.1 Notations

1. SAR: Supplier's acquisition rate
2. S INV: Supplier's raw material inventory
3. RM dispatch rate: Raw material dispatch rate of supplier
4. RM order BAKLG: Raw material order backlog at supplier end
5. M RM order: Manufacturer raw material order quantity
6. M RM Target INV: Target inventory of manufacturer
7. M RM ROPI : Reorder-point of manufacturer's raw material inventory
8. RM shortage: Raw material shortage at manufacturer's end
9. M POHS: Manufacturer's on-hand stock
10. RM in transit : Raw material in transit
11. RM received : Raw material received at manufacturer's end
12. M RM INV: Raw material inventory level of manufacturer
13. RM input 1: Raw material input to machine 1
14. PD 1 and PD 2: Raw material processing delay at machine 1 and machine 2
15. Leakage 1and leakage 2: Raw material removal rate from machine1 and machine 2 respectively when the machine fails
16. Delay DMF 1 and delay DMF 1: Delay due to failure at machine1 and machine2 respectively.
17. CR 1 and CR 2: Production completion rate of machine 1and machine 2 respectively
18. CR 11 and CR 22: Production completion rate after the occurrence of failure at

machine 1 and machine 2 respectively

19. NPR 1and NPR 2: Normal production rate of machine 1 and machine2
20. WIP: Work-in-progress inventory
21. MDPR 1 and MDPR 2: Desired production volume for machine 1 and machine 2
22. RM input 2: Material input from WIP to machine 2
23. Occurrence of failure 1 and failure 2: Time of failure for machine 1 and machine 2
24. F INV: Finished product inventory
25. M SR: Sales rate
26. PRD: Demand
27. T PRD: Total demand
28. PRD BPR: Backlog per period
29. PRD BPA: Backlog accumulated per period
30. PRD BTS: Amount of backlog to satisfy
31. M RM order to S: Order placed by manufacturer to major supplier
32. M RM required : Total raw material requirement at manufacturer's end
33. RM in transit 1and RM in transit 2 : Raw order in transit while supplied by major supplier and backup supplier respectively
34. BS INV: Inventory at backup supplier
35. BS AR: Backup supplier's acquisition rate.
36. BS dispatch: Dispatch rate of backup supplier
37. RMR FRM BS : Raw material received from backup supplier

Equations for the system dynamics model shown in Figure 5.2 are presented in Appendix 6. To analyse the behaviour of MTS manufacturing system under uncertainty, uncertainty in demand, raw material supply lead time, supplier's acquisition rate, processing time, occurrence of machine failure and time taken to repair the machine are considered. To analyse the effect of above described uncertainties on the performance of MTS manufacturing supply chain, the system dynamics model (Figure 5.2) is simulated for one year (364 days) time period. To determine the warm-up period, the time series plot for finished goods inventory is analysed (Figure 5.3). From the figure, it can be observed that initial 119-periods can be considered as warm-up period. Therefore, data from simulation is collected under steady state condition. In order to examine the effect of uncertainty on manufacturing supply chain, performance parameters such as backlog, raw material shortage at manufacturer's end and supplier's end, and work-in-progress (WIP) are estimated at the end of each simulation run during steady state period.

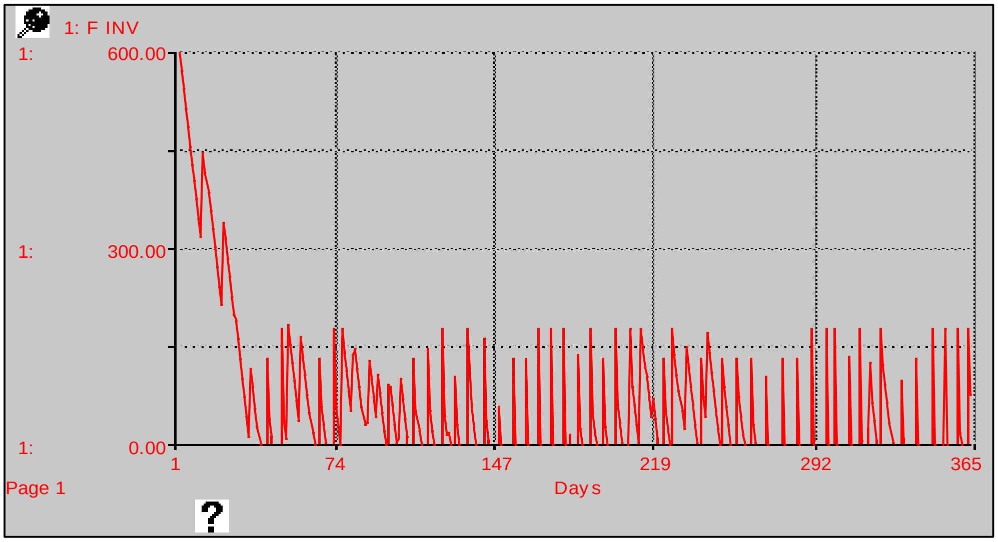

Figure 5.3 Time series plot for finished goods inventory

5.4 Results and discussions

To analyse the performance of MTS manufacturing system under the influence of uncertainty, different cases are considered here.

1. Base case

In order to set a benchmark for making comparative study, the system dynamics model (Figure 5.2) is simulated considering the demand ~N (27, 1), supplier's lead time ~N (5, 1), processing time for both machines ~ N (5, 1) and supplier's acquisition rate ~N (26, 1) with initial parameter settings as described in section 5.3. The different output parameters are estimated from the simulation runs during steady state period is described in Table 5.2. The service level at the manufacturing end is estimated using Equation (1.1) (in Chapter 1).

Table 5.2 Estimated performance measures for base case

Demand (in lots)	Backlog (in lots)	Average WIP inventory (in lots)	Raw material backlog at supplier's end (in lots)	Raw material shortage at manufacturer's end (in lots)	Service level (%)
6639	3605	97.629	0	185	46

2. Uncertainty in demand

To analyse the effect of uncertainty in demand on the performance of considered system, the system dynamics model shown in Figure 5.2 is simulated by gradually increasing the standard deviation of demand with 4, 5 and 6 lots per day keeping rest of the parameters at base case level. The estimated values of parameters from the simulation runs are described in the Table 5.3.

Table 5.3 Summary of the estimated values by increasing standard deviation of demand

Standard deviation of demand (in lots)	Demand (in lots)	Backlog at manufacturer's end (in lots)	Average WIP inventory (in lots)	Backlog at supplier's end (in lots)	Raw material shortage at manufacturer's end (in lots)	Service level (%)
4	6699	3931	94.873	0	185	41
5	6727	4266	152.155	0	195	37
6	6751	4493	152.094	0	200	33

From Table 5.3, it can be observed that increase in uncertainty in demand leads to increase in backlog at manufacturer's end. In fact, increase in demand uncertainty affects the finished goods inventory leading to stock-out situation. As a result, backlog gets increased causing decrease in service level. At base case, the service level is 46% whereas service level is gradually decreased to 41%, 37% and 33% as standard deviation of demand increases to 4, 5, 6 respectively (from Table 5.3). Equation (5.2) is used to find out production quantity needed as a function of backlog. As backlog increases, production quantity increases leading to increase of average WIP at shop floor. Demand variation also leads to increase in raw material shortage at manufacturer's end.

3. Uncertainty in supply lead time

To analyse the effect of uncertainty in raw material supply lead time, the model shown in Figure 5.2 is simulated by gradually increasing the standard deviation of supply lead time (supplier unreliability) at 10%, 50% and 60% (i.e. 1.1, 1.5, 1.6 in days) from the original standard deviation value as described in base case keeping all other parameters at their base case level. From the simulation runs, different performance measures are estimated as presented in Table 5.4. It can be observed that the service level gradually falls (38%, 35% and 34%) due to gradually increasing uncertainty in lead time.

Table 5.4 Summary of the estimated values by increasing standard deviation of lead time

Standard deviation of supplier's lead time (in days)	Demand (in lots)	Backlog at manufacturer's end (in lots)	Average WIP inventory (in lots)	Backlog at supplier's end (in lots)	Raw material shortage at manufacturer's end (in lots)	Service level (%)
1.1	6639	4083	122.359	0	170	38
1.5	6639	4306	124.310	0	195	35
1.6	6639	4353	121.747	0	240	34

4. Uncertainty in supplier's acquisition rate

To analyse the effect of uncertainty in supplier's acquisition rate on the performance of manufacturing supply chain, the mean value of supplier's acquisition rate is decreased by 4% (i.e. 24, 23, 22 and 21days) from its base value in a sequential manner and the model shown in Figure 5.2 is simulated keeping other parameters at base case level. The different parameters are estimated from the simulation runs are presented in Table 5.5. Decrease in mean acquisition rate leads to increase in raw material shortage at the supplier's end and insufficient quantity of raw material is supplied to manufacturer. Therefore, the raw material orders get backlogged at supplier's end. This leads to increase in raw material shortage at the manufacturer's end. Hence, there is decrease in WIP as shown in Table 5.5. As the production rate is adversely affected, there is increase in backlog at manufacture's end. Hence, service level is adversely affected as evident from Table 5.5.

Table 5.5 Summary of the estimated values by decreasing supplier's acquisition rate

Mean value for supplier's acquisition rate (in lots/day)	Demand (in lots)	Backlog at manufacturer's end (in lots)	Average WIP inventory (in lots)	Backlog at supplier's end (in lots)	Raw material shortage at manufacturer's end (in lots)	Service level (in %)
24	6639	3717	95.073	0	200	44
23	6639	4252	92.367	5471	388	36
22	6639	5072	90.376	11093	1192	24
21	6639	5755	84.698	22975	1604	13

5. Processing time variation of machine 1 and machine 2

To study the effect of increase in production uncertainty due to machine (machine 1 and machine 2), the standard deviation of material processing time is gradually increased with 10%, 50% and 60% from the base case value and the model in Figure 5.2 is simulated keeping other parameters at base case level. The estimated performance measures from the simulation runs are described in the Tables 5.6 and Table 5.7.

Table 5.6 Summary of the estimated values by varying processing time of machine 1

Standard deviation of processing time of machine 1 (in days)	Demand (in lots)	Backlog at manufacturer's end (in lots)	Average WIP (in lots)	Backlog at Supplier's end (in lots)	Raw material shortage at manufacturer end (in lots)	Service level (in %)
1.1	6639	3845	99.416	0	160	42
1.5	6639	4385	144.988	0	280	34
1.6	6639	4776	149.800	0	460	28

Increase in uncertainty in processing time affects the production rate leading to stock-out at finished goods inventory and hence, backlog increases at the manufacturer's end. Therefore, service level is decreased as shown in Table 5.6. From the Table 5.6, it can be observed that increase in backlog causes increase in total demand and this ultimately increases the raw material input as evident from Equation (5.2) and Equation (5.3). Increase in raw material input causes increase in raw material shortage at the manufacturer's end. The WIP inventory level is severely affected by processing time of machine 2 due to blocking effect. Due to increase in variation in processing time of machine 2, the finished goods inventory gets affected leading to occurrence of stock-out situation. This leads increase in backlog and decrease in service level as shown in Table 5.7.

Table 5.7 Summary of the estimated values by varying the processing time of machine 2

Standard deviation of processing time of machine 2 (in days)	Demand (in lots)	Backlog at manufacturer's (in lots)	Average WIP inventory (in lots)	Backlog at supplier's end (in lots)	Raw material shortage at manufacturer's end (in lots)	Service level (in %)
1.1	6639	3893	130.65	0	145	41
1.3	6639	4391	127.91	0	185	34
1.5	6639	4515	160.60	0	195	32

6. Repair time variation of machine 1 and machine 2

For determining the effect of uncertainty in machine repair time on the performance of manufacturing supply chain, the standard deviation of repair time of machine 1 and machine 2 is increased by 24 hrs. 36 hrs. and 40 hrs. and the model in Figure 5.2 is simulated keeping all other parameters at their base case level. The estimated values are described in Table 5.8 and Table 5.9.

Table 5.8 Summary of the estimated values by varying the repair time for machine 1

Standard deviation of repair time of machine 1 (in hrs)	Demand (in lots)	Backlog at manufacturer's end (in lots)	Average WIP inventory (in lots)	Backlog at supplier's end (in lots)	Raw material shortage at manufacturer's end (in lots)	Service level (in %)
24	6639	3717	95.29	0	200	44
36	6639	3891	129.64	0	200	41
40	6639	4597	116.40	0	185	31

Table 5.9 Summary of the estimated values by varying the repair time for machine 2

Standard deviation of repair time of machine 2 (in hrs)	Demand (in lots)	Backlog at manufacturer's end (in lots)	Average WIP (in lots)	backlog at Supplier's end (in lots)	Raw material shortage at Manufacturer's end (in lots)	Service Level (in %)
24	6639	4083	122.36	0	170	38
36	6639	4221	150.08	0	145	36
40	6639	4822	144.27	0	160	27

From Tables 5.8 and Table 5.9, it can be observed that backlog at manufacturer's end increases with increase in repair time as the production process is stopped for the duration from the time of occurrence machine failure till it gets repaired. Increase in backlog causes decrease in service level.

From the above study, it is found that the performance of MTS manufacturing system is severely influenced by demand variation, unreliable machine and unreliable supplier. However, variability in demand and machine unreliability is vital uncontrollable parameters. Although it is difficult to achieve the zero failures, frequency and time of occurrence of failure can be managed to some extent through an effective engineering and maintenance strategy. The product demand depends on the external customer demand and is an uncontrollable parameter. This can be controlled through a good forecasting technique. The above analysis also highlights that supplier reliability is vital for improving the performance of supply chain. The backlog estimated considering uncertainty in supplier's acquisition rate is higher than backlog estimated considering any other uncertainty factors. Uncertainty in raw material supply to manufacturing system can be avoided through adopting a backup supply strategy for raw materials and information sharing system to minimize shortage of raw materials at manufacturer's end. In other words, it is vital to have high service level at the supplier's end in order to achieve high service level at customer level. In order to incorporate these two conditions in the existing system, the model shown in Figure 5.2 is extended with a backup supplier as shown in Figure 5.4 and the equations are shown in Appendix 7.

In the above model (Figure 5.4), the information sharing is adopted to keep the information on supplier's inventory status by the manufacturer. The aim is to keep 90% lots of total raw material required for the period so the production process runs smoothly and service level can be improved under uncertain environment. When the major supplier is unable to fulfil 90% lots of raw material order placed by the manufacturer, the complete order is shifted to the backup supplier. Although backup supplier has enough capacity, manufacturer cannot place each order to backup supplier due to fact that unit cost of the raw material is higher in case of the backup supplier than the major supplier. To study the performance of the MTS manufacturing system with backup supply strategy under major supplier's acquisition uncertainty, the model Figure 5.4 is simulated for 364 days.

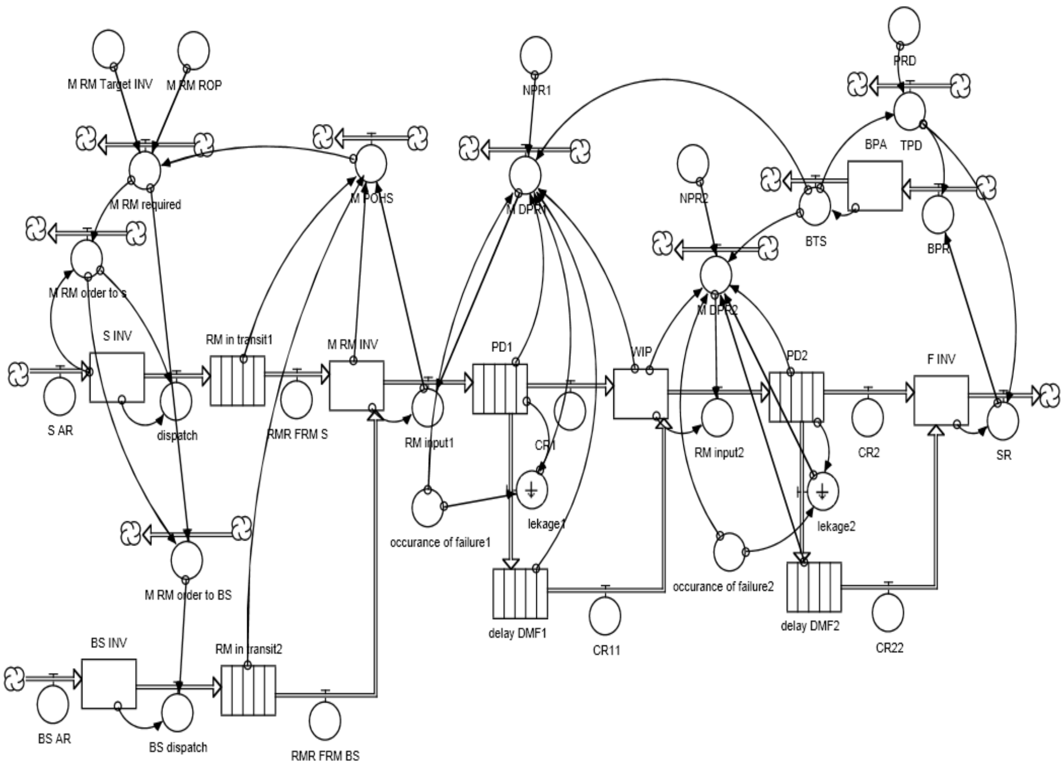

Figure 5.4 System dynamics model for MTS manufacturing system with backup supply

For the simulation purpose, certain assumptions have been made including all the assumptions described in section 5.3 as follows:

1) Backup supplier has infinite capacity.
2) The inventory status of major supplier is shared with the manufacturer.
3) In the perspective of maintaining 90% lots at manufacturer's raw material inventory, it places complete order to backup supplier while the major supplier is not capable to meet the 90% of the total order quantity.

The model shown in Figure 5.4 is simulated by decreasing the mean acquisition rate of the major supplier with 23 lots/day, 22 lots/day and 21 lots/day keeping all other parameters at base case level and the estimated backlog quantities are described in Table 5.10. From Table 5.10, it can be observed that the estimated backlog with backup supplier is comparatively less than the backlog estimated without backup supplier. Hence, it can be concluded that manufacturer's service level can be improved with backup supplier under the raw material supply uncertainty. The service level estimated from base level (Table 5.2) is 46% which is lower than the service level achieved through backup supply strategy. From this analysis, it can be concluded that high service level at the high end of supply chain is required to achieve high service level at customer end.

Table 5.10 Estimated backlogs with and without backup supply environment

Mean acquisition rate of supplier (in lots/day)	Demand (in lots)	Estimated backlog at manufacturer's end with backup supply strategy (in lots)	Estimated Backlog at manufacturer's end without backup supply strategy	Service level (in %)	
				With backup supply strategy	Without backup supply strategy
23	6639	3207	4252	51.69	35.95
22	6639	3243	5072	51.15	23.60
21	6639	3583	5755	46.03	13.31

5.5 Summary

A simulation modelling framework using system dynamics approach is proposed to examine the performance of the MTS manufacturing system under the influence of different uncertainties such as processing time, machine failure, supplier's acquisition rate, demand and raw material supply lead time. The performance of the manufacturing system is analysed through estimating various performance measures such as WIP inventory, raw material shortage and backlog. The effect of each kind of uncertainty on performance measures has been studied. From the analysis, it is found that increase in demand uncertainty affects the performance measures like finished goods inventory, WIP level and raw material inventory. Uncertainty in raw material supply lead time leads to stock-out at manufacturer's end and all interrelated measures like raw material input, production rate and finished goods inventory are affected. This ultimately results in increase of backlog. Processing time variability, one of the other issues, causes adverse effect on WIP level and the finished goods inventory and ultimately on service level. Due to random occurrence of machine failure, uncertain amount of time is required to repair the machine. Machine failures cause adverse effect on WIP and finished goods inventory. It has been found from the study that uncertainty in supplier's raw material acquisition rate has strong impact on the performance measures because uncertainty at higher level propagates to lower end. Variations in acquisition rate of the supplier causes stock-out at supplier's raw material inventory and manufacturer's raw material inventory gets reduced. As the raw material input to production process gets affected, there is a decrease in the WIP level and production rate. Decrease in production rate causes depletion in finished goods inventory leading to decrease in service level. In this way, the adverse effect of uncertainty at single entity propagates to other interrelated entities existing within the manufacturing supply chain. Uncertainty in demand, processing time, repair time and supply lead time are difficult to control but effective management and engineering practices can reduce the variations. However, supplier capacity is a convenient controllable parameter to improve the performance of MTS manufacturing system under uncertain situation. From the study, it is found that uncertainty in supplier's capacity causes high degradation in supplier's service level ultimately reflecting on degradation of service level at customer. However, it has been demonstrated that service level at customer's end can be improved through a strategic backup plan for raw material supply. The study proposes a system dynamic approach which can be modified by the managers to generate if-then scenarios to get insight into the operational behaviour of supply chains. Many policies and strategies can be tested to improve the service level at customer's end. However, a simple two machine serial manufacturing system dealing with only one kind of product is simulated in this work. The work can be extended to deal with a complex manufacturing system with multiple machines and dealing with variety of products. The model can be further improved by incorporating products requiring more than one raw material and seeking multiple sourcing options. Although there are various adverse effect of uncertainties on supply chain performance, bullwhip effect and net-stock amplification happens to be two major adverse effects. The next chapter deals with proposed forecasting models to reduce bullwhip effect and net-stock amplification.

CHAPTER 6

IMPROVED FORECASTING MODEL TO DEAL WITH BULLWHIP EFFECT AND NET-STOCK AMPLIFICATION

6.1 Introduction

In previous chapters (Chapter 3 and Chapter 4), the adverse effect of uncertainty in demand, raw material supply lead time and quantity and manufacturing process on the performance of supply chain has been discussed. In Chapter 5, a strategic plan is proposed to cope up the adverse effect of uncertainty in raw material supplied from the supplier. In section 2.6 (Chapter 2), it has been discussed that bullwhip effect (BWE) is one of the negative influences of uncertainties in supply chain. It leads increase in different cost component such as manufacturing cost, inventory holding cost, transportation cost, shipping and receiving cost giving rise to increase in total cost and replenishment lead time and decrease in fill rate and profitability (Chopra et al., 2006). Therefore, it is necessary to pay proper attention to reduce/eliminate BWE. According to Lee et al. (1997a), there are five major causes attributed to BWE such as demand forecasting, order batching, price fluctuations, supply shortages and non-zero lead-time. Inaccurate forecasting of demand leads to inaccurate estimation of order. It causes amplification of order with respect to variation in demand (BWE). Hence, demand forecasting is one of the essential tasks in the area of supply chain. Typically, demand follows a time series pattern. Therefore, different time series forecasting models like autoregressive (AR) (Luong, 2007; Luong and Phien, 2007), moving average (MA) (Chen et al., 2000a; Hong and Ping, 2007; Ma et al., 2013), exponential moving average (EMA) (Chen et al., 2000b), exponentially weighted moving average (EWMA) (Hong and Ping, 2007) autoregressive moving average (ARMA) (Zhang, 2004; Duc et al., 2008a; 2008b; Bandyopadhyay and Bhattacharya, 2013) and autoregressive integrated moving average (ARIMA) (Gilbert, 2005; Gilbert and Chatpattananan, 2006) are proposed for demand prediction in order to reduce the BWE through regulating the model parameters such as AR or MA coefficient including the lead time. However, it is difficult to control these model parameters (AR and MA coefficient and lead time) in practice.

The time series ARIMA model is one of the popular models for demand prediction. However, there are two limitations associated with this model. First it follows assumption of homoscedastic for demand variation in which variance is assumed to be constant over forecasting period. In practice, demand variance is heteroskedastic in nature i.e. variance of demand varies with time. To deal with the variation in demand, supply or manufacturing process, a buffer stock (safety stock) is maintained by the organisation. Safety stock serves as a safeguard against the stock-out situation. Hence, proper estimation of safety stock is vital to manage the not only the inventory but also demand.

The safety stock quantity is estimated considering the variation in demand (Equation 3.8, Chapter 3). Since, the time series ARIMA model is homoscedastic in nature, it is not possible to predict the changing demand variance. This leads inaccurate estimation of the safety stock level causing inaccurate estimation of order quantity. This problem can be overcome if the model has the ability to predict the demand variance. The generalized autoregressive conditional heteroskedasticity (GARCH) model can be used to predict the changing demand variance. To overcome the problem associated to the first limitation of the ARIMA model, a new forecasting approach is proposed in this study through integrating the ARIMA model with GARCH model and it is denoted as ARIMA-GARCH model.

Addressing second limitation, ARIMA model is applicable to linear and stationary demand series. In real practice, the demand pattern is non-linear and non-stationary in nature. To make prediction from non-stationary demand series, it must be first transformed into stationary form. This process causes loss of some useful information about the demand series. Hence, predicted demand values are not always satisfactory to estimate of order quantity. These issues can be resolved by adopting artificial intelligence (AI) techniques for developing the forecasting model applied to nonlinear data series. Different AI models have been successfully applied in various discipline of research for prediction purpose like artificial neural network (ANN) (Zhang et al., 2001; Doganis et al., 2006; Patnaik et al., 2008), adaptive neuro-fuzzy inference system (ANFIS) (Subasi, 2007; Sahu and Mahapatra, 2013; Sahu et al., 2011), least square support vector machine (LSSVM) (Chauchard et al., 2004; Lu et al., 2009; Kim, 2003; Li et al., 2011; Hong et al., 2013; Sudheer et al., 2013; Sudheer et al., 2013; Zhiqiang, 2013), genetic programming (GP) (Kaboudan, 1999; Salcedo-Sanz et al., 2005) and multi-gene genetic programming (MGGP) (Gandomi and Alavi, 2012; Garg et al., 2013). These models have the ability of self-learning and self-adapting the data pattern and do not require any statistical information related to a given data series for prediction. Therefore, AI models are used as a suitable predictive model for a data series exhibiting either linear/non-linear or stationary/non-stationary pattern. The prediction accuracy of AI models can be substantially improved when the data series contains adequate information relevant to its past pattern. The wavelet transformation (WT) theory is one of the powerful mathematical tools which provide data information based on time and frequency domain. Many studies address the application WT for extracting the data information (Aggarwal et al., 2009; Partal and Cigizoglu, 2009; Khan and Shahidehpour, 2009; Wei et al., 2012; Zhang and Tan, 2013). Therefore, in this study, four different hybrid models are proposed by integrating the discrete wavelet transformation (DWT) analysis with the AI models such as ANN, ANFIS, LSSVM and MGGP to predict the demand. The models are defined as DWT-ANN, DWT-ANFIS, DWT-LSSVM and DWT-GP. These models are validated using an example data set from open literature and performing a comparative study with ARIMA model by estimating forecasting error.

According to Bout and Lambrecht (2009), moderating BWE does not necessarily reflect the inventory fluctuations which influence associated inventory costs. In order to deal with fluctuation in inventory, organisations must maintain high safety stock to improve service level. This leads high holding cost. Hence, variation in net stock with respect to demand known as net-stock amplification (NSAmp) is treated as another major supply chain performance measures. Therefore, accuracy of demand forecasting must be enhanced in such a manner that both the important performance measures of supply chain such as BWE and NSAmp must be reduced. Once the models are validated, three case studies are considered to estimate the BWE and NSAmp by predicting the demand using the proposed models and estimating the order through the base-stock policy. The order quantities estimated based on predicted demand using the ARIMA and the proposed models ARIMA-GARCH, DWT-ANN, DWT-ANFIS, DWT-LSSVM and DWT-GP are analysed. From the analysis, it has been proved that the intelligence models (DWT-ANN, DWT-ANFIS, DWT-LSSVM and DWT-GP) outperform the ARIMA and ARIMA-GARCH process. Hence, further, the performance of the intelligence models are studied for different (R, S) policies like (R, S),$(R,\beta S)$, (R,D), $(R,\gamma O)$ and $(R,\gamma O,\beta S)$ suggested by Jakšič and Rusjan (2008) and Bandyopadhyay and Bhattacharya (2013).

6.2 Methodology

In order to develop the model and validate the model, following approaches are adopted in this study.

6.2.1 Time series forecasting models

The mathematical representation of the time series model can be express as follows (Equation (6.1)):

$$Y_{t+1} = f_{\theta}\left(Y_t + Y_{t-1} + \ldots + Y_{t-N+1}\right) \quad (6.1)$$

where Y_{t+1} is the unknown value to be predicted from the current and past value of the variable Y. Following paragraphs contains the brief introduction on different time series models.

6.2.1.1 Autoregressive integrated moving average (ARIMA) model

The autoregressive process (AR) is one of the time series models which can be used for demand forecasting. The AR model of order p denoted as AR (p) is presented in Equation (6.2) where Y_t is the forecasted demand for period t and Y_{t-1}, Y_{t-2},…, Y_{t-p} are the time lagged values of the demand variable (Y). Another time series model is moving average (MA) model. The MA model of order q can be expressed by the Equation (6.3). The combination of AR and MA process is known as ARMA (p, q). A typical ARMA model known as ARMA (1, 1) can be mathematically represented by Equation (6.4). The time series ARMA model has the limitation that it can be applied to predict stationary data series only. In order to make prediction from non-stationary data series, the ARMA model is extended allowing differencing to convert the data series into stationary form and known as Autoregressive Integrated Moving Average (ARIMA) model (Box and Jenkins, 1976; Box et al., 1994). ARIMA model is a univariate time series model. A data series may contain seasonality effect. The non-seasonal ARIMA process can be denoted as ARIMA (p, d, q) whereas seasonal version is represented as ARIMA (p, d, q)$(P,D,Q)_{s.}$ Equation (6.5) shows the ARIMA(1,1,1) process whereas ARIMA(1,1,1)(1,1,1) is given in Equation (6.6).

$$Y_t = c + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \ldots + \phi_p Y_{t-p} + e_t \tag{6.2}$$

$$Y_t = c - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \ldots - \theta_p e_{t-q} + e_t \tag{6.3}$$

$$Y_t = c + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \ldots + \phi_p Y_{t-p} - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \ldots - \theta_q e_{t-q} + e_t \tag{6.4}$$

$$Y_t = c + (1 + \phi_1)Y_{t-1} - \phi_1 Y_{t-2} + e_t - \theta_1 e_{t-1} \tag{6.5}$$

$$\begin{aligned} Y_t = c &+ (1+\phi_1)Y_{t-1} - \phi_1 Y_{t-2} + (1+\Phi_1)Y_{t-12} - (1+\phi_1+\Phi_1+\phi_1\Phi_1)Y_{t-13} + (\phi_1+\phi_1\Phi_1) \\ &Y_{t-14} - \Phi_1 Y_{t-24} + (\Phi_1+\phi_1\Phi_1)Y_{t-25} - \phi_1\Phi_1 Y_{t-26} + e_t - \theta_1 e_{t-1} - \Theta_1 e_{t-12} + \theta_1\Theta_1 e_{t-13} \end{aligned} \tag{6.6}$$

where,

p = non-seasonal order of the autoregressive part

d = non-seasonal degree of differencing involved

q = non-seasonal order of moving average part

P = seasonal order of the autoregressive part

D = seasonal degree of differencing involved

Q = seasonal order of moving average part

s = number of periods per season

c = constant term

ϕ_j = non-seasonal j^{th} autoregressive parameter

θ_j = non-seasonal j^{th} moving average parameter

e_{t-q} = error term at t-q

e_t = error term at time t

Φ_j = seasonal j^{th} autoregressive parameter

Θ_j = seasonal j^{th} moving average parameter

To make prediction using this model, it is assumed that the considered data series is linear and stationary. There are five general steps such as (i) data preparation (ii) model selection (iii) estimation (iv) diagnostic checking and (v) forecasting are followed to identify ARIMA model and make prediction (Makridakis et al., 1998). In this research work, the software STATISTICA 9 has been used to identify ARIMA model to predict the demand.

6.2.1.2 Generalized autoregressive conditional heteroskedasticity (GARCH) model

A fundamental assumption made while ARIMA model is that variance of the data series remains constant throughout the forecasting period. However, this assumption is relaxed by introducing a time series model known as autoregressive conditional heteroskedasticity (ARCH) model proposed by Engle (1982) to capture the changing variance in the financial time series data. The general mathematical expression for the ARCH model of order q (ARCH (q)) can be expressed as Equation (6.7) and Equation (6.8).

$$r_t = \sigma_t \varepsilon_t, \qquad \text{where } \varepsilon_t \sim N(0,1) \tag{6.7}$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 r_{t-1}^2 + \ldots + \alpha_q r_{t-q}^2 \tag{6.8}$$

Further, it is extended with a valid proof that conditional variance of the error process not only related to squares of the past error but also to the past conditional variance through the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) process (Bollerslev, 1986). The standardized mathematical expression of GARCH (p, q) process is shown in Equation (6.9) with restriction $\alpha_i \geq 0,\ i = 1,2,\ldots,q$, $\beta_j \geq 0,\ j = 1,2,\ldots,p$ and $\left|\sum \alpha_i + \sum \beta_j\right| < 1$.

$$\sigma_t^2 = \alpha_0 + \alpha_1 r_{t-1}^2 + ... + \alpha_q r_{t-q}^2 + \beta_1 \sigma_{t-1}^2 + ... + \beta_p \sigma_{t-p}^2 \quad (6.9)$$

where $\{r_t\}$ is the mean correlated return, σ_{t-p}^2 is the past conditional variance, ε_t is the Gaussian white noise with mean zero and unit variance and p and q are the positive integer representing the order of GARCH process, t > max (p, q). GARCH process is a part of solution and is applied to the return series. GARCH prediction process follows different statistical processes for model selection as described below:

i. Data transformation to obtain the return series.
ii. Testing of ARCH effect and serial correlation in the return series.
iii. Model estimation and analysis.
iv. A comparison of fitted model.
v. Diagnostic checking for the selected model.
vi. Forecasting with the selected model.

In this study, software MATLAB 2013 has been used for determining the GARCH model to predict the demand variance.

6.2.2 Artificial intelligence (AI) models

To make prediction using time series models (AR, MA, ARMA and ARIMA), the demand data needs to be linear and stationary. To make prediction using ARIMA model for non-stationary demand series, it must be first transform into stationary form. This process causes loss of information. However, artificial intelligence (AI) models make prediction based on learning the pattern of data series. Hence, AI models do not require any statistical information related to the data series for prediction and make prediction from non-linear and non-stationary data series. In this study, four different AI techniques such as artificial neural network (ANN), adaptive neuro-fuzzy inference system (ANFIS), least square support vector machine (LSSVM) and genetic programming (GP) are considered to develop an improved forecasting model to overcome the limitation of ARIMA model so as to reduce BWE and NSAmp. Following paragraphs contain brief introduction on these intelligent models.

6.2.2.1 Artificial neural network (ANN) model

A structure of an ANN model comprises of interconnected operating elements named as neurons (also called nodes) stimulated by the biological nervous system (Kumar, 2011). An ANN model has the capability to recognize and acquire the past data pattern to perform prediction. The feed-forward multilayer perceptron (FFML) network is one of the most commonly used types of ANN for forecasting. The ANN architecture generally comprises with three different layers called input, hidden and output layer. The model can be represented with l-m-n where l denotes the numbers of neurons at input layer which depends on the external input. The number of neurons in the hidden layer m is optimized through experimentation and n represents the number of output neurons. The number of neurons in the output layer depends on the desired number of outputs. Here, the desired number of outputs is one i.e. the predicted demand. Two processes called training and testing are involved in the prediction process. The process of training a neural network involves tuning the values of the weights and biases of the network to optimize network performance. Hence, a specific training function is used to train the network model. Training function maps the input and output for the supplied training data set through the weight value w_{ji} and w_{kj} during the training process where w_{ji} and w_{kj} are the connection weights between i^{th} input neuron to j^{th} hidden neuron and j^{th} hidden neuron to k^{th} output neuron respectively. In this study the training function called gradient descent with momentum has been carried out the network training process. The general structure of the ANN is shown in Figure 6.1.

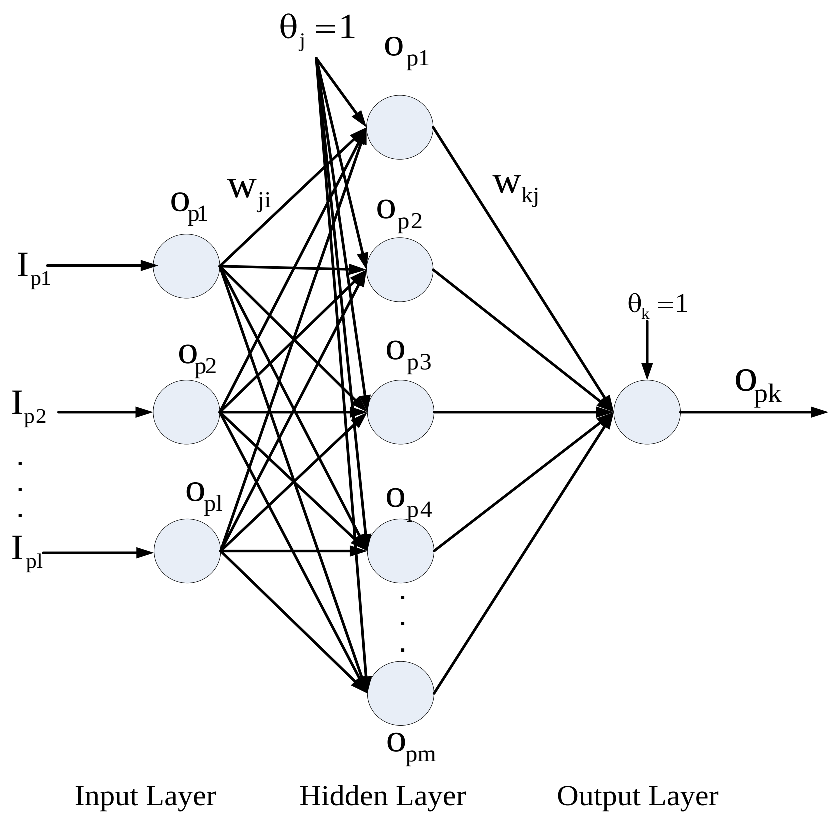

Figure 6.1 General structure of ANN model

Let $I_p = (I_{p1}, I_{p2}, ..., I_{pl})$, p= 1, 2 …. N is the p^{th} pattern among N input patterns. Output from neurons in input layer (O_{pi}) is given by Equation (6.10) whereas output from the hidden layer (O_{pj}) and output layer (O_{pk}) are given by Equation (6.11) and Equation (6.12) respectively.

$$O_{pi} = I_{pi}, i = 1,2,\ldots,l \tag{6.10}$$

$$O_{pj} = f\left(\sum_{i=0}^{l} w_{ji} O_{pi}\right), j = 1,2,...,m \tag{6.11}$$

$$O_{pk} = f\left(\sum_{j=0}^{m} w_{kj} O_{pj}\right), k = 1,2,...,n \tag{6.12}$$

The supplied input data set is modified using the connecting weights to generate sum of modified value (x) and again this is modified by sigmoidal transfer function f using Equation (6.13). In training process, the predicted output is compared with the desired output through estimating the error in terms of the mean square error (E_p) using Equation (6.14). If E_p is more than the defined limiting value, it is back propagated from output to input and weights are further modified using Equation (6.15) till the error or number of iteration reaches a prescribed limit. In this study, absolute mean square error of 0.10 is considered.

$$f(x) = \frac{1}{1+e^{-x}} \tag{6.13}$$

$$E_p = \frac{1}{n}\sum_{i-1}^{n} (D_{pi} - O_{pi})^2 \tag{6.14}$$

$$\Delta w(t) = -\eta E_p(t) + \alpha \times \Delta w(t-1) \tag{6.15}$$

$\eta = \text{learning rate},\ 0 < \eta < 1$

$\alpha = \text{momentum coefficien t},\ 0 < \alpha < 1$

t = iteration number (epochs)

n=number of training data set

The software MATLAB 2013 is used to develop the ANN model to make prediction.

6.2.2.2 Adaptive neuro-fuzzy inference system(ANFIS)

The adaptive neuro-fuzzy inference system (ANFIS) is a hybrid intelligent model that combines the feature of ANN and fuzzy inference system (FIS) together (Jang, 1993). ANN has the ability of self-learning and self-adapting the data pattern for prediction. However, it is a difficult task to understand the learning procedure followed by ANN model. However, fuzzy logic models are easy to realize as it uses linguistic terms in the form of IF-THEN rules. Since ANFIS learns through the fuzzy inference system, it becomes easy to understand its learning procedure. A classical structure of the ANFIS model consists of five layers and each layer comprises numbers of nodes interconnected through the directional links. These nodes are described by the node function with fixed or adjustable parameters. The output from nodes in previous layer is taken as input to the present layer. To explain the working principle of ANFIS model in a simplistic way, two inputs x and y and a single output f is considered for the fuzzy inference system. A one degree of Sugeno's function is adopted to represent the rule (Jang, 1993). The rule can be described as:

Rule 1: if x is A_1 and y is B_1 then $f_1 = p_1x + q_1y + r_1$

Rule 2: if x is A_2 and y is B_2 then $f_2 = p_2x + q_2y + r_2$

If f_i is the output within the fuzzy region specified by fuzzy rule, A_i and B_i are the linguistic variables, p_i, q_i and r_i are the design parameters determined during the training process. The ANFIS structure to implement these two rules is represented by the classical structure as shown in Figure 6.2. The square nodes in the Figure 6.2 are the adaptive nodes and the circle nodes are the fixed nodes in the system. Nodes present in each layer perform a particular function to carry out the prediction process for a given data series. The output of each layer is symbolized by O_i^L i.e. output of i[th] node of layer L (where L=1, 2,…, 5). The different layers are:

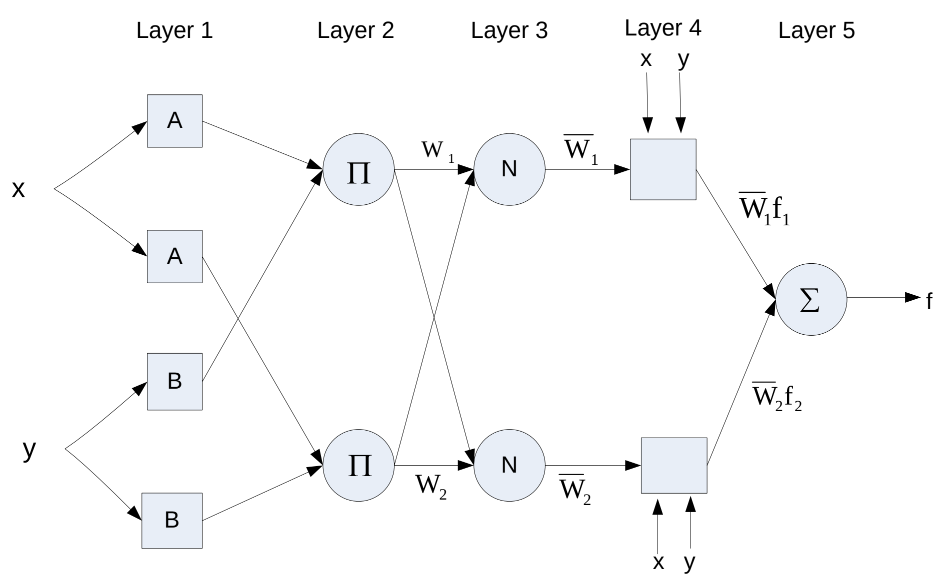

Figure 6.2 General structure of ANFIS model

Layer 1: Nodes present in this layer generates a membership grade of the linguistic label.

$$O_i^L = \mu_{A_i}(x) \qquad i=1, 2 \tag{6.16}$$

$$O_i^L = \mu_{B_{i-2}}(y) \qquad i=3, 4 \tag{6.17}$$

where x and y are the input to the node i, A_i and B_i are linguistic label and $\mu(x)$ and $\mu(y)$ are the membership function typically described by a bell-shape with maximum and minimum values equal to 1 and 0 respectively. The output of this layer is defined through Equation (6.18).

$$O_i^L = \mu_{A_i}(x) = \frac{1}{1 + \left\{((x + c_i)/a_i)^2\right\}^{b_i}} \tag{6.18}$$

where $\{a_i, b_i, c_i\}$ are the parameter sets that changes the shape of the membership function. These parameter set is also termed as “premise parameters”.

Layer 2: This layer calculates the firing strength w_i of each node through multiplication using Equation (6.19).

$$O_i^2 = w_i = \mu_{A_i}(x) \times \mu_{B_i}(y) \qquad i=1, 2 \tag{6.19}$$

Layer 3: The ith node present in this layer calculates “normalized firing strengths” using Equation (6.20).

$$O_i^3 = \overline{w}_i = \frac{w_i}{w_1 + w_2} \qquad i=1, 2 \tag{6.20}$$

Layer 4: Nodes in this layer are adaptive nodes and the node function can be defined as:

$$O_i^4 = \overline{w}_i f_i = \overline{w}_i(p_i x + q_i y + r_i) \qquad i=1, 2 \tag{6.21}$$

where $\overline{w}_i$ is the normalized firing strengths generated as output from third layer and p_i, q_i and r_i are the parameter set. Parameters in this layer are referred to as “consequent parameter”.

Layer 5: The overall output of the system is evaluated by the single node present in this layer through adding all incoming signals as described by Equation (6.22).

$$O_i^5 = \sum_{i=1}^{2} \overline{w_i} f_i = \frac{\sum_{i=1}^{2} w_i f_i}{\sum_{i=1}^{2} w_i} \tag{6.22}$$

Similar to feed forward neural network, the ANFIS model also follows the back propagation gradient descent learning principle. The task of the learning algorithm in ANFIS structure is to adjust all the regulating parameters $\{a_i, b_i, c_i\}$ and $\{p_i, q_i, r_i\}$ to make the output fit to the training data set. When the premise parameters a_i, b_i and c_i of the membership function are fixed, the output of the ANFIS model can be explained through Equation (6.23).

$$f = \left(\frac{w_1}{w_1 + w_2}\right)f_1 + \left(\frac{w_1}{w_1 + w_2}\right)f_2 \tag{6.23}$$

By substituting Equation (6.20) into Equation (6.23), the obtained equation can be given as:

$$f = \bar{w}_1 f_1 + \bar{w}_2 f_2 \tag{6.24}$$

Substituting the fuzzy if-then rules into Equation (6.24), it becomes

$$f = \bar{w}_1(p_1 x + q_1 y + r_1) + \bar{w}_2(p_2 x + q_2 y + r_2) \tag{6.25}$$

After rearranging, the output can be written as:

$$f = (\bar{w}_1 x) * p_1 + (\bar{w}_1 y) * q_1 + (\bar{w}_1) * r_1 + (\bar{w}_2 x) * p_1 + (\bar{w}_2 y) * q_1 + (\bar{w}_2) * r_1 \tag{6.26}$$

This represents the linear combination of adjustable parameters p_1, q_1, r_1, p_2, q_2 and r_2. Optimal values for these parameters are determined through least square method. While the premise parameters values are not fixed, the search space becomes larger and convergence of training becomes slower. Hybrid learning algorithm combines the back propagation gradient descent and least squares methods. In this study, the hybrid learning process is adopted to obtain optimal parameter setting of ANFIS. The software MATLAB 2013 has been used to develop the ANFIS model.

6.2.2.3 Least square support vector machine (LSSVM)

The support vector regression (SVR) is one of the AI tools based on statistical learning theory having the capability to develop a predictive model for a given data series. The origin of SVR lies in support vector machine (SVM) which has been developed for data classification problem. If $\{x_i, y_i\}$ represents the training data set where, $x_i \in R$ is the input data series and $y_i \in R$ is the output for i=1, 2… N where N represents number of observations then a regression model is built through non-linear mapping function $\phi(x)$ and the predictive model can be defined by Equation (6.27).

$$y = w^T \phi(x) + b \tag{6.27}$$

An advanced version of SVR is least square support vector machine (LSSVM) where the prediction error is minimized through the least square method. The major difference between SVR and LSSVM is that SVR uses an inequality constraint which is burdensome for solving the optimization problem whereas LSSVM use quadratic loss function for goal optimization and inequality constraints are converted into equality constraints. The optimization problem can be expressed through the cost function as described using Equation (6.28) and the constraint function by Equation (6.29).

$$\min C(w,e)=\frac{1}{2}w^{T}w+\frac{1}{2}\gamma\sum_{i=1}^{N}e_i^2 \tag{6.28}$$

subject to equality constraints:

$$y=w^{T}\phi(x_i)+b+e_i \quad i=1, 2\ldots N \tag{6.29}$$

where w is the weight vector and b is the bias term, γ is penalty factor and e_i is the loss function (regression error).

The cost function (Equation (6.28)) consists of a penalized regression error and is minimized by LSSVM. The first part of the cost function is a weight degeneration process used to regularize weight sizes and penalize large weights to converge the weights to fixed values. The second part is the regression error for training data and the regularization parameter, γ , which has to be optimized by the user. The regression error is defined through the constraint using Equation (6.29). In order to solve this optimization problem, it is converted into Lagrange function as defined by Equation (6.30):

$$L(w,b,e,\alpha)=\frac{1}{2}\|w\|^2+\gamma\sum_{i=1}^{N}e_i^2-\sum_{i=1}\alpha_i\left\{W^{T}\phi(x_i)+b+e_i-y_i\right\} \tag{6.30}$$

where α_i are the Lagrange multipliers, $\gamma>0$, α_i , b can be calculated based on Karush-Kuhn-Tucker (KKT) conditions. Now, LSSVM model for nonlinear system becomes:

$$y_i=w.\phi(x)+b=\sum_{i=1}^{k}\alpha_i k\left(x_i,x\right)+b \tag{6.31}$$

where $k(x,x_i)=\phi(x)^{T}\phi(x_i)$ is the kernel function.

The kernel function plays an important role in learning the hyperspace from the trained data set. There are different types of kernel functions are available. In this study, radial basis function (RBF) kernel function is chosen as it is well known for its shorter training mechanism and imparting high generalization ability to the model. The RBF kernel can be mathematically represented as:

$$K(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|}{\sigma_{sv}^2}\right) \tag{6.32}$$

where σ_{sv}^2 is the squared variance of the Gaussian function. To obtain support vectors, it should be optimized by user. In order to achieve good generalized model, it is very important to make a careful selection for the tuning parameters like α and γ . The parameters α and γ of the RBF are estimated through a combination of coupled simulated annealing (CSA) and a grid-search method. Firstly, the CSA determines the good initial value of α and γ then these are passed to the grid-search method which uses cross-validation to fine tune the parameters. The code for LSSVM model is developed in MATLAB 2013.

6.2.2.4 Genetic programming (GP) model

Genetic programming (GP) is an extension of the conventional genetic algorithm (GA) and grounded on the principle of GA as proposed by Koza (1992). Although GP is based on the working principle of the GA, there exists a major difference. GP model gives solutions defined by a model or weighted sum of coefficients i.e. in the form of tree structure whereas GA model provides solution in the form of real or binary number. Thus, it can be said that GP is a structure optimization method whereas GA is a parametric optimization method. GP uses symbolic regression technique for automatically invoking both the structure and parameter of the mathematical model for a data set acquired from a process or system. Symbolic regression is usually performed in GP to evolve population trees, each of which encodes a mathematical equation that predicts a (N ×1) vector of output y using a corresponding (N × M) matrix of inputs where N is the number of observations of the response variable and M is the number of input (predictor) variables. In multi-gene symbolic regression, each symbolic model (i.e. each member of the GP population) is a weighted linear combination of the outputs from a number of GP trees where each tree may be considered to be a “gene” in the overall genome. Initial population of model or the tree structure is randomly created consisting of function and terminal nodes as shown in Figure 6.3. The mathematical form of the multi-gene can be express as Equation (6.33):

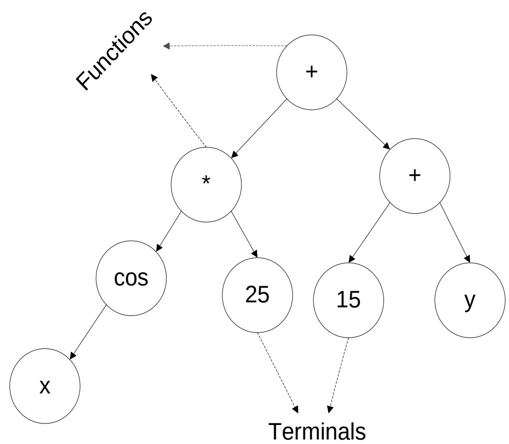

Figure 6.3 GP model $25\cos(x)+15+y$

$$y=\sum_{i=1}^{n} d_i G_i + d_0 \tag{6.33}$$

where y is the predicted output, G_i is the value of the i^{th} gene (generally a function of one or more of the input variables), d_i is the i^{th} weighting coefficient, n is the number of genes and d_0 is a bias/offset term. To control the complexity of the evolved models, the user needs to specify the maximum number of gene G_{max} and the maximum tree depth D_{max}. The fitness function generally used root mean square error (RMSE) given by Equation (6.34) based on which performance of initial population is evaluated on the training data.

$$RMSE=\frac{1}{N}\left(\sqrt{\sum_{i=1}^{N}\left|Y_i - A_i\right|^2}\right) \tag{6.34}$$

where Y_i is defined as the predicted value generated from GP model, A_i is the actual value of the i^{th} data sample and N is the number of training samples. The member of the population is selected based on the fitness function value for the genetic operations (crossover, mutation and reproduction) to reproduce new generation till the termination is not achieved. In crossover operation, sub-trees are randomly selected from two members and swapped to generate two new children (tree) as shown in Figure 6.4. In mutation operation, the terminals or the functional nodes are randomly selected from the tree to produce a new child as described in Figure 6.5.

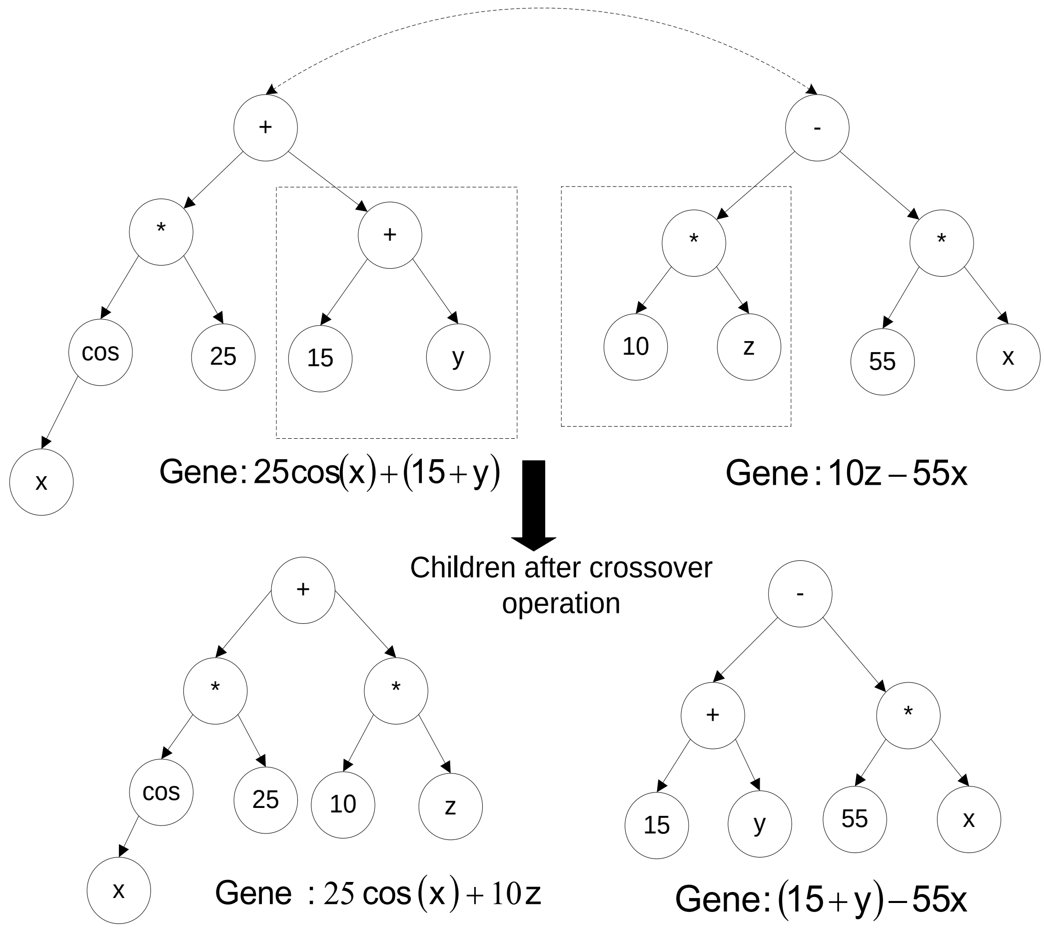

Figure 6.4 Crossover operation in GP

The mutation operation helps in avoiding local minima. This evolutionary process is continues till the termination criterion is met. The termination condition may be the maximum number of generation and the threshold error of the GP model set by the user. The best predictive model is selected based on minimum error on training data from entire set of generations. Unlike traditional GP, each model participating in the evolutionary process is made of several set of tree/genes combined together in multi-gene genetic programming (MGGP) method. The MGGP model formed is a weighted linear combination of output values from the number of trees/genes as shown in Figure 6.6. Two point high level crossovers allow the acquisition of new genes for both individuals but also allow genes to be removed. If an exchange of genes results in any individual containing more gene than G_{max} then genes are randomly selected and deleted until the individuals contains G_{max} genes. In this research work, an open source MATLAB toolbox called GPTIPS has been used for performing this multi-gene genetic programming (https://sites.google.com/site/ gptips4matlab /file-cabinet).

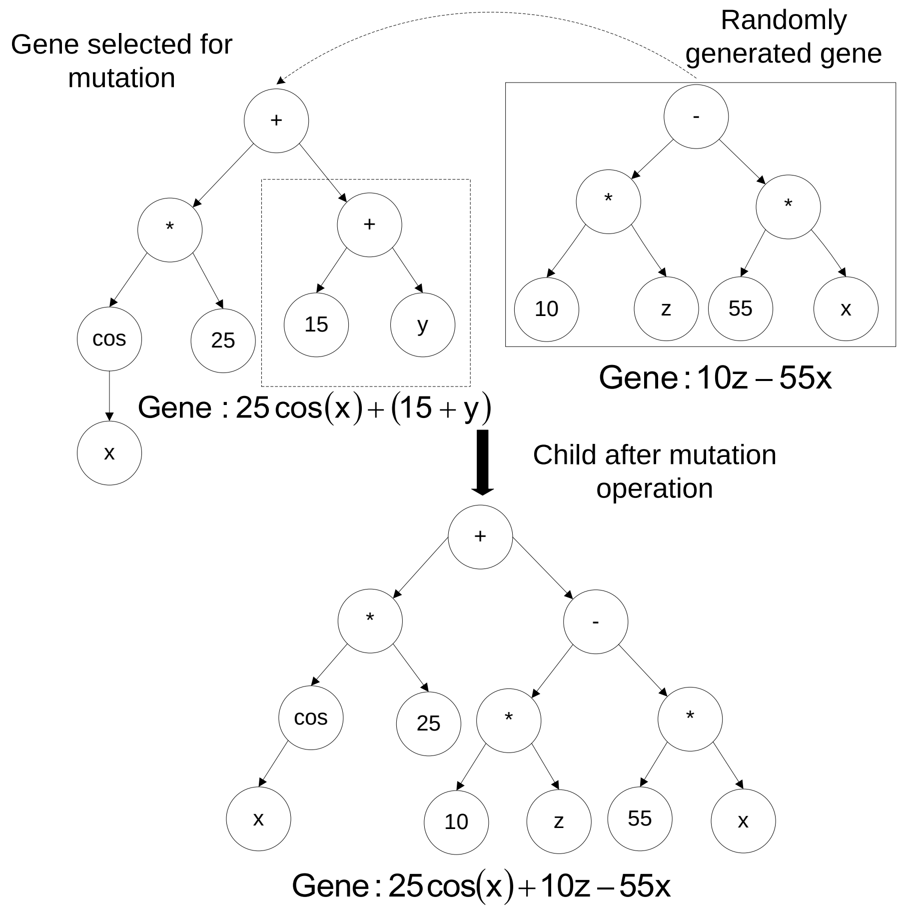

Figure 6.5 Mutation operation in GP

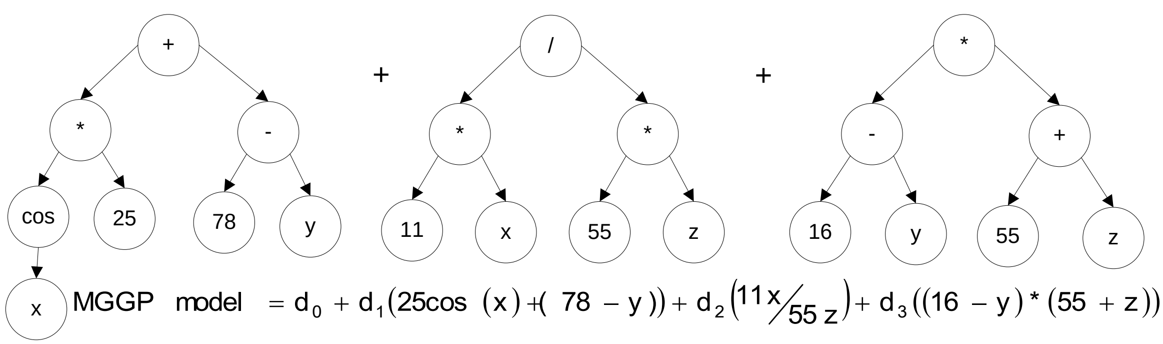

Figure 6.6 Formulation of MGGP model using least square method

6.2.3 Wavelet theory

Any forecasting model should have the capability to capture the existing pattern of the data series to make prediction. The AI models (ANN, ANFIS, LSSVM and MGGP) can make prediction based on learning the pattern of the past data series. Performance of these models can be improved through pre-processing the data series. Hence, in order to pre-process the data series for extracting the pattern, a mathematical tool known as wavelet theory (WT) has been applied. It has the ability to extract the data information in time and frequency domain. Wavelets are generally small waves located in different time and frequency domain and mathematically it is represented as:

$$\int_{\infty}^{\infty} \psi(t)\, dt = 0 \quad (6.35)$$

where $\psi(t)$ is the basic wavelet also known as mother wavelet.

Based on the sample data, WT deals with two types: continuous wavelet transformation (CWT) while the data series is in continuous form and discrete wavelet transformation (DWT) while sample data series is discrete in nature. When the scaling/frequency factor and shifting/time factor are denoted by 'a' and $'\tau'$ respectively, the mother wavelet is defined by $\psi_{a,\tau}$.The wavelet analysis becomes efficient and proficient of retaining the accuracy when 'a' and $'\tau'$ are selected as discrete values and this process known as DWT. It is one of the efficient tools to extract information (Khan and Shahidehpour 2009; Zhang and Tan 2013; Zhao et al., 2014). By selecting the discretized scaling parameter 'a' by taking power of fixed scaling step $a_0 > 1$ and $a = a_0^j$ with adopting discretized shifting step $\tau = ka_0^j\tau_0$ where j, k = 0,1,2,…, $m \in Z$ then $\psi_{a,\tau}(t)$ can be written as (Kim et al., 2006; Daubechies, 1990):

$$\psi_{j,k}(t) = a_o^{-j/2}\psi\left[a_0^{-j}\left(t - ka_0^j\tau_0\right)\right] = a_o^{-j/2}\psi\left(a_0^{-j}t - k\tau_0\right) \quad (6.36)$$

Similarly, DWT can be expressed through Equation (6.37)

$$W_f(j,k) = a_0^{-j/2}\int_{-\infty}^{+\infty} f(t)\,\psi \times \left(a_0^{-j}t - k\tau_0\right)dt \quad (6.37)$$

One of the most efficient and simplest ways of selecting scale and position value is dyadic form i.e. power of two where $a_0 = 2, \tau_0 = 1$. Based on this, the DWT is transformed to binary form as given in Equation (6.38).

$$W_f(j,k) = 2^{-j/2}\int_{-\infty}^{+\infty} f(t)\,\psi \times \left(2^{-j}t - k\right)dt$$

(6.38)

where $W_f(a,\tau)$ and $W_f(j,k)$ are the wavelet coefficients replicating the features of original time series in frequency (a or j) and in time domain (τ or k). When the discrete time series input $f(t)$, occurs at discrete integer time steps t then the dyadic form of DWT can be represented using Equation (6.39) and the $f(t)$ can be reconstructed using Equation (6.40).

$$W_f(j,k) = \sum_{j,k \in z} f(t) 2^{-j/2} \psi\left(2^{-j}t - k\right) \tag{6.39}$$

$$f(t) = \sum_{j,k \notin z} W_f(j,k)\, \psi_{j,k}(t) \tag{6.40}$$

Through a low pass filter $l(\psi_{i,k}(t))$ and a high-pass filter $h(\psi_{i,k}(t))$, the wavelet coefficient $W_f(j,k)$ is separated into an approximation (or low frequency) coefficient (cA_n) at level n and the detail (or high frequency) coefficients $(cD_1, cD_2, ..., cD_n)$ at different levels of 1,2,…,n. $cA_n(t)$. Hence, the original signal can be expressed by Equation (6.41).

$$f(t) = cA_n l\left(\psi_{i,k}(t)\right) + \sum_{n=1} cD_n h\left(\psi_{i,k}(t)\right) \tag{6.41}$$

The simplified form of Equation (6.41) can be represented as:

$$f(t) = A_n(t) + \sum D_n(t) \tag{6.42}$$

where $A_n(t)$ is the approximation subseries at level n and $D_n(t)$ are the detailed subseries at different levels (1,2,3,…,n) of the original signal. Daubechies wavelet family is usually written as ‘dbN’ where db is the ‘surname’ and N is the order of wavelet (Wei, 2012). In this study, db4 wavelet family is used for wavelet transformation using the software MATLAB 2013.

6.3 The proposed forecasting models

In this study, two different types of forecasting models are proposed to overcome the limitation associated with the time series ARIMA model and improve the forecasting model to reduce BWE and NSAmp so that performance of a supply chain can be improved. The proposed models are described in the following sections.

6.3.1 Forecasting model to deal with heteroskedastic demand series

An organisation needs to maintain a safety stock for raw material or final product to cope with stock-out situation due to uncertainty in demand, supply and processing unit. For safety stock estimation, variance of demand is one of the important parameter to be used in Equation (3.8) (Chapter 3) and it changes with time (i.e. heteroskedastic). When demand series is heteroskedastic in nature, it is essential to predict the changing variance of demand for the estimation of order. Since ARIMA model is homoscedastic in nature, the changing variance cannot be estimated. This problem can be overcome through the GARCH model. Therefore, ARIMA process is incorporated with the GARCH process for improving the accuracy of the forecasting model. Initially, the past demand data are collected to identify the ARIMA and GARCH model following different statistical procedure as described in section 6.2.1.1 and section 6.2.1.2. From the identified GARCH model, the variations in demand are predicted and mean demands are predicted through ARIMA. Further, the predicted demand variation and the mean demand used to estimate the safety stock and the order quantity. The schematic block diagram of the proposed model is shown in Figure 6.7. The model denoted as ARIMA-GARCH process.

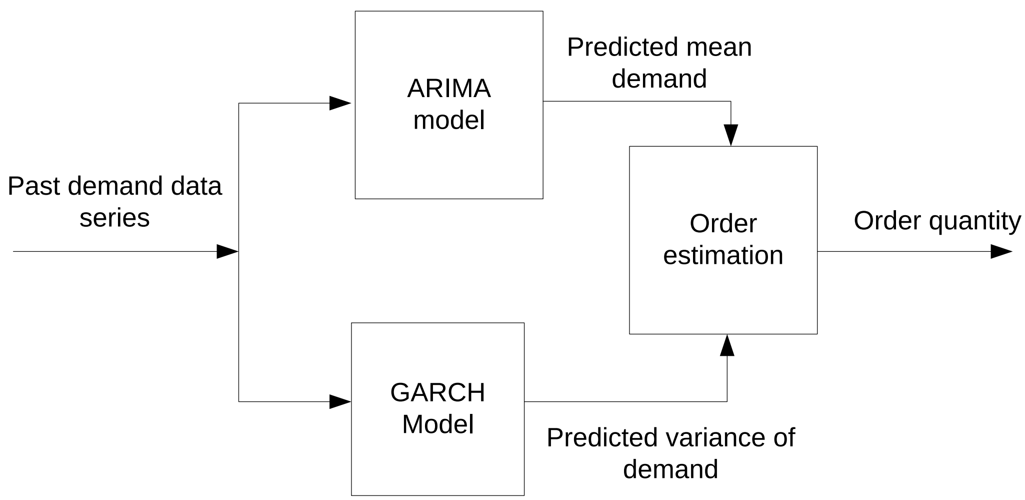

Figure 6.7 Schematic block diagram of ARIMA-GARCH model

6.3.2 Forecasting models to deal with non-stationary demand series

ARIMA model assumes that demand series is linear and stationary in nature. Therefore, the non-stationary demand series is first transformed into the stationary form using ARIMA model. In this process, the actual pattern of the demand series gets distorted. This limitation can be addressed through use of AI techniques for forecasting. The forecasting accuracy of the AI models can be improved if the pattern of the data series is identified. In section 6.2.3, it has been highlighted that wavelet analysis has the capability to extract the data pattern based on time. Therefore, in this study forecasting models are proposed through integrating the discrete wavelet transformation (DWT) analysis and AI approaches (ANN, ANFIS, LSSVM and MGGP) to deal with non-linear and non-stationary demand series. Initially, the demand data series are analysed through DWT analysis to capture the pattern. The DWT analysis decomposes the original demand series into different subseries called approximation (A_n) and detailed data subseries $(D_1, D_2, ..., D_n)$. These subseries provide information about variation in demand series according to time. The whole data in the subseries are further divided into training and testing data set. The training set is applied to AI model to train the model. After successful training of the model, the testing set is applied to make prediction. Figure 6.8 describes the schematic block diagram of the proposed model and its operations. In this study, DWT is integrated with four AI models such as ANN, ANFIS, LSSVM and MGGP. The proposed four hybrid models are named as DWT-ANN, DWT-ANFIS, DWT-LSSVM and DWT-MGGP. These proposed models are further validated through an example data set. The next section discusses the procedure for validation of proposed models.

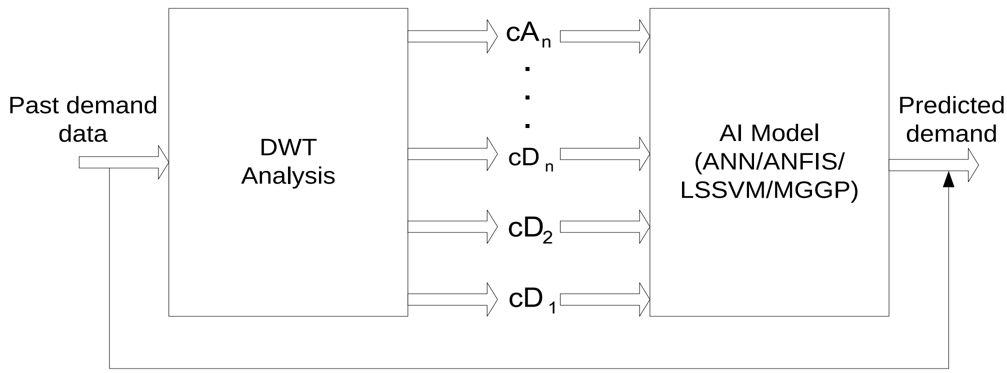

Figure 6.8 Schematic block diagram of DWT-AI model

6.4 Model Validation

To validate the proposed models, the performance in terms of forecasting error is tested in respect to the ARIMA model. An example data set (monthly sales data for printing and writing paper between the year 1963 and 1972) is taken from open literature (Makridakis, 1998). The ARIMA model is identified for the example data set following different steps as described in section 6.2.1.1. Initially, the time series plot for this data series is made as shown in Figure 6.9. From the figure, it can be observed that the sales data series is non-stationary in nature since the data points are not horizontally scattered around a constant mean. To check the existence of stationary in the data series, the Augmented Dickey-Fuller (ADF) t-tests is conducted at significance level of 0.05. ADF test for the example data set results in H=0 and p-Value = 0.2363 (fail to reject the null hypothesis) signifying non-stationary nature of data set. Further, statistical analysis is carried to identify the nature of the data series. The autocorrelation function (ACF) and partial autocorrelation function (PACF) plot is shown in Figure 6.10 and Figure 6.11 respectively.

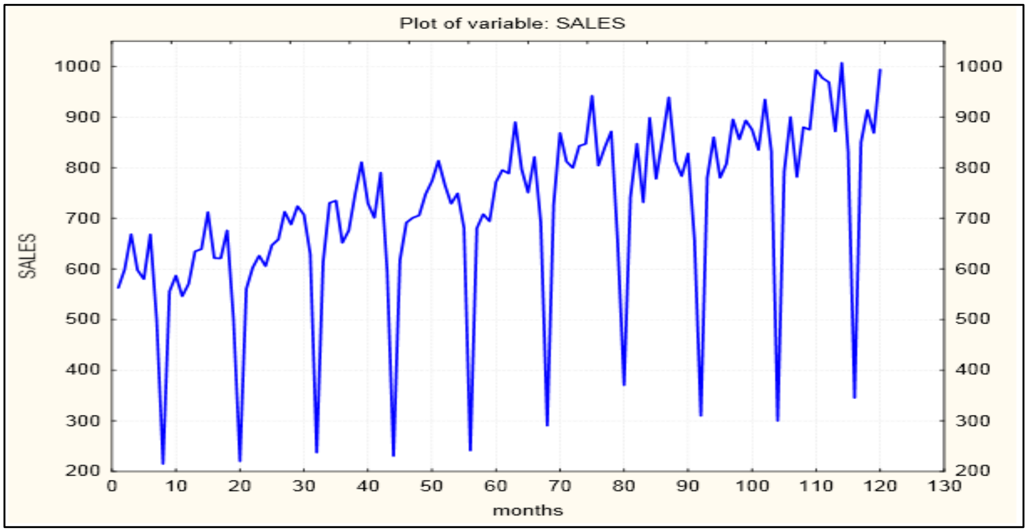

Figure 6.9 Time series plot for example dataset

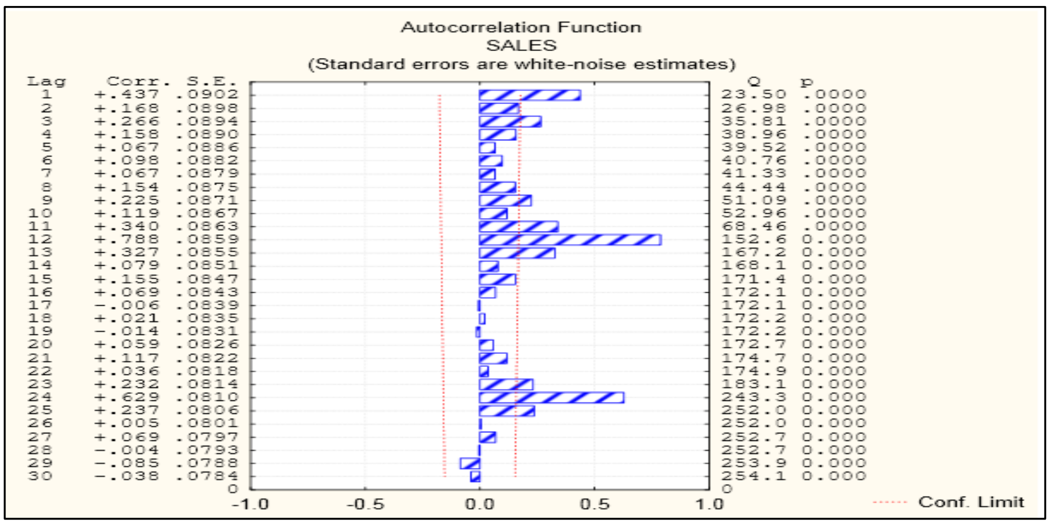

Figure 6.10 ACF plot for example dataset

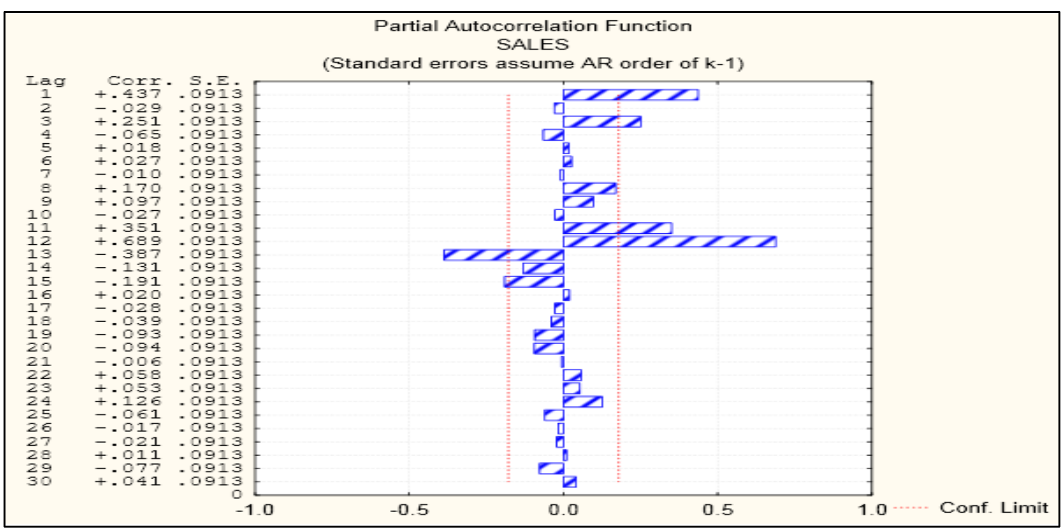

Figure 6.11 PACF plot of for example dataset

From the figures, it is found that values are not dropped to zero indicating non-stationary nature of the data series. From ACF plot analysis (Figure 6.10), it is found that nearly all autocorrelations are positive and significant spikes are observed at lag-12, lag-24 and lag-36 indicating presence of seasonality in the series. Therefore, the data series is initially differenced with lag-12 (i.e. seasonal difference D=1) then differenced by lag-1 to convert the data series into stationary form as shown in Figure 6.12. From the ADF test, the resultant series is identified as stationary because H=1 and p-Value = 0.001 at significance level of 0.05. The ACF and PACF plots for resultant data are shown in Figure 6.13 and Figure 6.14 respectively.

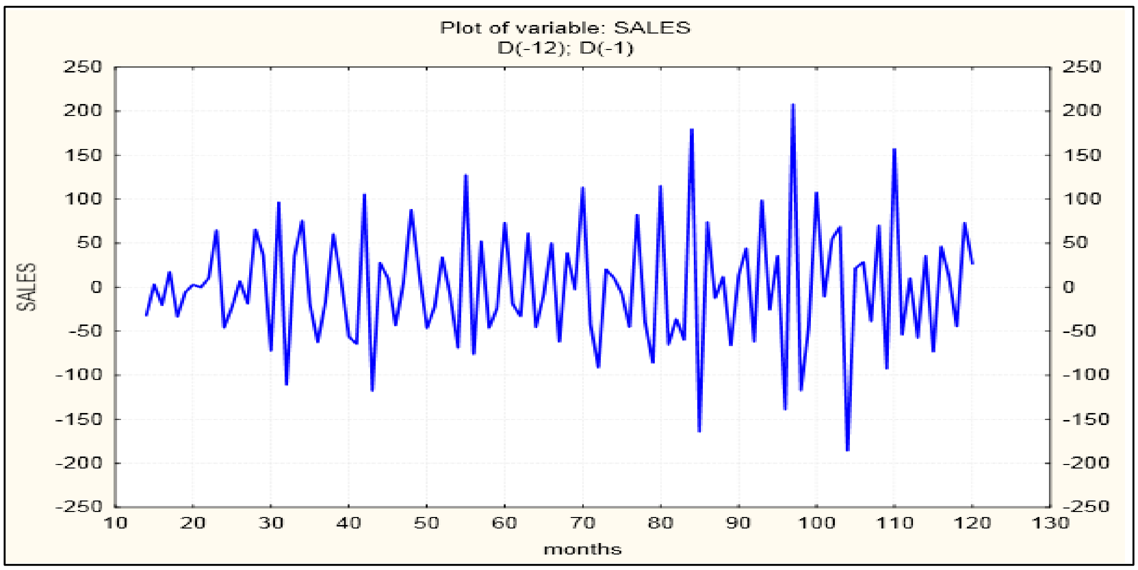

Figure 6.12 Time series plot of the transformed data series for example dataset

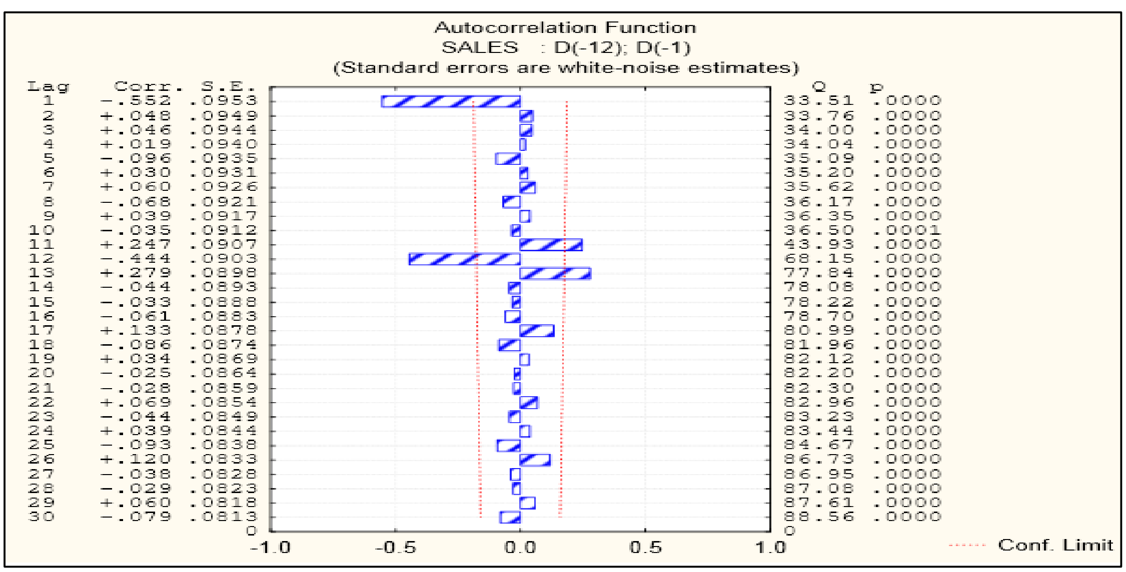

Figure 6.13 ACF plot of the transformed data series for example dataset

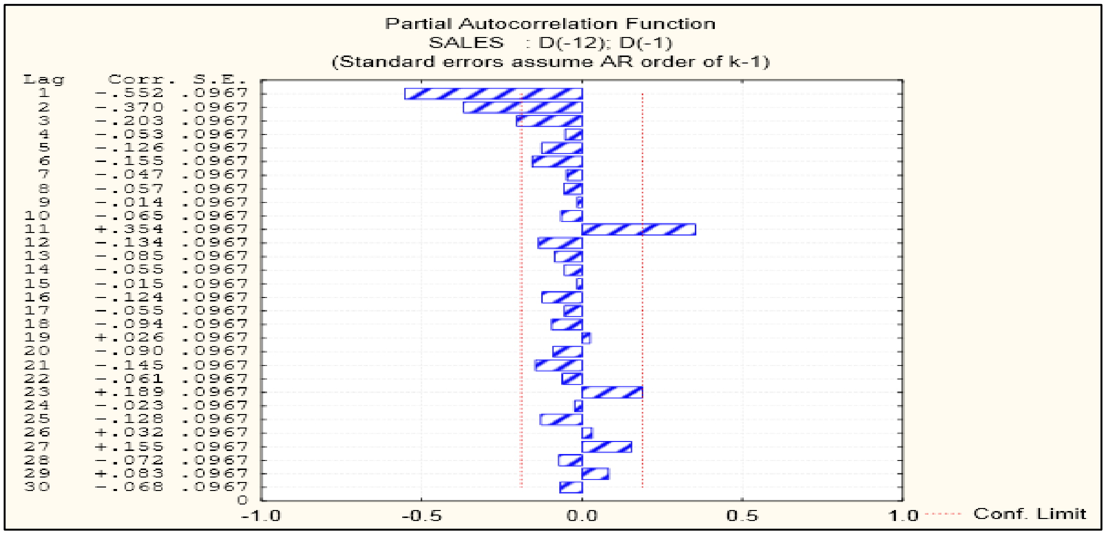

Figure 6.14 PACF plot of the transformed data series for example dataset

By examining the ACF and PACF plots, it is found that good number of autocorrelation and partial autocorrelation values are significant. Therefore, it is difficult to define the seasonal or non-seasonal AR and MA coefficients. Hence, the identified model can be represented as ARIMA (p, 1, q) (P, 1, Q) $_{12}$ where p and q represents the non-seasonal AR and MA coefficients and P and Q are the seasonal AR and MA coefficients. Alternately, varying these coefficient values, fourteen different models are developed as listed in Table 6.1. Using these models, 24-months ahead demands are predicted and forecast errors are estimated in terms of mean square error (MSE) using Equation (6.43) and described in Table 6.1.

$$MSE = \frac{(\text{Actual demand - Forecasted demand})^2}{\text{Number of forecasted period}} \tag{6.43}$$

In order to extract the data pattern, the original sales data series is analysed using DWT analysis. By applying db4 wavelet family, it is decomposed into five levels and six different sub-series are obtained in the form of an approximation (A_5) and five detail data subseries $(D_1, D_2, \ldots, D_5)$ as shown in Figure 6.15. The whole data in this subseries is divided into two sets as training set i.e. 80% of whole data (96 months) and rest 20% (24 months) as testing date set. Initially, the training set is used as input to train the AI models (ANN, ANFIS, LSSVM and MGGP). After successful training of the models, the obtained optimal model parameter setting is shown in Table 6.1. The automatically generated predictive model from the GPTIPS toolbox after successful training of the MGGP model is represented in Equation (6.44) where xtest is the array for testing data set.

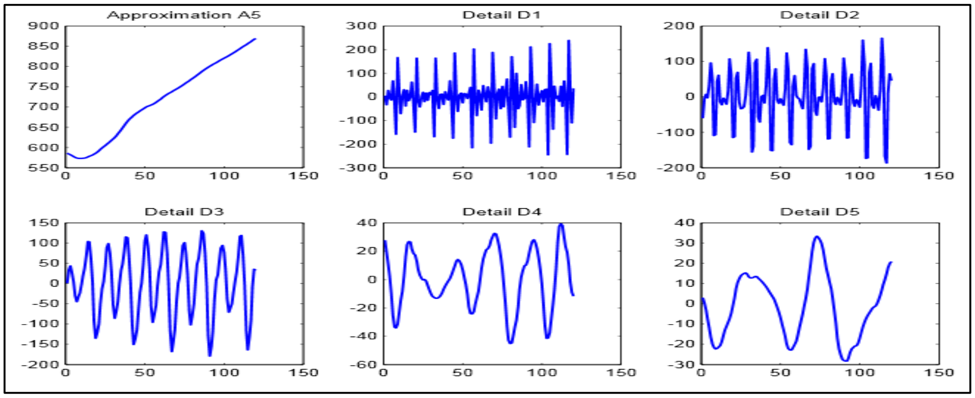

Figure 6.15 Decomposed data series for example dataset

$$ypred = xtest(:,1) + xtest(:,2) + xtest(:,3) + xtest(:,4) + xtest(:,5) + xtest(:,6) + 0.001775 \quad (6.44)$$

Next, the testing data set is fed to the AI models and 24-months ahead demands are predicted. Using the predicted demand values from the AI models, the forecast error in terms of MSE values are estimated using Equation (6.43) (Table 6.1). From Table 6.1, it can be observed that the MSE values of the proposed models (DWT-ANN, DWT-ANFIS, DWT-LSSVM and DWT-MGGP) are less as compared to the identified time series ARIMA models in all cases. This analysis concludes that the accuracy of the proposed model is reasonably good compared to the ARIMA model. The performance of the proposed models is tested with demand data from three case study examples as described in the next section.

Table 6.1 Performance of ARIMA and DWT-AI model for example dataset

MODELS	MSE	MODELS	MSE
ARIMA$(0,1,1)(0,1,1)_{12}$	5248.20	ARIMA$(0,1,1)(1,1,0)_{12}$	9587.80
ARIMA$(1,1,1)(0,1,1)_{12}$	5477.94	ARIMA$(1,0,1)(0,1,2)_{12}$	5792.23
ARIMA$(0,1,2)(0,1,1)_{12}$	5490.43	ARIMA$(1,1,1)(1,1,0)_{12}$	9979.24
ARIMA$(0,1,1)(0,1,2)_{12}$	5262.05	ARIMA$(1,1,0)(0,1,1)_{12}$	7963.26
ARIMA$(0,1,1)(1,1,1)_{12}$	5272.20	ARIMA$(0,1,1)(0,1,0)_{12}$	13884.48
ARIMA$(0,1,3)(0,1,1)_{12}$	5416.39	ARIMA$(1,1,0)(1,1,0)_{12}$	15529.24
ARIMA$(1,1,1)(1,1,1)_{12}$	5505.86	ARIMA$(1,1,0)(0,1,1)_{12}$	25091.38
DWT db4, 5 layer decomposition	ANN η =0.02, α = 0.1, epochs = 50000 Goal=10^{-3}, l=6, m=6, n=1		620.54
	ANFIS number of MF each input: 2 2 3 3 3 2, MF type: trimf; Error Tolerance=0.1; Epochs=15; output MF type: linear		4950.48
	LSSVM γ =576676.98, $\sigma^2 = 6373154.09$		7.27
	MGGP G_{max}=4, D_{max}=5, population size=100 Number of generation=100, probability of crossover =0.85 mutation events=0.1 and direct reproduction=0.05		0.0000031

trimf: Triangular-shaped membership function; MF: membership function

6.5 Case studies

To analyse the performance of the proposed model like ARIMA-GARCH and the intelligence models (DWT-ANN, DWT-ANFIS, DWT-LSSVM and DWT-GP) against the ARIMA model, three different case study examples have been considered in this section.

6.5.1 Case 1: PQR Pvt. Ltd.

PQR Pvt. Ltd. is located in the Eastern part of India dealing with automotive parts and supplies to different automobile companies in India. The annual turnover of the company is 871000 USD. Fan shroud is one of the major products for this company. For the study, 96-months (April 2005-March 2013) of demand data for fan shroud are collected from the firm. The steps described in section 6.2.1.1 are followed to identify the ARIMA model. The time series plot of this data set is presented in Figure 6.16. From the ADF test, it is found that demand series is non-stationary in nature as p-value = 0.08 is obtained at significance level of 0.05. Again ACF and PACF plots are identified as shown in Figure 6.17 and Figure 6.18 respectively.

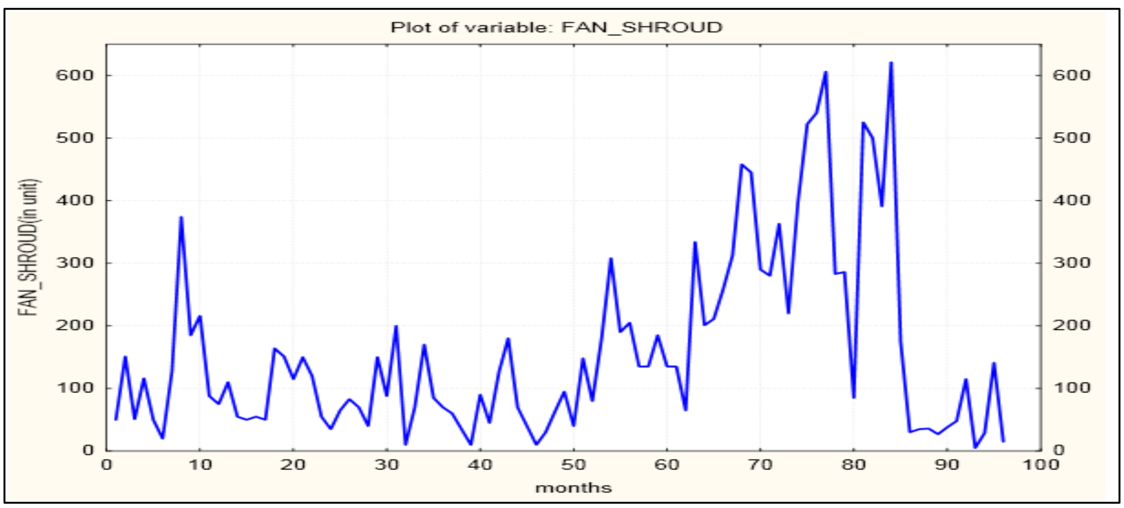

Figure 6.16 Time series plot of the fan shroud demand data

From the analysis of ACF plot (Figure 6.17) and PACF plots (Figure 6.18), it is observed that demand data does not contain seasonality. In order to convert the demand series into stationary, it is differenced by lag-1 (hence d=1) and plotted in Figure 6.19. The resultant demand series is tested using ADF test to examine the stationary nature of the demand series and found that it exhibits stationary in nature (H=1 and p-Value= 0.001). To identify the ARIMA model, ACF and PACF plot are plotted as shown in Figure 6.20 and Figure 6.21 respectively are used. From the ACF plot (Figure 6.20), significant spike are observed at lag-1 and lag-4. Similarly, significant spikes are observed at lag-1 and lag-4 in PACF plot (Figure 6.21). It results in the parameter values of p=2, q=2 and d=1 (differenced with lag-1) and the model is identified as ARIMA (2, 1, 2). Using these parameter settings, 12-months ahead demands are predicted.

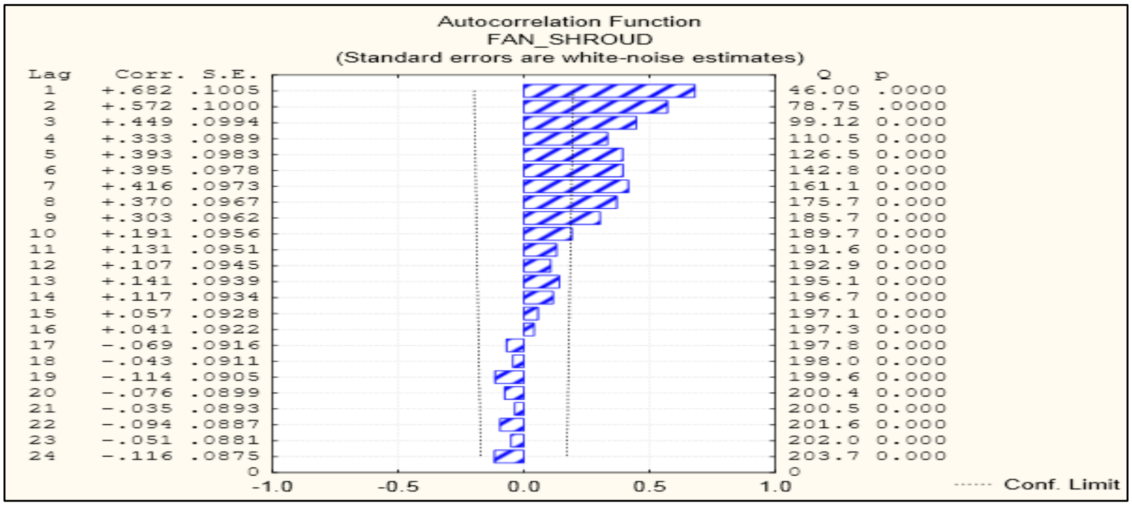

Figure 6.17 ACF plot for the fan shroud demand data

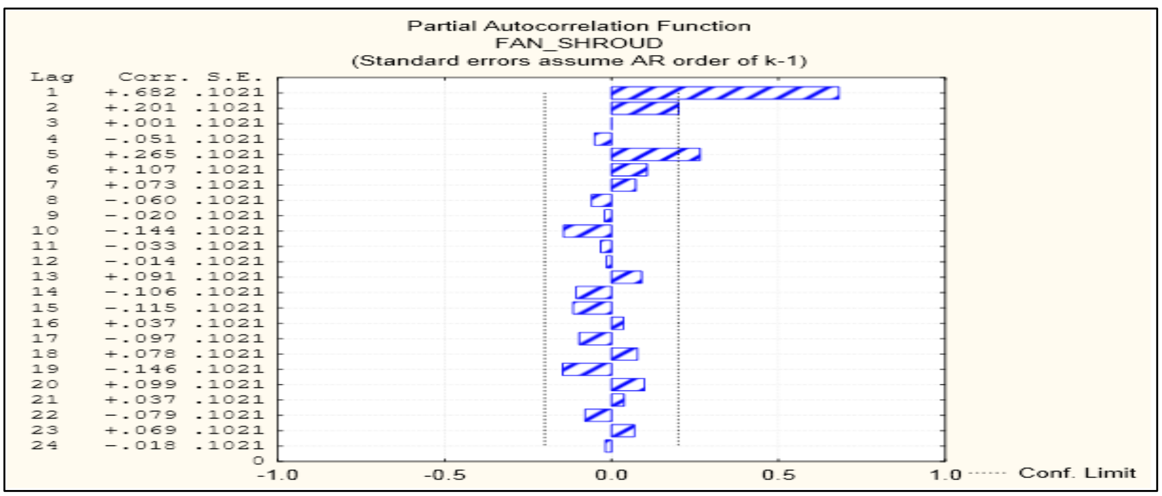

Figure 6.18 PACF plot for the fan shroud demand data

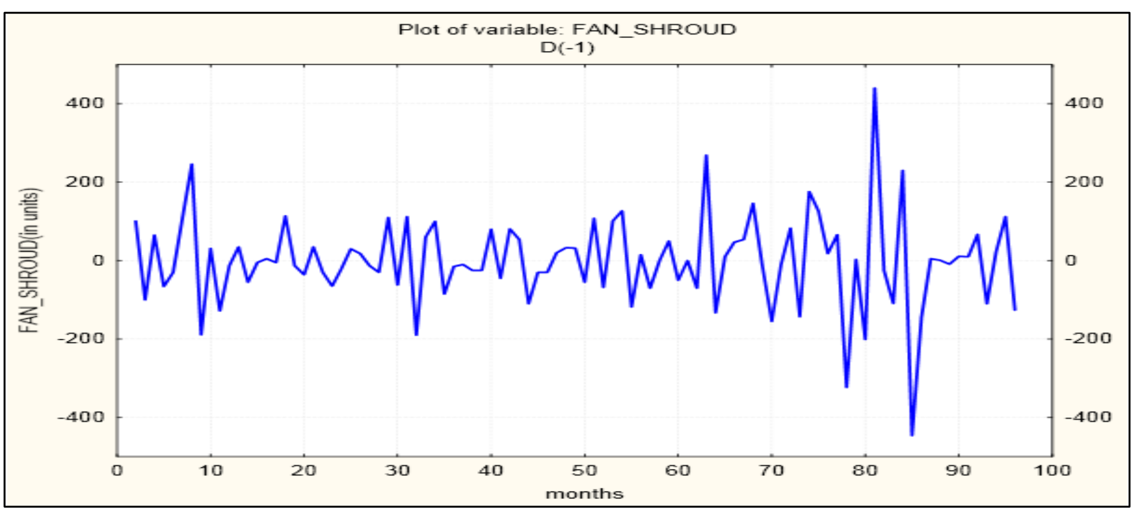

Figure 6.19 Time series plot for the differenced fan shroud demand data

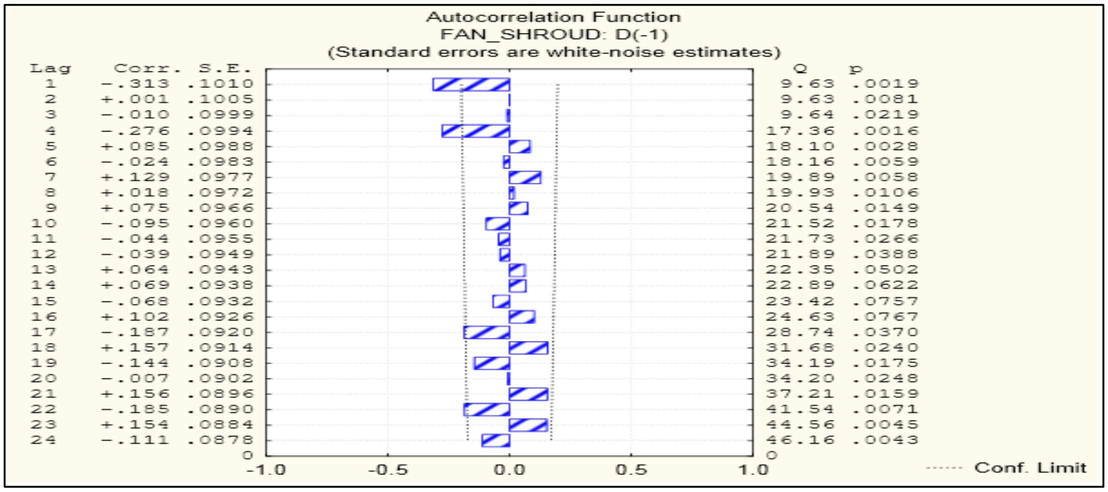

Figure 6.20 ACF plot of the differenced fan shroud demand data

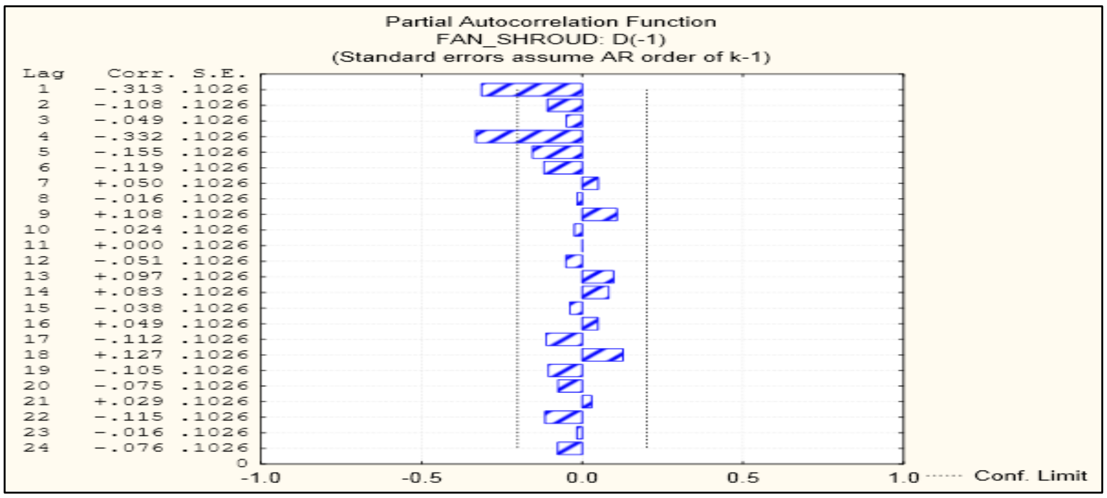

Figure 6.21 PACF plot of the differenced fan shroud demand data

Next to identify the GARCH model to predict the time varying demand variance, different steps for developing GARCH model as described in section 6.2.1.2 are followed. To define GARCH model for a data series, there must be correlation within series and influenced by ARCH effect. Initially, the differenced demand series (return series) as shown in Figure 6.19 is tested for existence of heteroskedasticity in the data series. This can be verified by conducting Ljung-Box-Pierce Q-test and ARCH test on the transformed data series termed as return series. According to Ljung-Box-Pierce Q-test, H=0 implies that no significant correlation exist whereas H=1 indicates the existence of correlation. Similarly, in case of Engle ARCH test, H=1 means presence of ARCH effect and H=0 means there is no ARCH effect. From Table 6.2 and Table 6.3, it can be observed that there is significant correlation exist in raw returns and squared returns of the demand data of fan shroud when tested for up to 10 and 20 lags of the ACF at significance level of 0.05. The ARCH test performed at lag 10 and 20 as summarized in

Table 6.4. In Table 6.4, H=0 at p-Value > 0.05 signifies that there is no ARCH effect present in the demand series. Hence, there is no GARCH model is possible for the fan shroud demand.

Table 6.2 Summary of Ljung-Box-Pierce Q-Test for return series data of fan shroud

Lag	H	p-Value	Stat	Critical Value
10	1	0.0178	21.5178	18.307
20	1	0.0248	34.2014	31.4104

Table 6.3 Summary of Ljung-Box-Pierce Q-Test for squared return of fan shroud demand

Lag	H	p-Value	Stat	Critical Value
10	1	0.0178	21.5178	18.307
20	1	0.0248	34.2014	31.4104

Table 6.4 Summary of Engle ARCH test for return series data of fan shroud demand

Lag	H	p-Value	Stat	Critical Value
10	0	0.0802	16.7449	18.307
20	0	0.0987	28.4693	31.4104

To make prediction from the AI models, DWT analysis is carried out for the original fan shroud demand series applying 4-level decomposition with db4 wavelet family. From the analysis, an approximation (A4) and four detailed subseries (D_1, D_2, D_3 and D_4) are obtained as shown in Figure 6.22. The whole data series contained in this subseries are divided into two parts 88% (84-months) as training and rest 12% (12-months) as testing data set. The AI models (ANN, ANFIS, LSSVM and MGGP) are trained with the training data set.

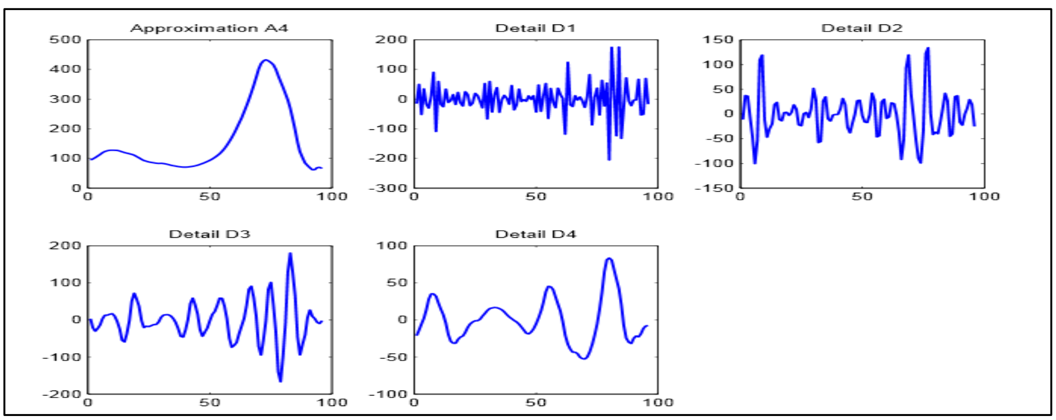

Figure 6.22 Decomposed data series of fan shroud demand

The predictive model obtained after successful training of MGGP is presented in Equation (6.45). After successful training of the models, the testing data set is applied to the AI models and 12-months ahead demand data are predicted.

$$
\begin{aligned}
ypred &= 1.0\times xtest(:,1) + 1.0\times xtest(:,2) + 1.0\times xtest(:,3) + 1.0\times xtest(:,4) + \\
&1.0\times xtest(:,5) - 6.818e-12\times(xtest(:,2) - xtest(:,3) + 9.673)\times(xtest(:,3) - \\
&2\times xtest(:,4) - xtest(:,5))\times(xtest(:,3) + xtest(:,4))) + xtest(:,1))\times xtest(:,2)) \\
&- 1.42e-9\times(xtest(:,1) - 9.673)\times(xtest(:,1) + xtest(:,2) + xtest(:,3) + xtest(:,4) \\
&- 9.181) - 0.0001614
\end{aligned}
\tag{6.45}
$$

6.5.2 Case 2: XYZ Pvt. Ltd.

XYZ Pvt. Ltd. is a major cement manufacturing company located in the Eastern part of India having an annual turnover is 310 million dollars. To compare the performance of ARIMA-GARCH process against ARIMA process, six years (April 2006-March 2013) demand data for a specific zone is collected from the company in metric ton (MT). Different steps as described in section 6.2.1.1 are followed to develop ARIMA model. The time series plot of the collected cement demand data is shown in Figure 6.23.

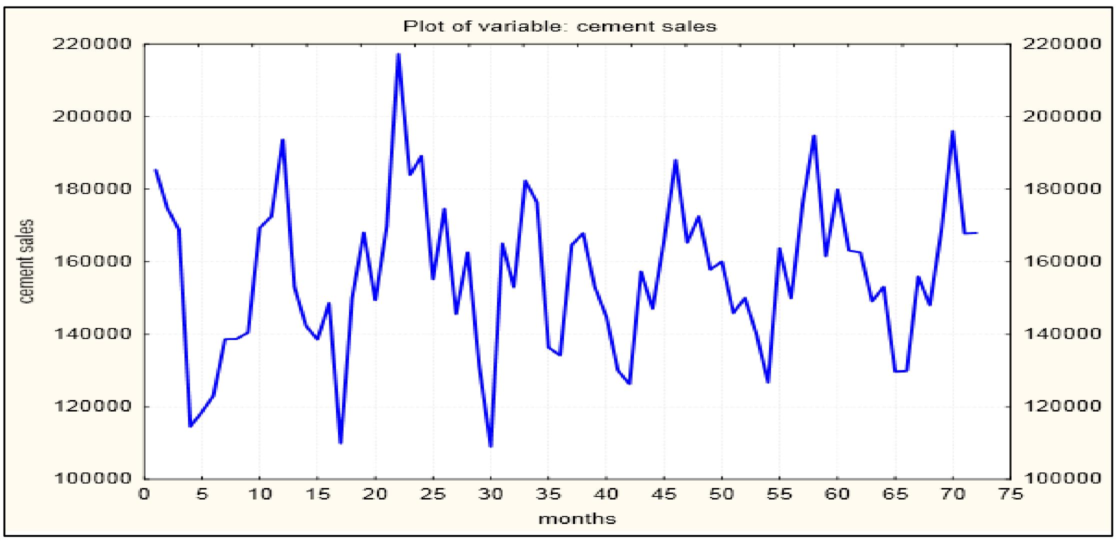

Figure 6.23 Time series plot for cement demand data

To identify the pattern of demand, the ADF test is conducted and it is found that demand series exhibits non-stationary pattern (H=0 and p-Value=0.3906). The ACF and PACF plots are studied for 18-lag period (Figure 6.24 and Figure 6.25 respectively). From the ACF plot (Figure 6.24), there is significant spike at lag-12 is observed. This signifies that demand series is seasonally affected. Therefore, it is seasonally differenced with lag-12 (hence D=1) and the resultant time series is again non-seasonally differenced with lag-1 (hence d=1). The resultant time series plot is shown in Figure 6.26.

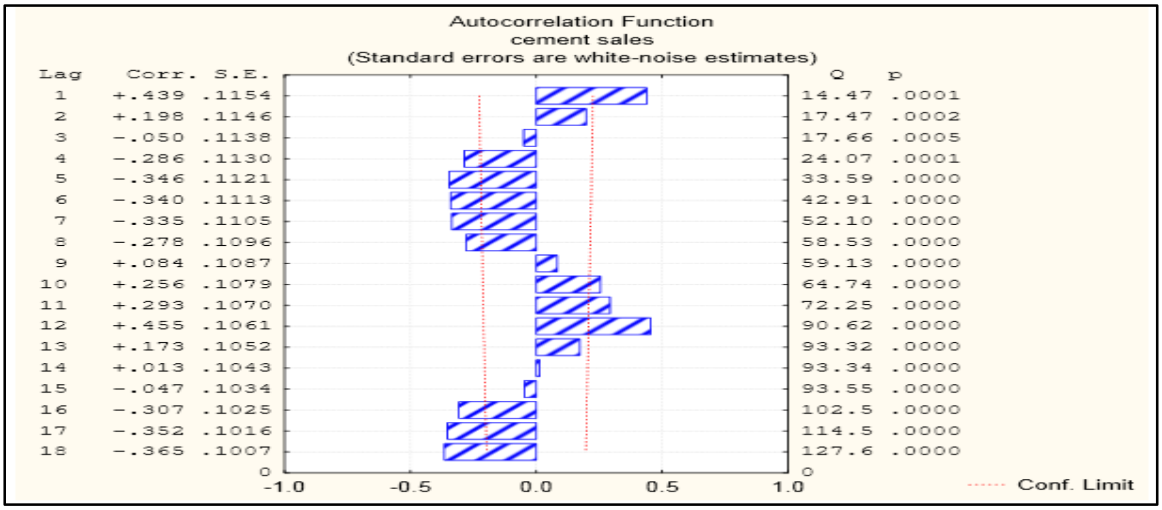

Figure 6.24 ACF plot of cement demand data

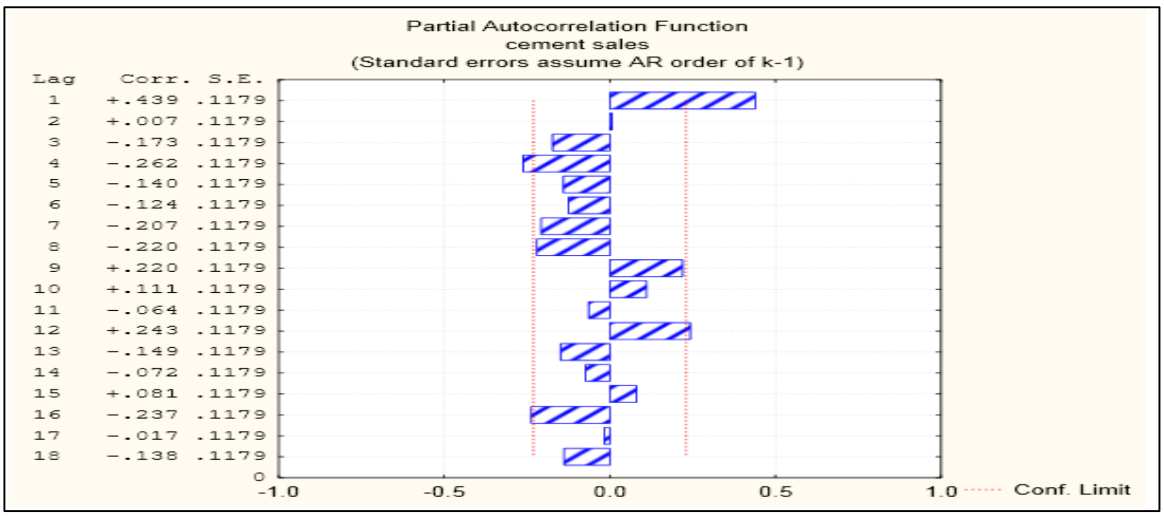

Figure 6.25 PACF plot of cement demand data

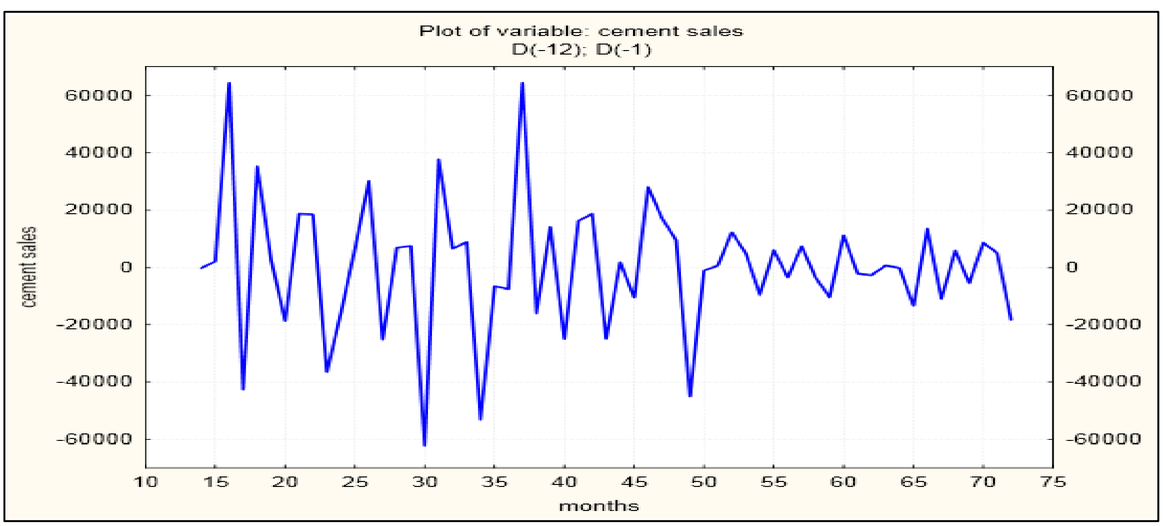

Figure 6.26 Seasonal and non-seasonal differenced cement demand data

The resultant transformed data series is tested with ADF test and found stationary in nature (H=1 and p-Value=0.001). To identify the ARIMA model, the ACF and PACF plots of the resultant series are plotted as shown in Figure 6.27 and Figure 6.28 respectively. From the ACF plot (Figure 6.27), it can be identified that there is significant spikes at lag-1 and lag-12 representing q=1 and Q=1. Similarly, from the PACF plot (Figure 6.28), most significant spikes can be observed at lag-1 and lag-3 (hence p=2). Under this identified parameters setting, the model selected is ARIMA (2, 1, 1) $(0, 1, 1)_{12}$. Using this model, 12-months ahead data are predicted.

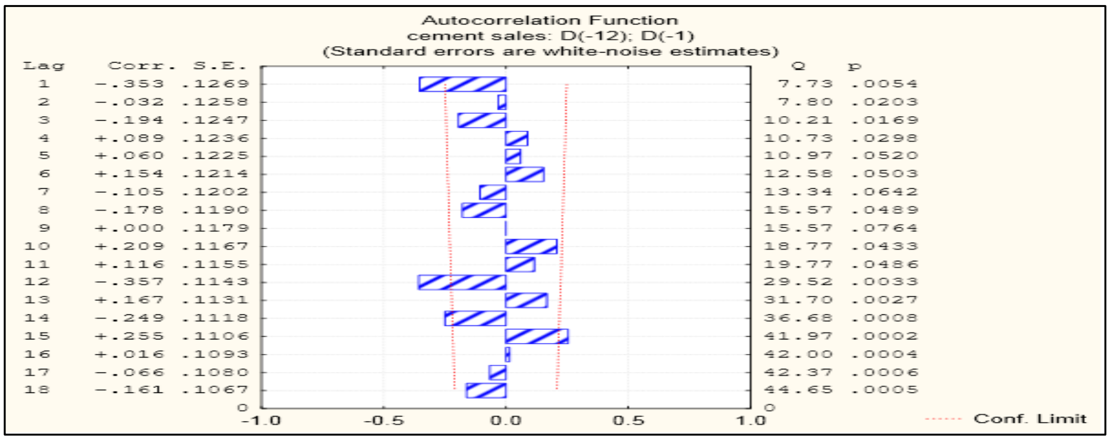

Figure 6.27 ACF plot for the transformed cement demand series

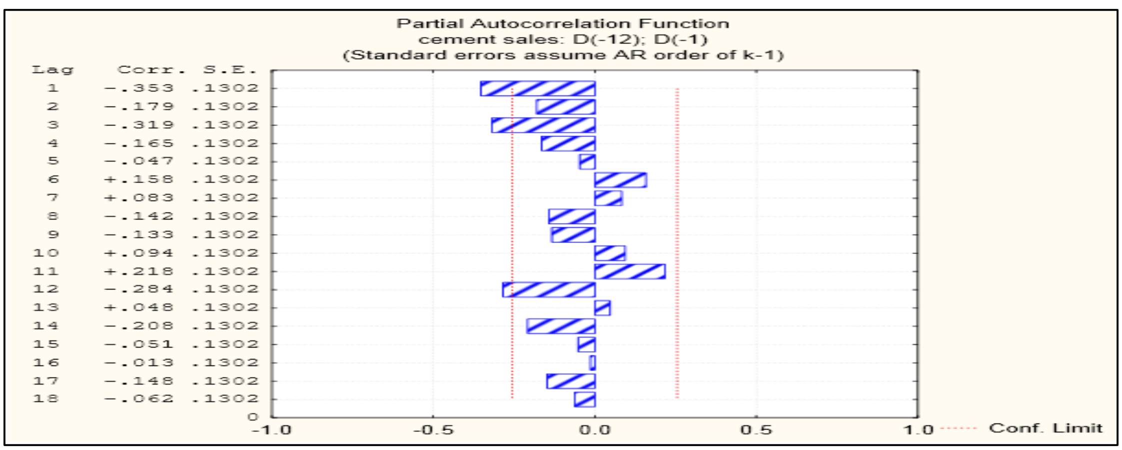

Figure 6.28 PACF plot transformed cement demand series

Similar to Case 1, Ljung-Box-Pierce Q-test and ARCH test are conducted on the transformed data series termed as return series to identify the GARCH model. The summary of the test is described in Tables 6.5-6.7. From Table 6.5 and 6.6, it can be concluded that there is significant correlation in raw returns and squared returns when tested for up to 10, 15 and 20 lags of the ACF at significance level of 0.05. In Table 6.7, H=1 and p-Value < 0.05 at significance level of 0.05 at lag 10, 15 and 20 signifies presence of ARCH effect.

Table 6.5 Ljung-Box-Pierce Q-Test for return of cement demand data

Lag	H	p-Value	Stat	Critical Value
10	1	0.0178	21.5178	18.307
15	1	0.0456	23.4199	24.9958
20	1	0.0248	34.2014	31.4104

Table 6.6 Ljung-Box-Pierce Q-Test for squared return of cement demand data

Lag	H	p-Value	Stat	Critical Value
10	1	0.0006	31.132	18.307
15	1	0	67.3172	24.9958
20	1	0	71.5217	31.4104

Table 6.7 Engle ARCH test for return of cement demand data

Lag	H	p-Value	Stat	Critical Value
10	1	0.0093	23.411	18.307
15	1	0.0227	27.8242	24.9958
20	1	0.0397	32.3486	31.4104

In order to select the suitable model from competing models, the statistical Akaike information criterion (AIC) and the Bayesian information (BIC) tests are performed. Usually, the simple GARCH model captures most of the variability in most stabilized series. Small lags for p and q are common in applications. Typically, GARCH (1, 1), GARCH (1, 2) or GARCH (2, 1) models are suitable for modelling volatilities even over a long sample periods (Bollerslev et al., 1992). However, Table 6.8 includes GARCH (0, 1), GARCH (0, 2) and GARCH (2, 2) to check appropriate model for the time varying variance data. The idea is to have a parsimonious model that captures most data series as possible. Small value of AIC and BIC make the model favourable. The calculated AIC and BIC values for six different models are described in Table 6.8. From the Table 6.8, it can be found the AIC and BIC value of the GARCH (2, 1) model is comparatively less and suggested as suitable model to predict the variance of cement demand.

Table 6.8 Comparison of suggested GARCH models for cement demand

Model	AIC	BIC
GARCH(1,1)	1382.1	1391.2
GARCH(1,2)	1384.1	1395.5
GARCH(2,1)	1380.1	1391.1
GARCH(2,2)	1382.1	1395.7
GARCH(0,1)	1502.9	1509.7
GARCH(0,2)	1394.2	1403.3

To test the model fitting, statistical test has been performed for all the models shown in Table 6.8 to estimate different parameters. From the statistical analysis, it is found that

GARCH (2, 1) satisfies the necessary conditions of $\alpha_1 + \beta_1 < 1, \beta_1 > \alpha_1$, $\alpha_1 > 0$ and $\beta_1 > 0$ (Table 6.9). Hence, GARCH (2, 1) can be selected as an appropriate model for further analysis.

Table 6.9 Parameter estimates for GARCH (2, 1)

Parameters	Value	Standard Error	T-Statistic
C	-312.05	3489.5	-0.0894
K	1.45E+08	0.006448	2.25E+10
GARCH(1)	0	0.23521	0
GARCH(2)	0.47633	0.25504	1.8677
ARCH(1)	0.38916	0.2018	1.9285

According to Takle (2003), goodness of fit of the ARCH-GARCH model depends on the residuals and more specifically the standardized residuals. In GARCH model selection, if the residual follow normal distribution the model is said to be a good fitted model. The relationship between residual series (innovations) from the identified GARCH (2, 1) model and corresponding conditional standard deviations and return series is shown in Figure 6.29. From the figure, both the returns series and innovation series exhibit volatility clustering.

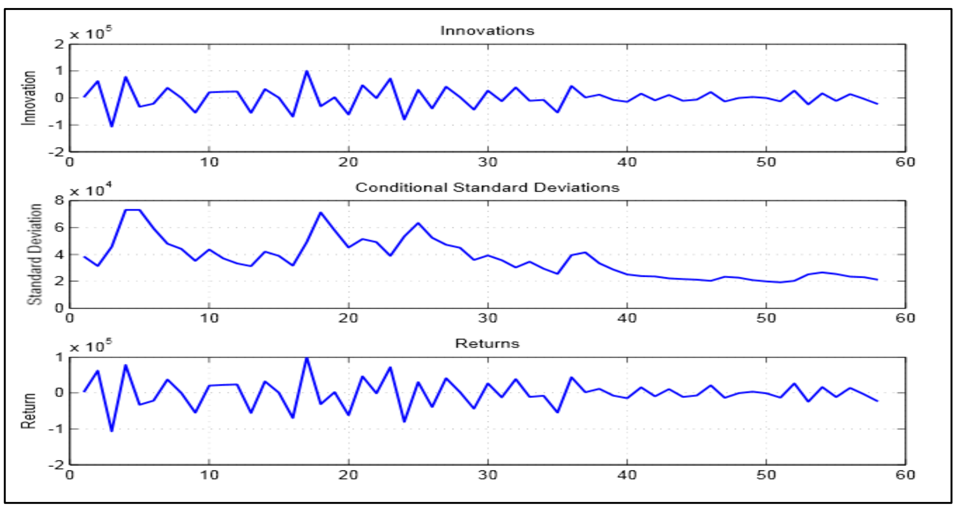

Figure 6.29 Plot of return, estimated volatility and innovation (residual)

The standardized innovation (i.e. innovation divided by its conditional standard deviation) is shown in Figure 6.30. This figure signifies standardized innovation series is stable with little clustering. The normal probability plot for residual from GARCH (2, 1) is shown in Figure 6.31 which signifies residuals follow normal distribution. For diagnostic check, ACF plot of the standardized residuals are shown in Figure 6.32 which indicates that there is no correlation left. Further, Ljung-Box-Pierce Q-test and ARCH test are performed on standardized innovation. The estimated parameters from the Ljung-Box-Pierce Q-test and ARCH test are shown in Table 6.10 and Table 6.11. From the tables, it can be observed that there is neither correlation nor ARCH effect is left in the residual series (H=0 p-Value >= 0.05). Hence, GARCH (2, 1) can be selected as best fitted model. Using this identified model, 12-months ahead changing cement demand variations are forecasted from data.

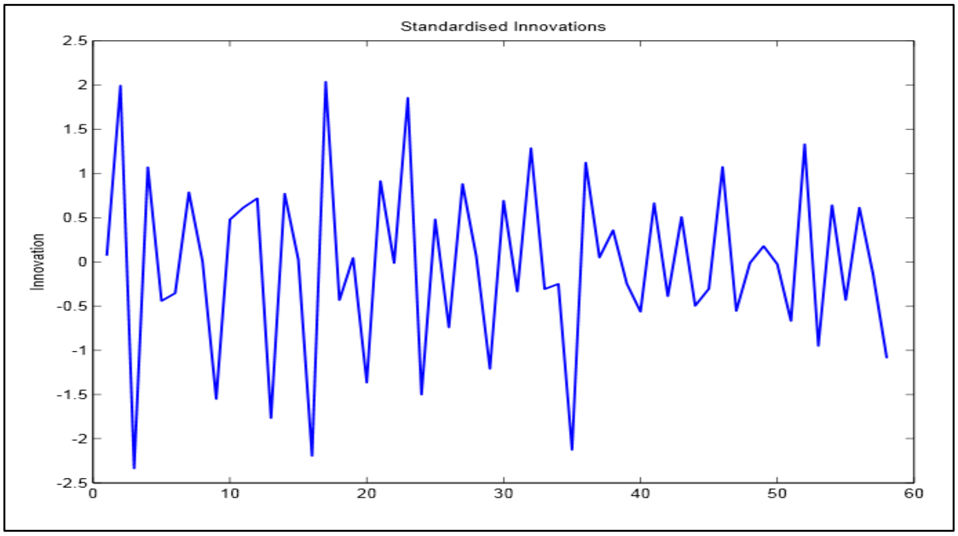

Figure 6.30 Time series plot of residuals from GARCH (2, 1)

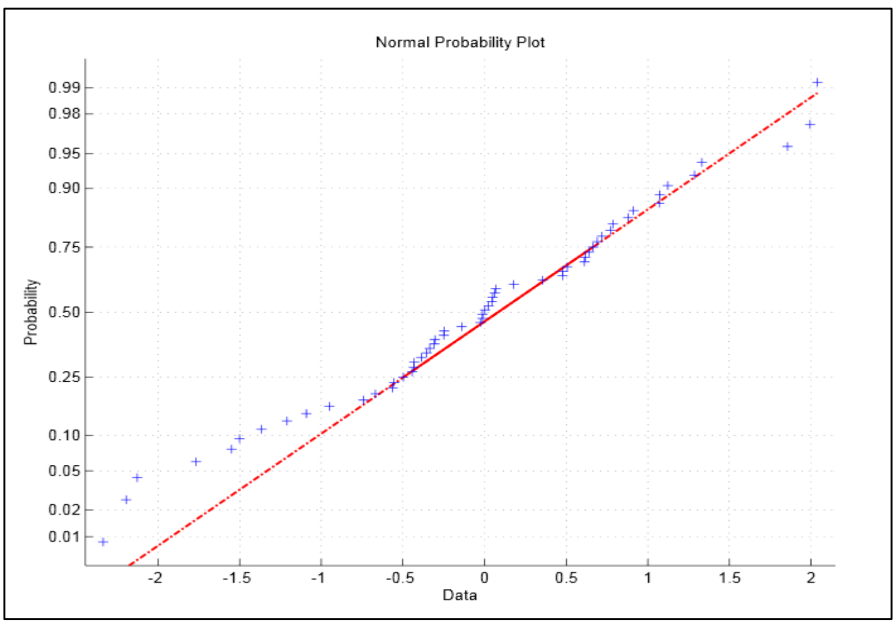

Figure 6.31 Normal probability plot of residuals from GARCH (2, 1)

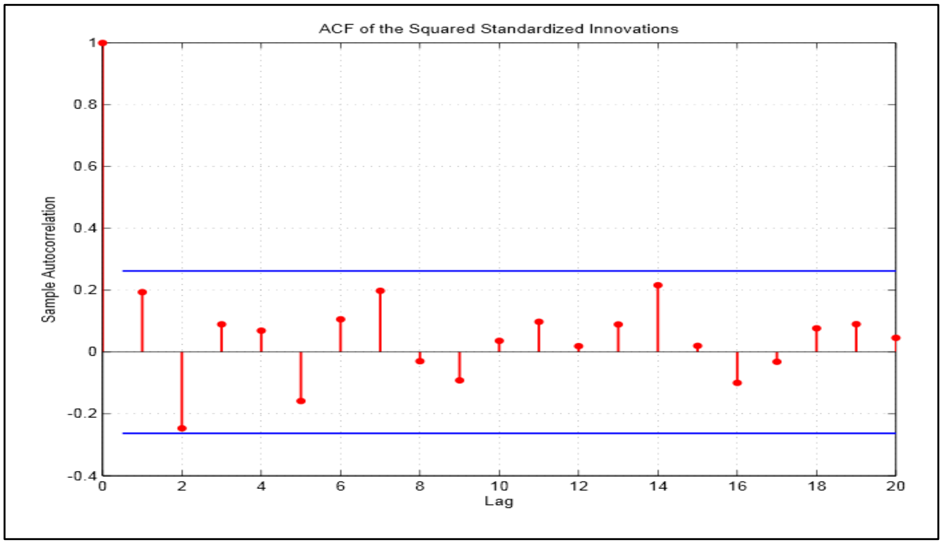

Figure 6.32 ACF of the squared standardized residuals

Table 6.10 Ljung-Box-Pierce Q-test on the standardized innovations

Lag	H	p-Value	Stat	Critical Value
10	0	0.2403	12.7111	18.307
15	0	0.2733	17.7998	24.9958
20	0	0.4491	20.1415	31.4104

Table 6.11 ARCH test on standardized innovations

Lag	H	p-Value	Stat	Critical Value
10	0	0.2225	13.0206	18.307
15	0	0.258	18.0898	24.9958
20	0	0.4497	20.1317	31.4104

To predict the demand from AI models, cement demand series is decomposed into 5-level applying the db4 wavelet family as shown in Figure 6.33. The subseries is divided into two parts, 83% (60-months) of whole data set as training and rest 17% (12-months) as testing set. The AI models are trained using the training set. The optimal mathematical model generated from training of MGGP model is expressed in Equation (6.46).

$$\begin{aligned} ypred &= xtest(:,1) + xtest(:,2) + 1.0 \times xtest(:,3) + xtest(:,4) \\ &+ 1.0 \times xtest(:,5) + 1.0 \times xtest(:,6) - 10.43 \end{aligned} \quad (6.46)$$

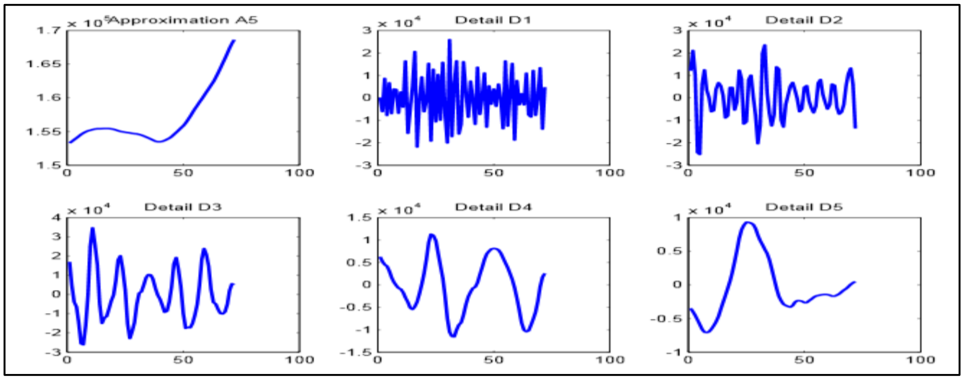

Figure 6.33 Decomposed data series of cement demand

6.5.3 Case 3: LMN Pvt. Ltd.

In this case, a steel processing industry is selected to analyse the performance of the proposed models. LMN Pvt. Ltd. is one of the well-known steel processing industries of India and its plants are situated in different parts of the country. The demand data in terms of quantity of steel (MT) required to manufacture different parts is collected during January 2009 to February 2013 (50-months) from a plant located in Southern part of India. The annual turnover of the company is 335 million dollars. The time series plot for the steel demand is shown in Figure 6.34. From the ADF test, it is identified that steel demand is non-stationary in nature (H=0 and p-value =0.3292). From ACF and PACF plot (Figure 6.35 and 6.36 respectively), it is identified that there is no seasonal effect. Therefore, the steel demand series double differenced at lag -1(hence d=2) to convert the data into stationary form (Figure 6.37).

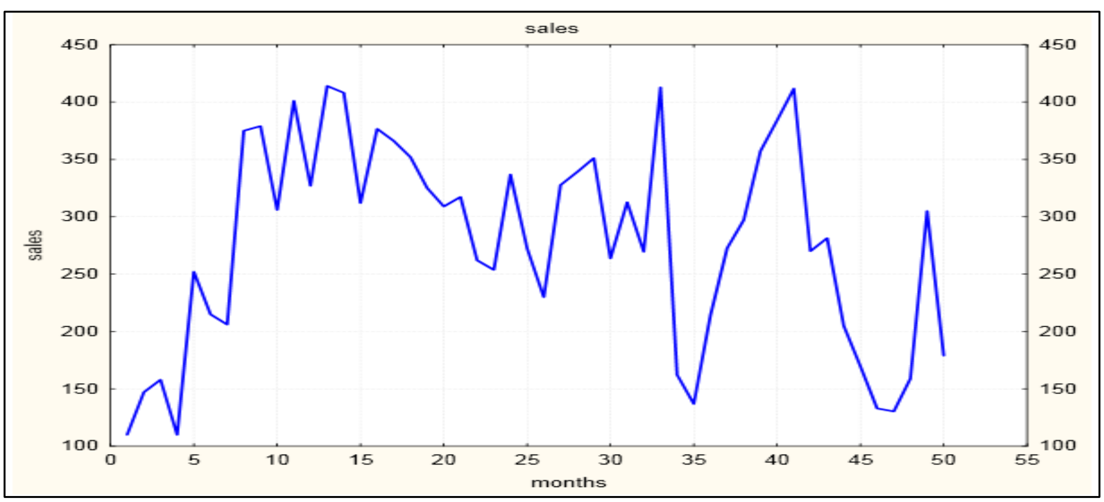

Figure 6.34 Time series plot for the steel demand

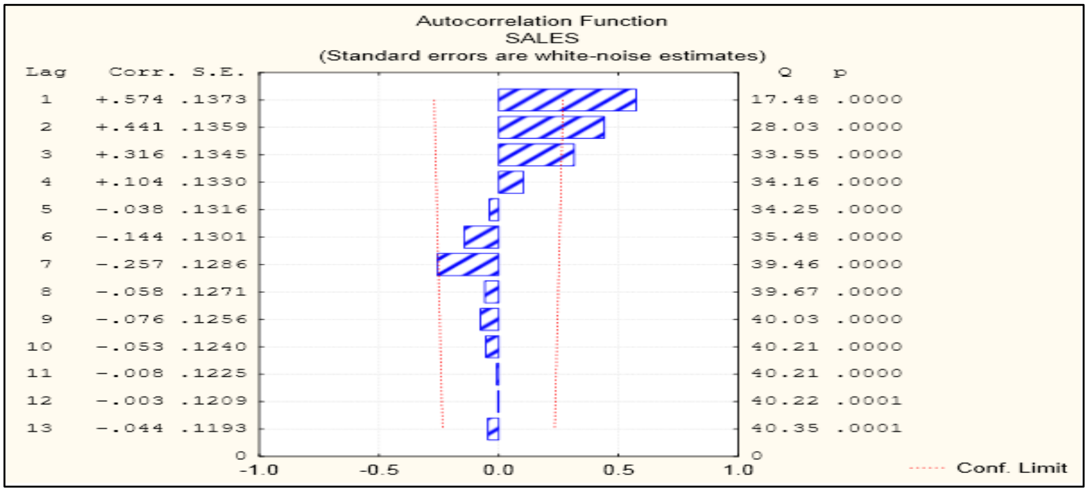

Figure 6.35 ACF plot of the steel demand data

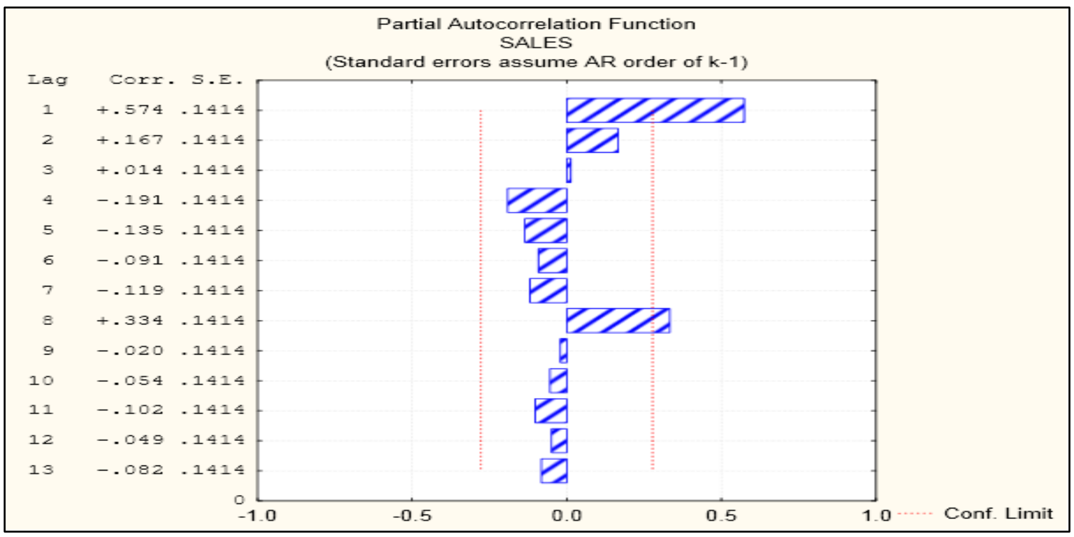

Figure 6.36 PACF plot of the steel demand data

From ADF test, it is found that resultant series is stationary in nature (H=1 p-value=0.0001). From the ACF and PACF plot (Figures 6.38 and 6.39 respectively) analysis, the model is identified as ARIMA (2, 2, 1). Using this selected model, 12-months ahead steel demands are forecasted.

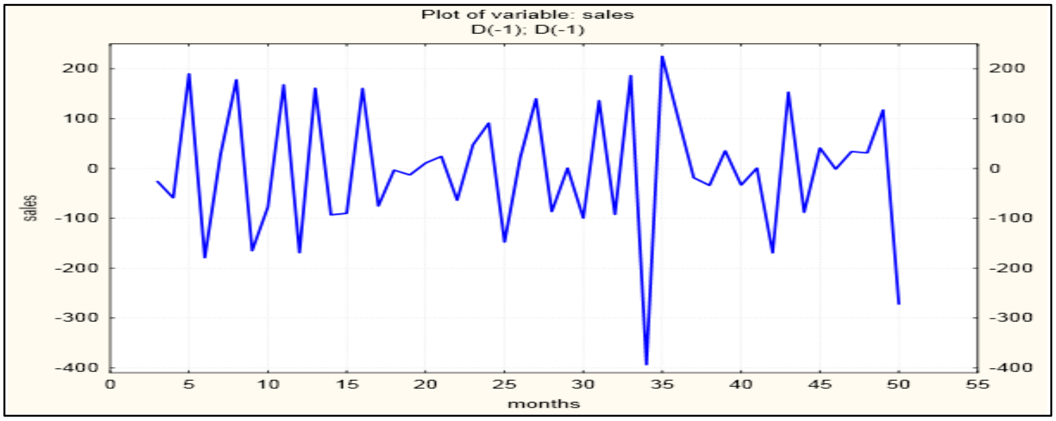

Figure 6.37 Non-seasonally double differenced time series plot of the steel demand

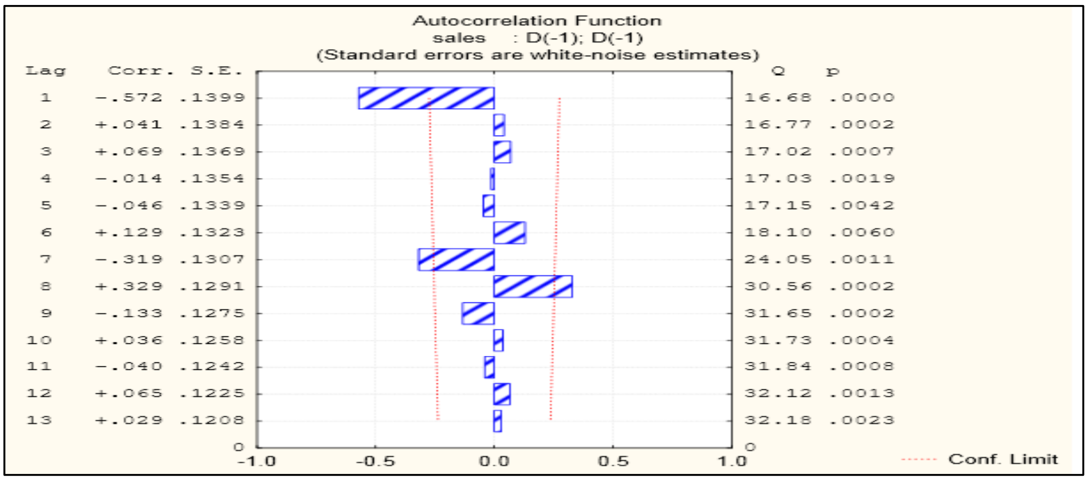

Figure 6.38 ACF plot for the double differenced steel demand data

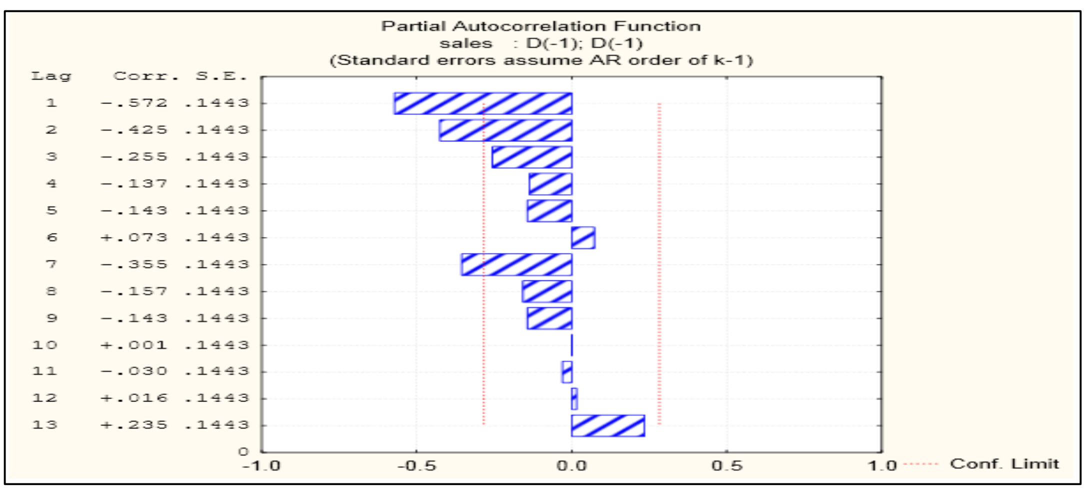

Figure 6.39 PACF plot for the double differenced steel demand data

Similar to Case 2, Ljung-Box-Pierce Q-test is performed on the obtained stationary steel demand series in order to identify the GARCH model (Tables 6.12 and 6.13). The tables signify that there is significant correlation exist in raw returns and squared returns when tested for up to 10, 15 and 20 lags of the ACF at significance level of 0.05 (as H=1 and p-Value < 0.05). Engle ARCH test performed at lag 10, 15 and 20 (Table 6.14) signifies that no ARCH effect (H=0 and p-Value > 0.05) exist in the steel demand series. Hence, there is no GARCH model is possible for this case.

Table 6.12 Ljung-Box-Pierce Q-Test for return of steel demand data

Lag	H	p-Value	Stat	Critical Value
10	1	0.0042	17.1463	11.0705
15	1	0.0004	31.7298	18.307
20	1	0.0031	34.2875	24.9958

Table 6. 13 Ljung-Box-Pierce Q-Test for squared return of steel demand data

Lag	H	p-Value	Stat	Critical Value
10	1	0.0042	17.1463	11.0705
15	1	0.0004	31.7298	18.307
20	1	0.0031	34.2875	24.9958

Table 6.14 Engle ARCH test for return of steel demand data

Lag	H	p-Value	Stat	Critical Value
10	0	0.1349	8.4131	11.0705
15	0	0.5017	9.3233	18.307
20	0	0.738	11.204	24.9958

To make prediction from steel demand series using AI model, the demand series is analysed through DWT and decomposed into 3-levels to obtain different subseries as shown in Figure 6.40. The whole data set contained in the subseries is divided into training set as 76% (38-months) of whole data set and rest 24% (12-months) as testing set. The AI models such as ANN, ANFIS, LSSVM and MGGP are trained using the training set. The forecasting model obtained after successful training of MGGP model is expressed in Equation (6.47). After successful training of the AI models, testing data set is presented to the models and 12-months ahead demand data are predicted.

$$\begin{aligned} \mathrm{ypred} &= \mathrm{xtest}(:,1) + \mathrm{xtest}(:,2) + \mathrm{xtest}(:,3) + \mathrm{xtest}(:,4) + 1.07\mathrm{e}-8 \times \\ &\mathrm{xtest}(:,2) \times \mathrm{xtest}(:,4) + 2.396\mathrm{e}-8 \times \mathrm{xtest}(:,3) \times \mathrm{xtest}(:,4) - 3.249\,\mathrm{e}-5 \end{aligned} \tag{6.47}$$

The model parameters settings for successful training of ANN, ANFIS, LSSVM and MGGP models for Case 1, Case 2 and Case 3 are summarized in Table 6.15.

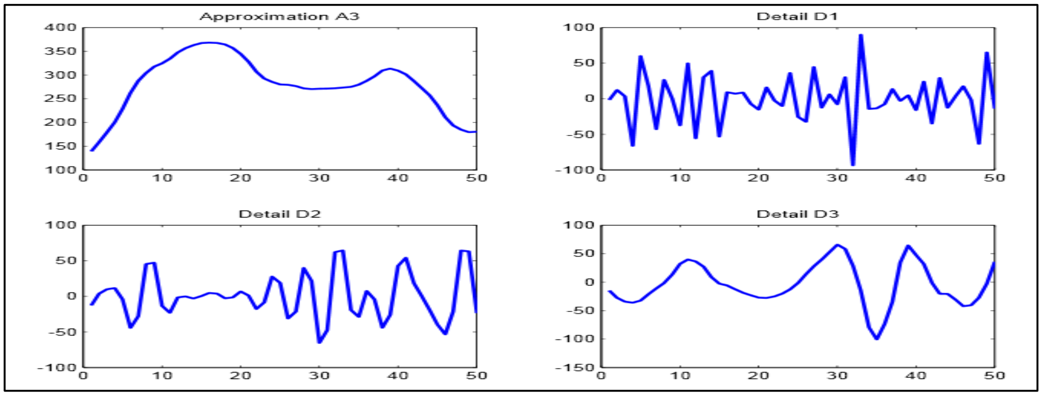

Figure 6.40 Decomposed data series of the steel demand data

Table 6.15 Model parameter settings for the ARIMA and proposed intelligent models

Models	Tuning parameters		Case-I PQR Pvt. Ltd.	Case -II XYZ Pvt. Ltd.	Case-III LMN Pvt. Ltd.
ARIMA			ARIMA(2,1,2)	ARIMA(2,1,1)(0,1,1)12	ARIMA(2,2,1)
DWT	Decomposition level		4	5	3
ANN	l		5	6	4
	m		6	8	6
	n		1	1	1
	α		0.1	0.1	0.1
	η		0.06	0.01	0.01
	epochs		500000	50000	500000
	goal		10-5	10-3	10-5
ANFIS	Number of MF for each input		2 2 2 2 2	2 2 2 2 2 2	2 2 2 2
	MF type		gauss2mf	trimf	gaussmf
	Error Tolerance		0.1	0.1	0.1
	epochs		6	8	6
	output MF type		linear	linear	linear
LSSVM	γ		3778865.67	6.97235e-13	1286899.32
	σ^2		265043.383	2630.2743	7145220.115
MGGP	Gmax		4	4	4
	Dmax		5	4	5
	Population size		100	100	100
	Number of generation		100	100	100
	Probability values	Crossover event	0.85	0.85	0.85
		Mutation event	0.1	0.1	0.1
		Direct reproduction	0.05	0.05	0.05

*gauss2mf: two side Gaussian membership function; trimf: Triangular-shaped membership function; gaussmf: Gaussian curve membership function; MF: membership function

6.6 Performance analysis of proposed models

Considering 12-month ahead prediction of demand from identified ARIMA model and AI models (DWT-ANN, DWT-ANFIS, DWT-LSSVM and DWT-MGGP) in Case 1, Case 2 and Case 3, the MSE values are estimated using Equation (6.43) (Table 6.16). From the table, it can be observed that MSE values in case of intelligent models are low as compared to the ARIMA model signifying high accuracy of the intelligent models. From Table 6.16, it can also be observed that accuracy of the DWT-LSSVM is comparatively better than the DWT-ANN and DWT-ANFIS model.

Table 6.16 Summery of estimated MSE values

Cases	Parameters	Forecasting Models				
		ARIMA	DWT-ANN	DWT-ANFIS	DWT-LSSVM	DWT-MGGP
Case 1: PQR Pvt. Ltd.	MSE	178544.01	4.392	28.469	0.0007	0.000000028
Case 2: XYZ Pvt. Ltd		228018346.7	77274529.83	64741185.4	234.664	97.670
Case 3: LMN Pvt. Ltd.		12046.768	229.552	761.496	0.003	0.000000007

According to Lee et al. (1997), a proper forecasting model always reduces the BWE. To campare the performance of the proposed forecasting models (ARIMA-GARCH and intelligent models) with ARIMA model, the BWE are estimated through estimating the order quantities (Q_t) using a simple review period order-up-to level (R, S) replenishment policy i.e. base-stock policy using Equation (6.48) and Equation (6.49) considering lead time (L) and review period (R) equals to one time period.

$$Q_t = \left(\hat{D}_t^L + z\hat{\sigma}_t^L\right) - \left(\hat{D}_{t-1}^L + z\hat{\sigma}_{t-1}^L\right) + D_{t-1} \tag{6.48}$$

$$Q_t = \left(\hat{D}_t^L - \hat{D}_{t-1}^L\right) + D_{t-1} \tag{6.49}$$

where the variable D_{t-1} is the actual demand for (t-1) period. z represents the service level (assumed as 95% service level resulting a z value of 1.96). The parameter $\hat{\sigma}_t^L$ is the forecasted demand variation during the lead time while $\hat{\sigma}_{t-1}^L$ is the forecasted demand variation during the just previous period t-1. $\hat{D}_t^L$ is the forecasted demand during the lead time at time period t. Similarly, $\hat{D}_{t-1}^L$ is the forecasted demand during the lead time just the previous period, (t-1). The Equation (6.48) is applicable for heteroskedastic demand series (i.e. demand variance changes with time) for which the forecasting model should have the ability to predict the changing demand variance whereas Equation (6.49) is applied to homoscedastic demand series. Since Case 1 and Case 3 do not exhibit heteroskedastic demand, 12-months ahead changing demand variance is predicted using the identified GARCH (2, 1) model only in Case 2 and mean demand are predicted using the identified ARIMA (2, 1, 1) (0, 1, 1)$_{12.}$ Using the predicted demand variance and mean demand, the safety-stock quantities ($z\hat{\sigma}_t^L / z\hat{\sigma}_{t-1}^L$) are updated in each replenishment period to estimate the order quantities using Equation (6.48). When changing variation in demand is not considered, the order quantities are estimated using Equation (6.49). Through the estimated order quantities and actual demand observed in Case 2, the BWE and NSAmp are estimated from ARIMA (without considering demand variance) and ARIMA-GARCH (considering demand variance) model using Equations (1.2) and (1.3) (in Chapter 1) respectively (Table 6.17).

Table 6.17 Estimated BWE and NSAmp using ARIMA and ARIMA-GARCH model

Model (Case 2)	BWE	NSAmp
ARIMA	0.881	1.041
ARIMA-GARCH	0.953	1.024

From the Table 6.17, it can be observed that BWE approaches to one in case of ARIMA-GARCH model signifying less BWE. When BWE is estimated using ARIMA model, it is less than one indicating the damping scenario (i.e. variation in order is low compared to variation in demand). The NSAmp value estimated in case of ARIMA-GARCH model is less as compared to ARIMA model. From the above analysis, it has been verified that proposed ARIMA-GARCH model can estimate the order quantity with relatively high degree of accuracy through updating safety stock using predicted demand variance.

From Table 6.16, it has been verified that accuracy of the proposed intelligent models is better as compared to the ARIMA model in three cases. To analyse the performance of the intelligent models, BWE and NSAmp values are estimated. For this purpose, order quantities are estimated using Equation (6.49) based on predicted demand from identified ARIMA models for various cases and BWE and NSAmp are calculated using Equation (1.2) and Equation (1.3) (Chapter 1). Similarly, BWE and NSAmp are calculated using intelligent models for all cases. The results are summarised in Table 6.18.

Table 6.18 Estimated BWE and NSAmp using ARIMA and intelligent models

Cases	Parameters	Forecasting Models				
		ARIMA	DWT-ANN	DWT-ANFIS	DWT-LSSVM	DWT-MGGP
Case 1: PQR Pvt. Ltd.	BWE	1.27	0.99	1.062	0.999	0.999
Case 2: XYZ Pvt. Ltd		0.881	1.005	1.033	0.999	0.999
Case 3: LMN Pvt. Ltd.		1.182	1.006	1.079	0.999	1
Case 1: PQR Pvt. Ltd.	NSAmp	1.02	0.024	0.021	0.0004	7.33E-06
Case 2: XYZ Pvt. Ltd		1.041	0.46	0.778	0.021	0.007158
Case 3: LMN Pvt. Ltd.		0.8701	0.577	0.269	0.007	1.25E-06

From the table, it can be observed that the BWE estimated from the intelligent models are either equal to one or approaches to one. This signifies that there is no BWE or less BWE. However, BWE is more than one in case of ARIMA model for Case 1 and Case 3 and less than one in Case 2. This signifies high BWE in Case 1 and Case 3 and damping case (high variation in demand with respect to order) in Case 2. From Table 6.18, it can be observed that NSAmp values estimated using intelligent models are less compared to the ARIMA model. In other words, less variation is inventory is observed when demand is predicted through the intelligent models and hence holding cost can be reduced. From the above analysis, it can be concluded that proposed intelligent models outperform the ARIMA model. Hence, it has been verified that proposed intelligent models help in accurate demand forecasting to reduce the BWE and NSAmp to enhance the performance of supply chain under uncertainty. From the Table 6.18, it can be observed that DWT-LSSVM and DWT-MGGP is better than the DWT-ANN and DWT-ANFIS model. It is to be noted that BWE and NSAmp value estimated for Case 2 considering ARIMA-GARCH is higher than the intelligent models. Hence, it can be concluded that intelligent models (DWT-ANN, DWT-ANFIS, DWT-LSSVM and DWT-MGGP) outperforms the ARIMA-GARCH model also. Further, the performance of the proposed intelligent models is tested for different varieties of (R, S) policy to test the robustness of the approach.

Based on different smoothing parameters for demand, order and inventory position, there are five replenishment policies such as (R,S), $(R,\beta S)$, (R,D), $(R,\gamma O)$ and $(R,\gamma O,\beta S)$ (Jakšič and Rusjan, 2008; Bandyopadhyay and Bhattacharya, 2013). For (R, S) policy, the analysis has already been made in the previous sections. In (R, D) policy if $Q_t = D_{t-1}$ results in BWE=1. Therefore, these two policies are excluded from further analysis. To study the performance of the intelligence models with respect to ARIMA model for $(R,\beta S)$ policy, the Q_t values are estimated using the predicted demand from identified ARIMA and intelligence models using Equation (6.50) through increasing the inventory smoothing parameter β from 0.1 to 0.9. Based on the estimated order quantities, the BWE are estimated using Equation (1.2) (in Chapter 1) for Case 1, Case 2 and Case 3 and shown in Figures 6.41, Figure 6.42 and Figure 6.43 respectively.

$$Q_t = \beta\left(\hat{D}_t^L - \hat{D}_{t-1}^L\right) + D_{t-1} \tag{6.50}$$

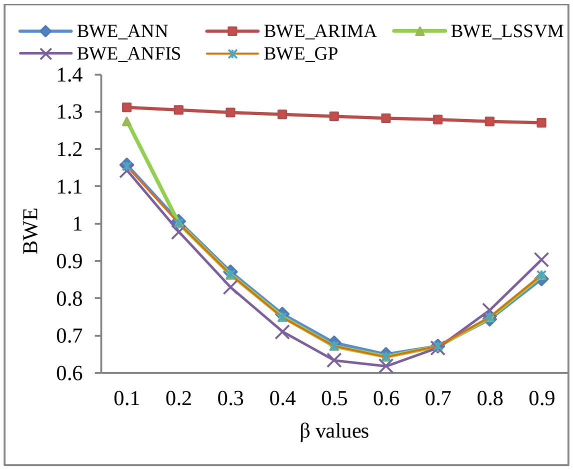

Figure 6.41 Estimated BWE employing $(R, \beta S)$ policy for Case 1

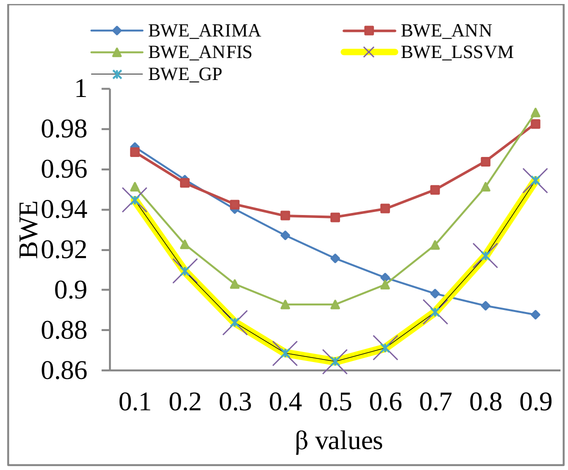

Figure 6.42 Estimated BWE employing $(R, \beta S)$ policy for Case 2

From the figures, it can be observed that BWE is either equals to one or approaches to one when β assumes a value at 0.2 for Case 1, 0.1 or 0.9 for Case 2 and 0.1 to 0.2 or 0.9 for Case 3. BWE is either more than or less than one when demand is predicted using ARIMA model for any value (0.1 to 0.9) is selected for β to estimate the order. This proves that performance of intelligent models is better than the ARIMA model for $(R, \beta S)$ policy. To analyses the performance of the intelligence model for $(R, \gamma O)$ inventory replenishment policy, the order smoothing parameter γ is varied from 0.1 to 0.9 and Q_t values are estimated from Equation (6.51) using the predicted demand from the intelligence models and ARIMA model. Based on Q_t, the BWE are computed using Equation (1.2) (Chapter 1) for three cases (Figure 6.44, 6.45 and 6.46 for Case 1, Case 2 and Case 3 respectively).

$$Q_t = Q_{t-1} + \gamma\left(\hat{D}_t^L - Q_{t-1}\right) \tag{6.51}$$

From the Figure 6.44, it can be observed that BWE approaches to one when γ approaches to any value from 0.4 to 0.6 if demand is predicted using intelligent models. However, BWE is always more than one for any value of γ when demand is predicted using ARIMA model.

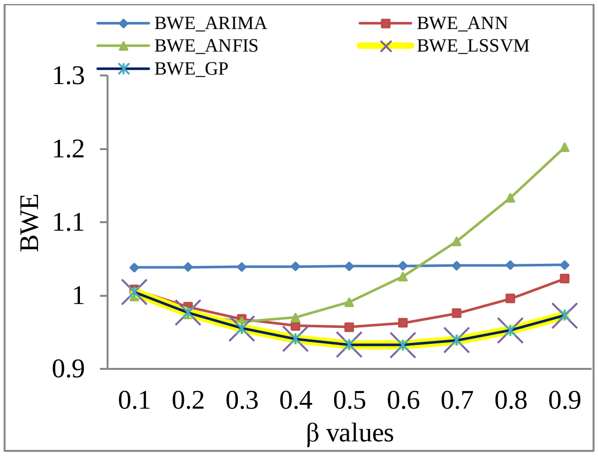

Figure 6.43 Estimated BWE employing $(R, \beta S)$ policy for Case 3

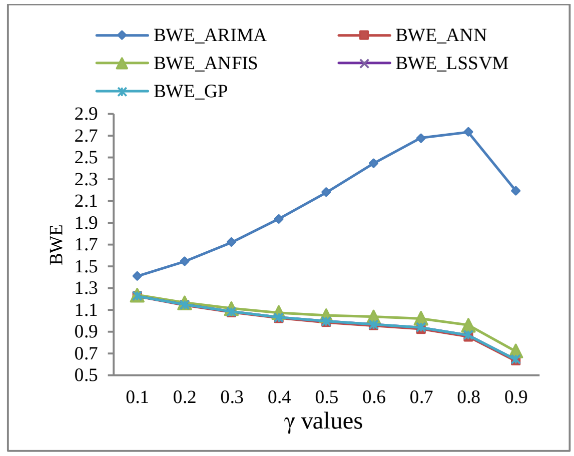

Figure 6.44 Estimated BWE employing $(R, \gamma O)$ policy for Case 1

From Figure 6.45, it can be observed that the BWE is same for any value (0.1 to 0.9) of γ whether demand is predicted using ARIMA or intelligence models. The BWE can be reduced while γ value is selected at 0.1 for order estimation. From Figure 6.46, it can be observed that ARIMA model can help in reducing the BWE when γ selected at 0.1 and 0.2. When demand is predicted through intelligent models and γ is selected between 0.1 and 0.3 for order estimation, the BWE can be reduced.

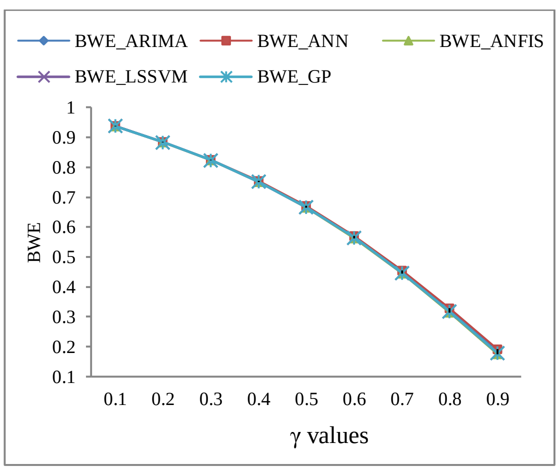

Figure 6.45 Estimated BWE employing $(R, \gamma O)$ for Case 2

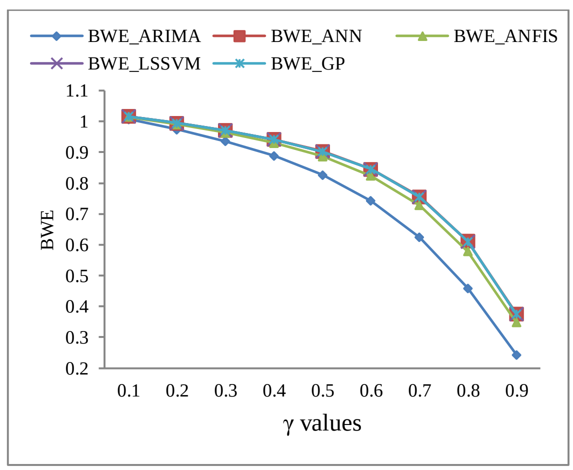

Figure 6.46 Estimated BWE employing $(R, \gamma O)$ policy for Case 3

To analyse the performance of the intelligent models for $(R, \gamma O, \beta S)$ replenishment policy, three values such as 0.1, 0.5 and 0.9 are considered for the smoothing parameters γ and β. Using predicted demand from identified ARIMA model and intelligent models, the Q_t values are estimated using Equation (6.52) by varying the β for a constant value of γ.

$$Q_t = D_{t-1} + \gamma(Q_{t-1} - D_{t-1}) + \beta(\hat{D}_t^L - \hat{D}_{t-1}^L) \tag{6.52}$$

Based on the Q_t value, the BWE is estimated. The behaviour of BWE under the influence of γ and β and forecasting models are shown in Figures 6.47- 6.49 for three cases. Figure 6.47 described the behaviour of BWE for Case 1. From the figure, it can be observed that for any value of γ when β varies, the BWE is always more than one (high BWE) when demand is predicted through the ARIMA model. The BWE can be reduced when the demand is predicted using intelligent models and Q_t are estimated using $(R,\gamma O,\beta S)$ policy considering γ and β at 0.1. This analysis concludes that intelligent models can be used as suitable forecasting model when $(R,\gamma O,\beta S)$ policy used for inventory replenishment. Figure 6.48 describes the behaviour of BWE when order is estimated using $(R,\gamma O,\beta S)$ policy (Equation 6.52) for Case 2. From the figure, it can be observed that BWE is less than one when demand is predicted through the ARIMA model whereas BWE approaches to one when demand is predicted through intelligent models and order quantities are estimated using $(R,\gamma O,\beta S)$ policy selecting γ value at 0.1 and β value at 0.9

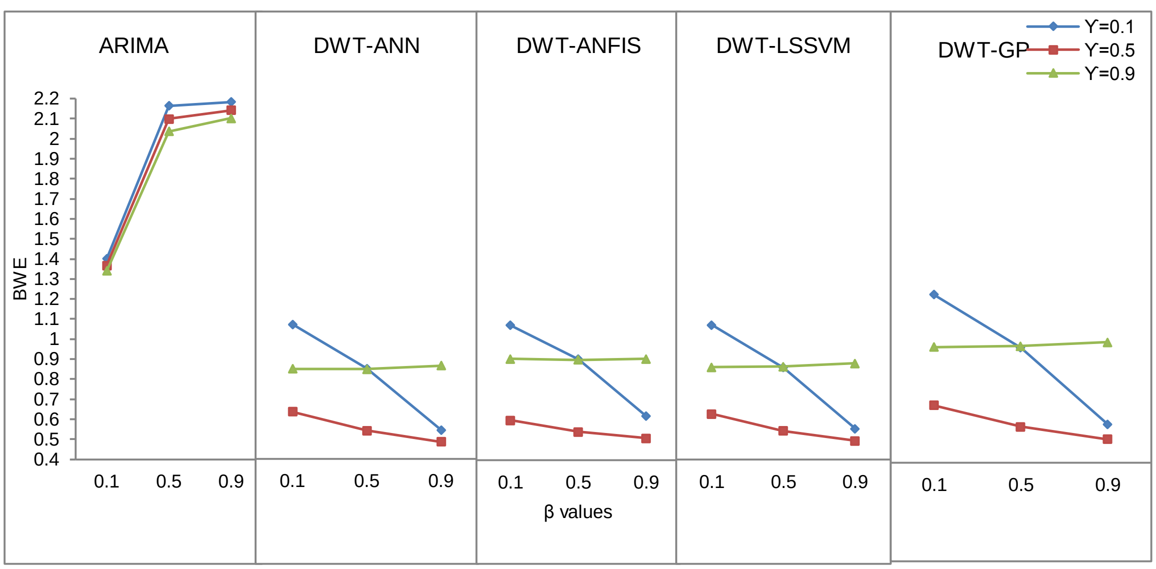

Figure 6.47 Estimated BWE employing $(R,\beta S,\gamma O)$ by varying β at constant γ value for Case 1

Figure 6.49 shows the behaviour of BWE for Case 3. From the figure, it can be observed that BWE can be reduced when demand is predicted either using ARIMA model or intelligent models and orders are estimated using $(R, \gamma O, \beta S)$ policy (Equation (6.52)) selecting β value at 0.1 and γ value 0.9. From the study, it is found that BWE can be reduced when the smoothing parameter β and γ are properly selected to estimate the order quantity using the predicted demand from intelligent models.

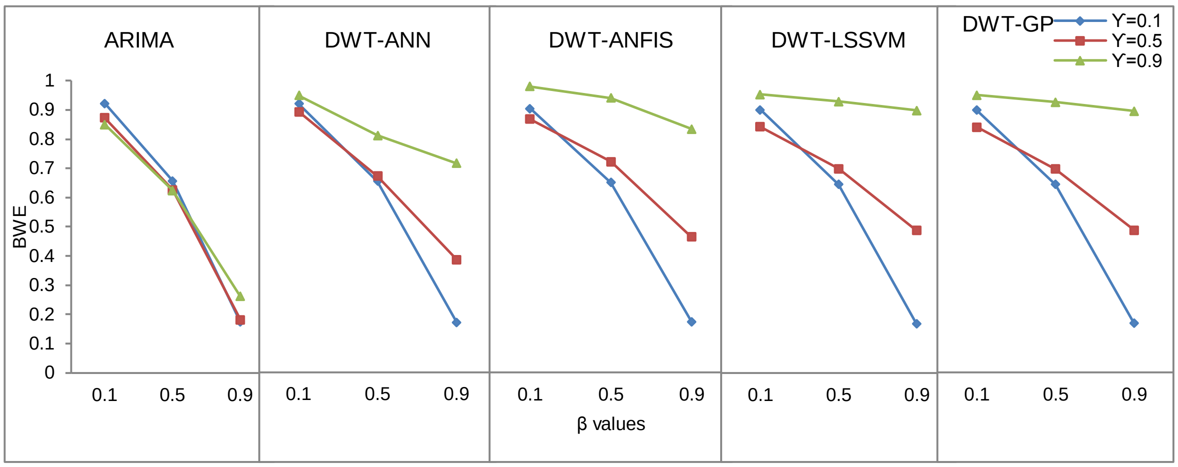

Figure 6.48 Estimated BWE employing $(R, \beta S, \gamma O)$ by varying β at constant γ value for Case 2

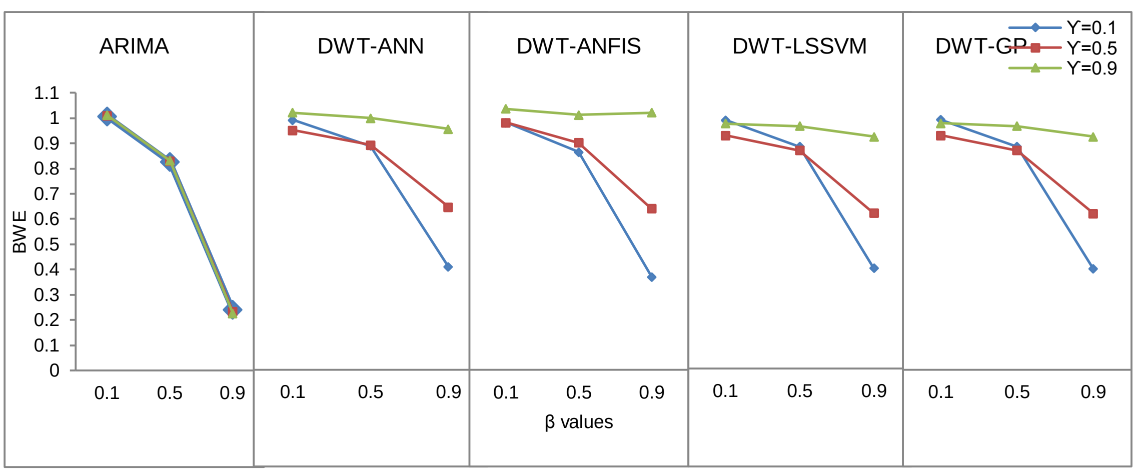

Figure 6.49 Estimated BWE employing $(R, \beta S, \gamma O)$ by varying β at constant γ value for Case 3

6.7 Summary

In this chapter, two types of forecasting models are proposed. First model is the integrated approach of ARIMA-GARCH to deal with heteroskedastic demand series. This model predicts the changing demand variance to update the safety stock at each replenishment period for proper estimation of order quantity to reduce the BWE and NSAmp. Second model is a relatively new approach proposed through embedding the

DWT analysis with AI techniques (DWT-ANN, DWT-ANFIS, DWT-LSSVM and DWT-GP) to improve the forecasting accuracy to reduce the BWE and NSAmp. The proposed intelligence models are validated by analysing an example data set from open literature through estimating MSE value.

In order to evaluate the performance of the proposed forecasting models, demand data from three cases is used to estimate BWE and NSAmp considering the base-stock inventory replenishment policy. Through judicious selection of GARCH model, the variation in cement demand is forecasted for 12-months ahead and mean demand is estimated from the selected ARIMA model to estimate the safety stock quantity for estimating the order (from Case 2). A comparative analysis has been carried out through estimating BWE and NSAmp considering ARIMA only (i.e. without considering predicted demand variation) and ARIMA-GARCH model (i.e. considering forecasted demand variation to estimate the order). From the analysis, it is found that BWE and NSAmp values are less if forecasted demand variance is considered.

Similarly, predicted demand from the intelligent models is used to estimate the order quantity using base-stock policy to calculate BWE and NSAmp. From the analysis, it is found that BWE and NSAmp are comparatively less when demand is predicted using the intelligent models. From further analysis, it has been observed that DWT-MGGP model outperforms the other proposed models. However, DWT-LSSVM is equally a competing method with DWT-MGGP as far as forecasting accuracy is concerned. The DWT-ANN and DWT-ANFIS are definitely better than ARIMA model but their performance seems to be poor as compared to DWT-MGGP. Further, it is found that intelligent models outperform the ARIMA-GARCH model. Further, different variants of order-up-to policies like $(R,\beta S)$, $(R,\gamma O)$ and $(R,\gamma O,\beta S)$ are tested by changing the smoothing parameters. From the study, it is observed that BWE is either greater than one (existence of BWE) or less than one (damping scenario) when demand is predicted using ARIMA model and order quantities are estimated using $(R,\beta S)$, $(R,\gamma O)$ and $(R,\gamma O,\beta S)$ replenishment policies. BWE can possibly be reduced when demand is predicted through intelligent models and order quantities are estimated using $(R,\beta S)$, $(R,\gamma O)$ and $(R,\gamma O,\beta S)$ policies through appropriate selection of smoothing parameters. In future, the proposed models can be tested for other order replenishment policy and filtering techniques instead of DWT. The Chapter 7 concludes the work covered in the thesis including practical and managerial implication, limitation and future scope of the work.

CHAPTER 7

EXECUTIVE SUMMARY AND CONCLUSIONS

7.1 Introduction

Dealing with uncertainties in supply chain management for improving its performance is a major issue these days. Existence of uncertainty in demand, supply lead time, supplier acquisition rate, processing time taken by machine, delay due to machine failure and random occurrence of machine failure adversely affects the performance of supply chain through increasing the backlog, decreasing the service level and increasing the total cost. Uncertainties also lead to bullwhip effect and net-stock amplification. Bullwhip effect (BWE) causes increase in ordering/production switching cost. Net-stock amplification (NSAmp) results in increase in holding cost and decrease in service level. In this direction, the present work emphasises on study of impact of uncertainties on supply chain performance and different approaches to reduce the adverse effect of uncertainties.

7.2 Summary of findings

System dynamics is one of the useful approaches to study the behaviour of multi-echelon serial supply chain employed with reorder point order-up-to level ((s, S)) inventory control policy performing under uncertainty. From the analysis, it is found that the order variance and variation in inventory level increases in the upward stream of the SC (towards wholesaler). The bottom echelon (retailer) accumulates higher backorder than the upper echelon in a supply chain. Through design of experiments (DOE) approach, the influence of uncertainty in demand and lead time and target inventory on BWE and total cost is investigated. From the analysis, it is found that uncertainty in demand and the target inventory has significant effect on supply chain cost. The supply chain cost can be reduced through keeping target inventory at medium level when there is low variation in demand and lead time. Target inventory has significant effect on BWE and it can be reduced through keeping target inventory at low level when there is low uncertainty in demand and lead time. Through the grey relational analysis, it is found that BWE and total cost can be simultaneously reduced keeping low target inventory when there is low variation in demand and supply lead time.

Next the behaviour of manufacturing system is analysed considering make-to-stock (MTS) and assemble-to-stock (ATS) manufacturing system. The performance of the serial MTS manufacturing system is analysed through generating six different scenarios based on uncertainty in supply lead time, processing time and delay due to machine failure using system dynamics approach. From the study, it is found that backlog increases when uncertainty in various parameters acts upon the system. From DOE approach, it is determined that uncertainty in lead time, processing time and delay due to machine failure has significant effect on backlog. Interaction of processing time and delay due to machine failure largely influence backlog. The backlog can be reduced through reducing the uncertainty. A regression model is developed to represent the relationship between the backlog and uncertain parameters. Through the cuckoo search algorithm, the optimal parameter setting is obtained to reduce backlog. To analyse the performance of serial multistage ATS manufacturing system, the system is modelled using system dynamics approach. Various scenarios are generated using response surface methodology approach. The performance of the ATS manufacturing system is analysed in terms of backlog and work in progress (WIP) inventory. From the analysis of variance (ANOVA), it is found that backlog is significantly affected due to uncertainty in processing time and delay due to machine failure. Similarly, interaction of these two factors has significant effect on backlog.

Similarly, the behaviour of serial two-stage MTS manufacturing system under the influence of uncertainty in (i) demand (ii) lead time (iii) supplier's acquisition rate (iv) processing time and (v) delay due to machine failure through system dynamics approach is studied. Effect of uncertainty on raw material shortage, WIP, and backlog at manufacturer's end and supplier's end is analysed. From the analysis, it is found that performance of manufacturing system is highly affected when uncertainty in supplier's acquisition rate increases. This study also analyses the benefits of a backup supply strategy. From the study, it is found that high service level should be maintained at the upper echelon of the supply chain in order to maintain high service level at the bottom of the echelon.

Under the uncertain environment it is very hard to predict accurate demand to reduce BWE and NSAmp. Therefore, to enhance the forecasting accuracy and reduce BWE and NSAmp, different improved forecasting models are proposed such as ARIMA-GARCH and intelligence models (DWT-ANN, DWT-ANFIS, DWT-LSSVM and DWT-MGGP). The models are successfully validated using an example from open literature. The performance of models are analysed through data obtained from three different case-study examples. From the analysis, it is found that the ARIMA-GARCH model is a suitable model for demand forecasting when demand exhibits heteroskedastic nature and supply chain is employed with (R, S) policy. Similarly, from the analysis, it is found that demand forecasting using AI models helps in reducing BWE and NSAmp when demand series is linear/non-linear or stationary/non-stationary in nature. Further to check the robustness of the intelligence models, their performance is tested for different varieties of (R, S) policies.

7.3 Contribution of the research work

The behaviour of multi-echelon serial supply chain employed with (s, S) policy is studied under the influence of uncertainty in demand and lead and inventory decision parameter the target inventory. The impact of uncertainty in demand and lead time and the target inventory on supply chain performance such as BWE and total cost is investigated. Optimal parameter settings are determined to simultaneously reduce the BWE and total cost under uncertainty. Further, the behaviour of MTS and ATS manufacturing system is studied under the influence of uncertainty in raw material supply lead time, production delay and delay due to machine failure considering backlog as performance parameter. The impact of uncertainty on MTS and ATS system is systematically analysed through the DOE approach. Cuckoo search algorithm is proposed to find the optimal parameter setting to reduce the effect of uncertainty.

A Backup supply strategy is proposed to cope with uncertainty in supplier's acquisition rate in a two stage MTS manufacturing system. Different improved forecasting methods are proposed to overcome the problem associated with time series ARIMA model for prediction of accurate demand to reduce BWE and NSAmp. The ARIMA-GARCH model is proposed to make prediction when demand series is heteroscedastic in nature and order quantity estimated using base-stock policy in a supply chain. The intelligence models DWT-ANN, DWT-ANFIS, DWT-LSSVM and DWT-MGGP are proposed to make prediction when demand series is followed linear/non-linear or stationary/non-station pattern and order is estimated using base-stock policy and different varieties of (R,S) policies like $(R, \beta S), (R, \gamma O) \text{and} (R, \gamma O, \beta S)$ to reduce BWE and NSAmp.

7.4 Research implications

In Chapter 3, system dynamics approach is proposed to analyse the impact of uncertainty in demand and lead time, and target inventory decision on the behaviour of multi-echelon serial supply chain is studied. This idea can be adopted to study the behaviour of multi-echelon serial/network supply chain under the influence of uncertainties. Through the proper decision of target inventory level, the BWE and total cost throughout the supply chain can be moderated. Similarly, in Chapter 4, a framework is proposed to study the behaviour of manufacturing system under the influence of uncertain conditions. This idea can be implemented by an organisation to identify the impact of different uncertainties on the behaviour of a manufacturing system. Based on which different strategies can be developed to control the adverse effect of uncertainties associated with the supply chain activities. The importance of backup supply strategy under uncertain environment is analysed in Chapter 5. Through adopting backup supply strategy, an organisation can avoid stock-out situation. In Chapter 6, the advantages of forecasting techniques such as ARIMA-GARCH, DWT-ANN, DWT-ANFIS, DWT-LSSVM and DWT-MGGP over the time series ARIMA model is analysed. The ARIMA-GARCH model can be used to apply to predict when demand pattern is heteroskedastic in nature. With the help of ARIMA-GARCH model, an organisation can predict the changing demand variation to update the safety-stock level. Similarly, intelligence forecasting techniques (DWT-ANN, DWT-ANFIS, DWT-LSSVM and DWT-MGGP) can be applied to predict the demand when the demand pattern exhibits non-linear and non-stationary pattern. The intelligence forecasting techniques can be used as a suitable forecasting technique to reduce BWE and NSAmp when order quantities are decided through order-up-to level inventory control policy.

7.5 Limitations of the study and directions for future research

The model proposed for multi-echelon serial supply chain in Chapter 3 is consist of single retailer, distributor, wholesaler and manufacturer and confined to a single product. This model can be further improved with multiple retailers, distributors, wholesalers and manufacturers dealing with multiple products. The MTS and ATS manufacturing supply chain model proposed in Chapter 4 is confined to a single product and raw material supplied from a single supplier. The model can be further improved with multiple products requiring more than one type of raw material for production. In Chapter 5, backup supply strategy is proposed to cope with raw material supply uncertainty at the manufacturing end. There is no remedial approach or strategy is proposed for the uncertainty in production process. Hence, different strategies can be explored to reduce the uncertainty in production process. In Chapter 6, proposed forecasting models are tested for the (R, S) policy. These models can be tested for different inventory control policies like (s, S) inventory control policy.

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APPENDIX

Appendix 1

Mapping between research objectives, research questions and sources of literature

Sl. No.	Research Objectives	Research Question	Mapped chapter	Primary literature sources
1	To study and analyse the performance of multi-echelon serial supply chain under uncertain environment using system dynamics approach.	How can the influence of uncertainty on supply chain be studied in an efficient and effective manner?	Chapter 3	Petrovic et al., (1998); Petrovic et al., (1999); Petrovic, (2001); Xie et al., (2006); Hwarng and Xie, (2008); Mahnam et al., (2009) O'donnell et al., (2006); Coppini et al., (2010)
2	To study and analyse the performance of manufacturing supply chain under the influence of uncertainty.	How does the manufacturing system, an important subsystem of a supply chain, behave under the uncertain environment?	Chapter 4	Bera and Sharma, (1999); Williams, (1984); Silver et al., (1998); Xu and Zhai (2010); Özbayrak et al. (2007); Groenevelt et al. (1992a,1992b)
3	To propose a back-up supply strategy to reduce the adverse effect of supply uncertainty in make-to-stock manufacturing supply chain.	What type of strategy and policy should be adopted to mitigate the effect of uncertainty?	Chapter 5	Vorst and Beulens, (2002); Prater, (2005); Koh and Tan, (2005); Groenevelt et al., (1992a,1992b); Chakraborty et al., (2008) Ramasesh (1991)
4	To reduce the BWE and NSAmp amplification through improved forecasting approaches.	How can the adverse effect of uncertainty (bullwhip effect and net-stock amplification) be reduced to improve the performance of a supply chain?	Chapter 6	Hong and Ping, (2007); Geary et al., (2006); Chen et al., (2000a); Fransoo and Wouters, (2000); Disney et al., (2003a,2003b); Lee et al., (1997a), Mason-Jones et al., (2000); Dejonckheere et al., (2003); Kim et al., (2006); Croson and Donohue, (2005); Chatfield et al., (2004); Bout and Lambrecht, (2009);

Appendix 2

Equations for stock-flow diagram shown in Figure 3.3

D_backorder_aquisition(t) = D_backorder_aquisition(t - dt) + (D_backorder_per_period - D_totalback_order) * dt
INIT D_backorder_aquisition = 0
INFLOWS:
D_backorder_per_period = IF(dispatch_to_R<total_demand_at_D)THEN(total_demand_at_D-dispatch_to_R)ELSE(0)
OUTFLOWS:
D_totalback_order = D_backorder_aquisition

D_INV(t) = D_INV(t - dt) + (D_order_received - dispatch_to_R) * dt
INIT D_INV = 100
INFLOWS:
D_order_received = CONVEYOR OUTFLOW
TRANSIT TIME = ROUND(NORMAL(2,0.2,500))
OUTFLOWS:
dispatch_to_R = MIN(total_demand_at_D,D_INV)

D_order_in_transit(t) = D_order_in_transit(t - dt) + (dispatch_to_D - D_order_received) * dt
INIT D_order_in_transit = 0
TRANSIT TIME = varies
INFLOW LIMIT = INF
CAPACITY = INF
INFLOWS:
dispatch_to_D = MIN(total__demand_at_W,W_INV)
OUTFLOWS:
D_order_received = CONVEYOR OUTFLOW
TRANSIT TIME = ROUND(NORMAL(2,0.2,500))

F_backorder_aquisition(t) = F_backorder_aquisition(t - dt) + (F_backorder_per_period - total_backorder) * dt
INIT F_backorder_aquisition = 0
INFLOWS:
F_backorder_per_period = IF(dispatch_to_W<total_W_demand)THEN(total_W_demand-dispatch_to_W)ELSE(0)
OUTFLOWS:
total_backorder = F_backorder_aquisition

F_INV(t) = F_INV(t - dt) + (production_completion_rate - dispatch_to_W) * dt
INIT F_INV = 100
INFLOWS:
production_completion_rate = CONVEYOR OUTFLOW
TRANSIT TIME = ROUND(NORMAL(4,0.4,300))
OUTFLOWS:
dispatch_to_W = MIN(total_W_demand,F_INV)

production_delay(t) = production_delay(t - dt) + (production_rate - production_completion_rate) * dt
INIT production_delay = 0
TRANSIT TIME = varies
INFLOW LIMIT = INF
CAPACITY = INF
INFLOWS:

production_rate = 25
OUTFLOWS:
production_completion_rate = CONVEYOR OUTFLOW
TRANSIT TIME = ROUND(NORMAL(4,0.4,300))

R_backorder_aqusition(t) = R_backorder_aqusition(t - dt) + (R_backorder_per_period - R_total_backorder) * dt
INIT R_backorder_aqusition = 0
INFLOWS:
R_backorder_per_period = IF(sales_rate<total_demand_at_R)THEN(total_demand_at_R-sales_rate)ELSE(0)
OUTFLOWS:
R_total_backorder = R_backorder_aqusition

R_INV(t) = R_INV(t - dt) + (R_order_received - sales_rate) * dt
INIT R_INV = 100
INFLOWS:
R_order_received = CONVEYOR OUTFLOW
TRANSIT TIME = ROUND(NORMAL(1,0.1,300))
OUTFLOWS:
sales_rate = MIN(total_demand_at_R,R_INV)

R_order_in_transit(t) = R_order_in_transit(t - dt) + (dispatch_to_R - R_order_received) * dt
INIT R_order_in_transit = 0
TRANSIT TIME = varies
INFLOW LIMIT = INF
CAPACITY = INF
INFLOWS:
dispatch_to_R = MIN(total_demand_at_D,D_INV)
OUTFLOWS:
R_order_received = CONVEYOR OUTFLOW
TRANSIT TIME = ROUND(NORMAL(1,0.1,300))

W_backorder_aquisition(t) = W_backorder_aquisition(t - dt) + (W_backorder_per_period - W_totalback_order) * dt
INIT W_backorder_aquisition = 0
INFLOWS:
W_backorder_per_period = IF(dispatch_to_D<total__demand_at_W)THEN(total__demand_at_W-dispatch_to_D)ELSE(0)
OUTFLOWS:
W_totalback_order = W_backorder_aquisition

W_INV(t) = W_INV(t - dt) + (W_order_received - dispatch_to_D) * dt
INIT W_INV = 100
INFLOWS:
W_order_received = CONVEYOR OUTFLOW
TRANSIT TIME = ROUND(NORMAL(3,0.3,300))
OUTFLOWS:
dispatch_to_D = MIN(total__demand_at_W,W_INV)

W_order_in_transit(t) = W_order_in_transit(t - dt) + (dispatch_to_W - W_order_received) * dt
INIT W_order_in_transit = 0
TRANSIT TIME = varies
INFLOW LIMIT = INF
CAPACITY = INF

INFLOWS:

dispatch_to_W = MIN(total_W_demand,F_INV)

OUTFLOWS:

W_order_received = CONVEYOR OUTFLOW
TRANSIT TIME = ROUND(NORMAL(3,0.3,300))

UNATTACHED:

customer_demand = ROUND(NORMAL(20,2,300))

UNATTACHED:

D_projected_onhand_INV = (D_INV-total_demand_at_D)+D_order_in_transit

UNATTACHED:

order_placed_by_R =
IF(R_projected_onhand_INV<=R_ROP)THEN(R_target_INV-R_projected_onhand_INV)ELSE(0)

UNATTACHED:

order_placed_by_W =
IF(W_projected_onhand_INV<=W_ROP)THEN(W_target_INV-W_projected_onhand_INV)ELSE(
0)

UNATTACHED:

order_plaed_by_D =
IF(D_projected_onhand_INV<=D_ROP)THEN(D_target_INV-D_projected_onhand_INV)ELSE(0)

UNATTACHED:

R_projected_onhand_INV = (R_INV-total_demand_at_R)+R_order_in_transit

UNATTACHED:

total_demand_at_D = order_placed_by_R+D_totalback_order

UNATTACHED:

total_demand_at_R = customer_demand+R_total_backorder

UNATTACHED:

total_W_demand = order_placed_by_W+total_backorder

UNATTACHED:

total__demand_at_W = order_plaed_by_D+W_totalback_order

UNATTACHED:

W_projected_onhand_INV = (W_INV-total__demand_at_W)+W_order_in_transit

D_ROP = 67

D_target_INV = 86

R_ROP = 24

R_target_INV = 44

W_ROP = 93

W_target_INV = 112

Appendix 3

Equations for stock-flow diagram shown in Figure 4.3

F_INV(t) = F_INV(t - dt) + (production_completion_rate - sales_rate) * dt
INIT F_INV = 100
INFLOWS:
production_completion_rate = CONVEYOR OUTFLOW
TRANSIT TIME = ROUND(NORMAL(1.33,0.217,20117))
OUTFLOWS:
sales_rate = MIN(F_INV,total_demand_of_product)

M_RM_INV(t) = M_RM_INV(t - dt) + (raw_material_received - production_input) * dt
INIT M_RM_INV = 100
INFLOWS:
raw_material_received = CONVEYOR OUTFLOW
TRANSIT TIME = ROUND(NORMAL(4,1.3,28087))
OUTFLOWS:
production_input = MIN(desired_production_rate,M_RM_INV)

production_delay(t) = production_delay(t - dt) + (production_input - production_completion_rate) * dt
INIT production_delay = 0
TRANSIT TIME = varies
INFLOW LIMIT = INF
CAPACITY = INF
INFLOWS:
production_input = MIN(desired_production_rate,M_RM_INV)
OUTFLOWS:
production_completion_rate = CONVEYOR OUTFLOW
TRANSIT TIME = ROUND(NORMAL(1.33,0.217,20117))

product_backlog_acculation(t) = product_backlog_acculation(t - dt) + (prod_backlog_per_period - prod_backlog_to_satisfied) * dt
INIT product_backlog_acculation = 0
INFLOWS:
prod_backlog_per_period = IF(total_demand_of_product>sales_rate)THEN(total_demand_of_product-sales_rate)ELSE(0)
OUTFLOWS:
prod_backlog_to_satisfied = product_backlog_acculation

RM_order_backlog_accumulation(t) = RM_order_backlog_accumulation(t - dt) + (RM_order_backlog_per_period - RM_order_backlog_Qty_to_satisfied) * dt
INIT RM_order_backlog_accumulation = 0
INFLOWS:
RM_order_backlog_per_period = IF(RM_order_Qty>RM_dispatch_rate)THEN(RM_order_Qty-RM_dispatch_rate)ELSE(0)

OUTFLOWS:

RM_order_backlog_Qty_to_satisfied = RM_order_backlog_accumulation

RM_supply_lead_time(t) = RM_supply_lead_time(t - dt) + (RM_dispatch_rate - raw_material_received) * dt

INIT RM_supply_lead_time = 0

TRANSIT TIME = varies

INFLOW LIMIT = INF

CAPACITY = INF

INFLOWS:

RM_dispatch_rate = MIN(S_RM_INV,total_RM_demand_at_S)

OUTFLOWS:

raw_material_received = CONVEYOR OUTFLOW

TRANSIT TIME = ROUND(NORMAL(4,1.3,28087))

S_RM_INV(t) = S_RM_INV(t - dt) + (aqusition_rate - RM_dispatch_rate) * dt

INIT S_RM_INV = 200

INFLOWS:

aqusition_rate = ROUND(NORMAL(20,1,31081))

OUTFLOWS:

RM_dispatch_rate = MIN(S_RM_INV,total_RM_demand_at_S)

UNATTACHED:

desired_production_rate = IF(production_delay>0)THEN(0)ELSE(IF(prod_backlog_to_satisfied>=0 AND prod_backlog_to_satisfied<=3)THEN(normal_production_rate)ELSE(IF(prod_backlog_to_satisfied>=4 AND prod_backlog_to_satisfied<10)THEN(normal_production_rate+ROUND(normal_production_rate*.15))ELSE(normal_production_rate+ROUND(0.25*normal_production_rate))))

UNATTACHED:

market_demand = ROUND(NORMAL(19,1,10133))

UNATTACHED:

M_projected_on_hand_stock = (M_RM_INV+RM_supply_lead_time)-desired_production_rate

UNATTACHED:

RM_order_Qty = IF(M_projected_on_hand_stock<=ROP)THEN(Target_INV-M_projected_on_hand_stock)ELSE(0)

UNATTACHED:

total_demand_of_product = market_demand+prod_backlog_to_satisfied

UNATTACHED:

total_RM_demand_at_S = RM_order_backlog_Qty_to_satisfied+RM_order_Qty

normal_production_rate = 40

ROP = 135

Target_INV = 154

Appendix 4

Equations for stock-flow diagram shown in Figure 4.4

```
DLY_due_FAILURE1(t) = DLY_due_FAILURE1(t - dt) + (LEKAGE1 - PR11) * dt
INIT DLY_due_FAILURE1 = 0
 TRANSIT TIME = varies
 INFLOW LIMIT = INF
 CAPACITY = INF
 INFLOWS:
   LEKAGE1 = LEAKAGE OUTFLOW
    LEAKAGE FRACTION =
   IF(ocurence_of_MC1_failure_rate<=365)THEN(PRD_DELAY1)ELSE(0)
    NO-LEAK ZONE = 0%
 OUTFLOWS:
   PR11 = CONVEYOR OUTFLOW
    TRANSIT TIME = ROUND(NORMAL(3,0.333,22717))
DLY_due_FAILURE2(t) = DLY_due_FAILURE2(t - dt) + (LEKAGE2 - PR22) * dt
INIT DLY_due_FAILURE2 = 0
 TRANSIT TIME = varies
 INFLOW LIMIT = INF
 CAPACITY = INF
 INFLOWS:
   LEKAGE2 = LEAKAGE OUTFLOW
    LEAKAGE FRACTION =
   IF(ocurence_of_MC2_failure_rate<=365)THEN(PRD_DELAY2)ELSE(0)
    NO-LEAK ZONE = 0%
 OUTFLOWS:
   PR22 = CONVEYOR OUTFLOW
    TRANSIT TIME = ROUND(NORMAL(3,0.6665,12101))
DLY_due_FAILURE3(t) = DLY_due_FAILURE3(t - dt) + (LEKAGE3 - PR33) * dt
INIT DLY_due_FAILURE3 = 0
 TRANSIT TIME = varies
 INFLOW LIMIT = INF
 CAPACITY = INF
 INFLOWS:
   LEKAGE3 = LEAKAGE OUTFLOW
    LEAKAGE FRACTION =
   IF(ocurence_of_MC3_failure_rate<=365)THEN(PRD_DELAY3)ELSE(0)
    NO-LEAK ZONE = 0%
 OUTFLOWS:
   PR33 = CONVEYOR OUTFLOW
    TRANSIT TIME = ROUND(NORMAL(3,0.6665,19387))
F_INV(t) = F_INV(t - dt) + (PR3 + PR33 - SR) * dt
INIT F_INV = 800
 INFLOWS:
   PR3 = CONVEYOR OUTFLOW
    TRANSIT TIME = ROUND(NORMAL(5,0.6665,15101))
   PR33 = CONVEYOR OUTFLOW
    TRANSIT TIME = ROUND(NORMAL(3,0.6665,19387))
 OUTFLOWS:
   SR = MIN(F_INV,TPRDD)
```

```
LT1(t) = LT1(t - dt) + (DISPATCH1 - RM1_RECEIVED) * dt
INIT LT1 = 0
 TRANSIT TIME = varies
 INFLOW LIMIT = INF
 CAPACITY = INF
 INFLOWS:
    DISPATCH1 = MIN(S1_INV,total_RM1_demand_at_S1)
 OUTFLOWS:
    RM1_RECEIVED = CONVEYOR OUTFLOW
     TRANSIT TIME = ROUND(NORMAL(5,0.5,30817))
LT2(t) = LT2(t - dt) + (DISPATCH2 - RM2_RECEIVED) * dt
INIT LT2 = 0
 TRANSIT TIME = varies
 INFLOW LIMIT = INF
 CAPACITY = INF
 INFLOWS:
    DISPATCH2 = MIN(S1_INV_2,total_RM1_demand_at_S1_2)
 OUTFLOWS:
    RM2_RECEIVED = CONVEYOR OUTFLOW
     TRANSIT TIME = ROUND(NORMAL(5,1,22973))
LT3(t) = LT3(t - dt) + (DISPATCH3 - RM3_RECEIVED) * dt
INIT LT3 = 0
 TRANSIT TIME = varies
 INFLOW LIMIT = INF
 CAPACITY = INF
 INFLOWS:
    DISPATCH3 = MIN(S3_INV,total_RM3_demand_at_S3)
 OUTFLOWS:
    RM3_RECEIVED = CONVEYOR OUTFLOW
     TRANSIT TIME = ROUND(NORMAL(5,1,32561))
PRD_BKLG_ACC(t) = PRD_BKLG_ACC(t - dt) + (PRD_BKLG_PER_PERIOD -
PRD_BKLG_to_SATISFIED) * dt
INIT PRD_BKLG_ACC = 0
 INFLOWS:
    PRD_BKLG_PER_PERIOD = IF(TPRDD>SR)THEN(TPRDD-SR)ELSE(0)
 OUTFLOWS:
    PRD_BKLG_to_SATISFIED = PRD_BKLG_ACC
PRD_DELAY1(t) = PRD_DELAY1(t - dt) + (RM1_INP - PR1 - LEKAGE1) * dt
INIT PRD_DELAY1 = 0
 TRANSIT TIME = varies
 INFLOW LIMIT = INF
 CAPACITY = INF
 INFLOWS:
    RM1_INP = MIN(DSPR1,RM1_INV)
 OUTFLOWS:
    PR1 = CONVEYOR OUTFLOW
     TRANSIT TIME = ROUND(NORMAL(5,0.333,10337))
    LEKAGE1 = LEAKAGE OUTFLOW
     LEAKAGE FRACTION =
    IF(ocurence_of_MC1_failure_rate<=365)THEN(PRD_DELAY1)ELSE(0)
     NO-LEAK ZONE = 0%
```

```
PRD_DELAY2(t) = PRD_DELAY2(t - dt) + (RM2_INP - PR2 - LEKAGE2) * dt
INIT PRD_DELAY2 = 0
 TRANSIT TIME = varies
 INFLOW LIMIT = INF
 CAPACITY = INF
 INFLOWS:
    RM2_INP = MIN(RM2_INV_2,DSPR2)
 OUTFLOWS:
    PR2 = CONVEYOR OUTFLOW
     TRANSIT TIME = ROUND(NORMAL(5,0.6665,32717))
    LEKAGE2 = LEAKAGE OUTFLOW
     LEAKAGE FRACTION =
    IF(ocurence_of_MC2_failure_rate<=365)THEN(PRD_DELAY2)ELSE(0)
     NO-LEAK ZONE = 0%
PRD_DELAY3(t) = PRD_DELAY3(t - dt) + (RM3_INP - PR3 - LEKAGE3) * dt
INIT PRD_DELAY3 = 0
 TRANSIT TIME = varies
 INFLOW LIMIT = INF
 CAPACITY = INF
 INFLOWS:
    RM3_INP = MIN(RM3_INV,DSPR3)
 OUTFLOWS:
    PR3 = CONVEYOR OUTFLOW
     TRANSIT TIME = ROUND(NORMAL(5,0.6665,15101))
    LEKAGE3 = LEAKAGE OUTFLOW
     LEAKAGE FRACTION =
    IF(ocurence_of_MC3_failure_rate<=365)THEN(PRD_DELAY3)ELSE(0)
     NO-LEAK ZONE = 0%
RM1_BKLG_ACC_at_S1(t) = RM1_BKLG_ACC_at_S1(t - dt) + (RM1_BKLG_PER_PERIOD -
RM1_to_satisfied) * dt
INIT RM1_BKLG_ACC_at_S1 = 0
 INFLOWS:
    RM1_BKLG_PER_PERIOD =
    IF(total_RM1_demand_at_S1>DISPATCH1)THEN(total_RM1_demand_at_S1-DISPATCH1
    )ELSE(0)
 OUTFLOWS:
    RM1_to_satisfied = RM1_BKLG_ACC_at_S1
RM1_BKLG_ACC_at_S2(t) = RM1_BKLG_ACC_at_S2(t - dt) + (RM1_BKLG_PER_PERIOD2 -
RM1_to_satisfied2) * dt
INIT RM1_BKLG_ACC_at_S2 = 0
 INFLOWS:
    RM1_BKLG_PER_PERIOD2 =
    IF(total_RM1_demand_at_S1_2>DISPATCH2)THEN(total_RM1_demand_at_S1_2-DISPAT
    CH2)ELSE(0)
 OUTFLOWS:
    RM1_to_satisfied2 = RM1_BKLG_ACC_at_S2
RM1_BKLG_ACC_at_S3(t) = RM1_BKLG_ACC_at_S3(t - dt) + (RM1_BKLG_PER_PERIOD3 -
RM2_to_satisfied3) * dt
INIT RM1_BKLG_ACC_at_S3 = 0
 INFLOWS:
```

RM1_BKLG_PER_PERIOD3 = IF(total_RM3_demand_at_S3>DISPATCH3)THEN(total_RM3_demand_at_S3-DISPATCH3)ELSE(0)

OUTFLOWS:

RM2_to_satisfied3 = RM1_BKLG_ACC_at_S3

RM1_INV(t) = RM1_INV(t - dt) + (RM1_RECEIVED - RM1_INP) * dt
INIT RM1_INV = 800

INFLOWS:

RM1_RECEIVED = CONVEYOR OUTFLOW
TRANSIT TIME = ROUND(NORMAL(5,0.5,30817))

OUTFLOWS:

RM1_INP = MIN(DSPR1,RM1_INV)

RM2_INV_2(t) = RM2_INV_2(t - dt) + (RM2_RECEIVED - RM2_INP) * dt
INIT RM2_INV_2 = 800

INFLOWS:

RM2_RECEIVED = CONVEYOR OUTFLOW
TRANSIT TIME = ROUND(NORMAL(5,1,22973))

OUTFLOWS:

RM2_INP = MIN(RM2_INV_2,DSPR2)

RM3_INV(t) = RM3_INV(t - dt) + (RM3_RECEIVED - RM3_INP) * dt
INIT RM3_INV = 800

INFLOWS:

RM3_RECEIVED = CONVEYOR OUTFLOW
TRANSIT TIME = ROUND(NORMAL(5,1,32561))

OUTFLOWS:

RM3_INP = MIN(RM3_INV,DSPR3)

S1_INV(t) = S1_INV(t - dt) + (AQSR1 - DISPATCH1) * dt
INIT S1_INV = 800

INFLOWS:

AQSR1 = ROUND(NORMAL(50,1,30013))

OUTFLOWS:

DISPATCH1 = MIN(S1_INV,total_RM1_demand_at_S1)

S1_INV_2(t) = S1_INV_2(t - dt) + (AQSR2 - DISPATCH2) * dt
INIT S1_INV_2 = 800

INFLOWS:

AQSR2 = ROUND(NORMAL(50,1,20071))

OUTFLOWS:

DISPATCH2 = MIN(S1_INV_2,total_RM1_demand_at_S1_2)

S3_INV(t) = S3_INV(t - dt) + (AQSR3 - DISPATCH3) * dt
INIT S3_INV = 800

INFLOWS:

AQSR3 = ROUND(NORMAL(50,1,24671))

OUTFLOWS:

DISPATCH3 = MIN(S3_INV,total_RM3_demand_at_S3)

WIP1(t) = WIP1(t - dt) + (PR1 + PR11 - DSPR2) * dt
INIT WIP1 = 0

INFLOWS:

PR1 = CONVEYOR OUTFLOW
TRANSIT TIME = ROUND(NORMAL(5,0.333,10337))

PR11 = CONVEYOR OUTFLOW
TRANSIT TIME = ROUND(NORMAL(3,0.333,22717))

OUTFLOWS:

DSPR2 = IF(DLY_due_FAILURE2>0 OR PRD_DELAY2>0 OR LEKAGE2>0 OR ocurence_of_MC2_failure_rate<=365)THEN(0)ELSE(MIN(WIP1,NPR2))

WIP2(t) = WIP2(t - dt) + (PR2 + PR22 - DSPR3) * dt
INIT WIP2 = 0

INFLOWS:

PR2 = CONVEYOR OUTFLOW
TRANSIT TIME = ROUND(NORMAL(5,0.6665,32717))

PR22 = CONVEYOR OUTFLOW
TRANSIT TIME = ROUND(NORMAL(3,0.6665,12101))

OUTFLOWS:

DSPR3 = IF(DLY_due_FAILURE3>0 OR PRD_DELAY3>0 OR LEKAGE3 >0 OR ocurence_of_MC3_failure_rate<=365)THEN(0)ELSE(MIN(WIP2,NPR3))

UNATTACHED:

DSPR1 = IF(ocurence_of_MC1_failure_rate<=365 OR PRD_DELAY1>0 OR LEKAGE1>0 OR DLY_due_FAILURE1>0)THEN(0)ELSE(ROUND(IF(PRD_BKLG_to_SATISFIED>=0 AND PRD_BKLG_to_SATISFIED<=3) THEN(NPR1)ELSE(IF(PRD_BKLG_to_SATISFIED>3AND PRD_BKLG_to_SATISFIED<=10)THEN(NPR1*0.20+NPR1)ELSE(IF(NPR1>10 AND PRD_BKLG_to_SATISFIED<=20)THEN(NPR1*0.25+NPR1)ELSE(NPR1*0.30+NPR1)))))

UNATTACHED:

ORD_RM1 = IF(PRJ_OH_STK_RM1<=ROP1)THEN(S1-PRJ_OH_STK_RM1)ELSE(0)

UNATTACHED:

ORD_RM2 = IF(PRJ_OH_STK_RM2<=ROP_2)THEN(S_2-PRJ_OH_STK_RM2)ELSE(0)

UNATTACHED:

ORD_RM3 = IF(PRJ_OH_STK_RM3<=ROP_3)THEN(S_3-PRJ_OH_STK_RM3)ELSE(0)

UNATTACHED:

PRJ_OH_STK_RM1 = (RM1_INV-RM1_INP)+LT1

UNATTACHED:

PRJ_OH_STK_RM2 = (RM2_INV_2-RM2_INP)+LT2

UNATTACHED:

PRJ_OH_STK_RM3 = (RM3_INV-RM3_INP)+LT3

UNATTACHED:

total_RM1_demand_at_S1 = ORD_RM1+RM1_to_satisfied

UNATTACHED:

total_RM1_demand_at_S1_2 = ORD_RM2+RM1_to_satisfied2

UNATTACHED:

total_RM3_demand_at_S3 = ORD_RM3+RM2_to_satisfied3

UNATTACHED:

TPRDD = PRD_BKLG_to_SATISFIED+DR

DR = ROUND(NORMAL(25,0.5,17911))
NPR1 = 150
NPR2 = 150
NPR3 = 150
ocurence_of_MC1_failure_rate = -(1/0.0001)*LOGN(1-(RANDOM(0,1,18719)))
ocurence_of_MC2_failure_rate = -(1/0.0001)*LOGN(1-(RANDOM(0,1,25673)))
ocurence_of_MC3_failure_rate = -(1/0.0001)*LOGN(1-(RANDOM(0,1,11383)))
ROP1 = 895
ROP_2 = 895

ROP_3 = 895
S1 = 1053
S_2 = 1053
S_3 = 1053

Appendix 5

Equations for stock-flow diagram shown in Figure 4.6

dealy_due_machine_failure(t) = dealy_due_machine_failure(t - dt) + (lekage - production_completion) * dt
INIT dealy_due_machine_failure = 0
TRANSIT TIME = varies
INFLOW LIMIT = INF
CAPACITY = INF

INFLOWS:

lekage = LEAKAGE OUTFLOW
LEAKAGE FRACTION = IF(occurance_of_failure<=365)THEN(production_delay)ELSE(0)
NO-LEAK ZONE = 0%

OUTFLOWS:

production_completion = CONVEYOR OUTFLOW
TRANSIT TIME = ROUND((EXPRND(0.833,17077)))+ROUND(NORMAL(1.33,0.217,20117))

F_INV(t) = F_INV(t - dt) + (production_completion_rate + production_completion - sales_rate) * dt
INIT F_INV = 100

INFLOWS:

production_completion_rate = CONVEYOR OUTFLOW
TRANSIT TIME = ROUND(NORMAL(1.33,0.217,20117))

production_completion = CONVEYOR OUTFLOW
TRANSIT TIME = ROUND((EXPRND(0.833,17077)))+ROUND(NORMAL(1.33,0.217,20117))

OUTFLOWS:

sales_rate = MIN(F_INV,total_demand_of_product)

M_RM_INV(t) = M_RM_INV(t - dt) + (raw_material_received - production_input) * dt
INIT M_RM_INV = 100

INFLOWS:

raw_material_received = CONVEYOR OUTFLOW
TRANSIT TIME = ROUND(NORMAL(4,1.3,28087))

OUTFLOWS:

production_input = MIN(desired_production_rate,M_RM_INV)

production_delay(t) = production_delay(t - dt) + (production_input - lekage - production_completion_rate) * dt
INIT production_delay = 0
TRANSIT TIME = varies
INFLOW LIMIT = INF
CAPACITY = INF

INFLOWS:

production_input = MIN(desired_production_rate,M_RM_INV)

OUTFLOWS:

lekage = LEAKAGE OUTFLOW
LEAKAGE FRACTION = IF(occurance_of_failure<=365)THEN(production_delay)ELSE(0)
NO-LEAK ZONE = 0%

production_completion_rate = CONVEYOR OUTFLOW
TRANSIT TIME = ROUND(NORMAL(1.33,0.217,20117))

product_backlog_acculation(t) = product_backlog_acculation(t - dt) + (prod_backlog_per_period - prod_backlog_to_satisfied) * dt
INIT product_backlog_acculation = 0

INFLOWS:

prod_backlog_per_period = IF(total_demand_of_product>sales_rate)THEN(total_demand_of_product-sales_rate)ELSE(0)

OUTFLOWS:

prod_backlog_to_satisfied = product_backlog_acculation

RM_order_backlog_accumulation(t) = RM_order_backlog_accumulation(t - dt) + (RM_order_backlog_per_period - RM_order_backlog_Qty_to_satisfied) * dt

INIT RM_order_backlog_accumulation = 0

INFLOWS:

RM_order_backlog_per_period = IF(RM_order_Qty>RM_dispatch_rate)THEN(RM_order_Qty-RM_dispatch_rate)ELSE(0)

OUTFLOWS:

RM_order_backlog_Qty_to_satisfied = RM_order_backlog_accumulation

RM_supply_lead_time(t) = RM_supply_lead_time(t - dt) + (RM_dispatch_rate - raw_material_received) * dt

INIT RM_supply_lead_time = 0

TRANSIT TIME = varies

INFLOW LIMIT = INF

CAPACITY = INF

INFLOWS:

RM_dispatch_rate = MIN(S_RM_INV,total_RM_demand_at_S)

OUTFLOWS:

raw_material_received = CONVEYOR OUTFLOW

TRANSIT TIME = ROUND(NORMAL(4,1.3,28087))

S_RM_INV(t) = S_RM_INV(t - dt) + (aqusition_rate - RM_dispatch_rate) * dt

INIT S_RM_INV = 200

INFLOWS:

aqusition_rate = ROUND(NORMAL(20,1,31081))

OUTFLOWS:

RM_dispatch_rate = MIN(S_RM_INV,total_RM_demand_at_S)

UNATTACHED:

desired_production_rate = IF(occurance_of_failure<=365 OR production_delay>0 OR lekage>0 OR dealy_due_machine_failure>0)THEN(0)ELSE(IF(prod_backlog_to_satisfied>=0 AND prod_backlog_to_satisfied<=3)THEN(normal_production_rate)ELSE(IF(prod_backlog_to_satisfied>=4 AND prod_backlog_to_satisfied<10)THEN(normal_production_rate+ROUND(normal_production_rate*.15))ELSE(normal_production_rate+ROUND(0.25*normal_production_rate))))

UNATTACHED:

market_demand = ROUND(NORMAL(19,1,10133))

UNATTACHED:

M_projected_on_hand_stock = (M_RM_INV+RM_supply_lead_time)-desired_production_rate

UNATTACHED:

RM_order_Qty = IF(M_projected_on_hand_stock<=ROP)THEN(Target_INV-M_projected_on_hand_stock)ELSE(0)

UNATTACHED:

total_demand_of_product = market_demand+prod_backlog_to_satisfied

UNATTACHED:

total_RM_demand_at_S = RM_order_backlog_Qty_to_satisfied+RM_order_Qty

normal_production_rate = 40

occurance_of_failure = -(1/0.0001)*LOGN(1-(RANDOM(0,1,18719)))

ROP = 135

Target_INV = 154

Appendix 6

Equations for stock-flow diagram shown in Figure 5.2

delay_DMF1(t) = delay_DMF1(t - dt) + (lekage1 - CR11) * dt
INIT delay_DMF1 = 0
TRANSIT TIME = varies
INFLOW LIMIT = INF
CAPACITY = INF

INFLOWS:

lekage1 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = IF(occurance_of_failure1<=365)THEN(PD1)ELSE(0)
NO-LEAK ZONE = 0%

OUTFLOWS:

CR11 = CONVEYOR OUTFLOW
TRANSIT TIME = ROUND((EXPRND(0.8333,17077)))+ROUND(NORMAL(2,0.5,22717))

delay_DMF2(t) = delay_DMF2(t - dt) + (lekage2 - CR22) * dt
INIT delay_DMF2 = 0
TRANSIT TIME = varies
INFLOW LIMIT = INF
CAPACITY = INF

INFLOWS:

lekage2 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = IF(occurance_of_failure2<=365)THEN(PD2)ELSE(0)
NO-LEAK ZONE = 1%

OUTFLOWS:

CR22 = CONVEYOR OUTFLOW
TRANSIT TIME = ROUND((EXPRND(0.8333,17053)))+ROUND(NORMAL(2,0.5,32411))

F_INV(t) = F_INV(t - dt) + (CR2 + CR22 - M_SR) * dt
INIT F_INV = 700

INFLOWS:

CR2 = CONVEYOR OUTFLOW
TRANSIT TIME = ROUND(NORMAL(5,1,32491))

CR22 = CONVEYOR OUTFLOW
TRANSIT TIME = ROUND((EXPRND(0.8333,17053)))+ROUND(NORMAL(2,0.5,32411))

OUTFLOWS:

M_SR = MIN(F_INV,TPRD)

M_RM_INV(t) = M_RM_INV(t - dt) + (RM_received - RM_input1) * dt
INIT M_RM_INV = 600

INFLOWS:
RM_received = CONVEYOR OUTFLOW
TRANSIT TIME = ROUND(NORMAL(5,1.6,30047))
OUTFLOWS:
RM_input1 = MIN(M_RM_INV,M_DPR1)
PD1(t) = PD1(t - dt) + (RM_input1 - CR1 - lekage1) * dt
INIT PD1 = 0
TRANSIT TIME = varies
INFLOW LIMIT = INF
CAPACITY = INF
INFLOWS:
RM_input1 = MIN(M_RM_INV,M_DPR1)
OUTFLOWS:
CR1 = CONVEYOR OUTFLOW
TRANSIT TIME = ROUND(NORMAL(5,1,22717))
lekage1 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = IF(occurance_of_failure1<=365)THEN(PD1)ELSE(0)
NO-LEAK ZONE = 0%
PD2(t) = PD2(t - dt) + (RM_input2 - CR2 - lekage2) * dt
INIT PD2 = 0
TRANSIT TIME = varies
INFLOW LIMIT = INF
CAPACITY = INF
INFLOWS:
RM_input2 = MIN(WIP,M_DPR2)
OUTFLOWS:
CR2 = CONVEYOR OUTFLOW
TRANSIT TIME = ROUND(NORMAL(5,1,32491))
lekage2 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = IF(occurance_of_failure2<=365)THEN(PD2)ELSE(0)
NO-LEAK ZONE = 1%
PRD_BPA(t) = PRD_BPA(t - dt) + (PRD_BPR - PRD_BTS) * dt
INIT PRD_BPA = 0
INFLOWS:
PRD_BPR = IF(TPRD>M_SR)THEN(TPRD-M_SR)ELSE(0)

```
OUTFLOWS:
   PRD_BTS = PRD_BPA
RM_in_transit(t) = RM_in_transit(t - dt) + (RM_dispatch - RM_received) * dt
  INIT RM_in_transit = 0
  TRANSIT TIME = varies
  INFLOW LIMIT = INF
  CAPACITY = INF
  INFLOWS:
   RM_dispatch = MIN(S_INV,M_RM_order)
  OUTFLOWS:
   RM_received = CONVEYOR OUTFLOW
     TRANSIT TIME = ROUND(NORMAL(5,1.6,30047))
S_INV(t) = S_INV(t - dt) + (S_AR - RM_dispatch) * dt
  INIT S_INV = 600
  INFLOWS:
   S_AR = ROUND(NORMAL(28,1,18379))
  OUTFLOWS:
   RM_dispatch = MIN(S_INV,M_RM_order)
WIP(t) = WIP(t - dt) + (CR1 + CR11 - RM_input2) * dt
  INIT WIP = 0
  INFLOWS:
   CR1 = CONVEYOR OUTFLOW
     TRANSIT TIME = ROUND(NORMAL(5,1,22717))
   CR11 = CONVEYOR OUTFLOW
     TRANSIT TIME = ROUND((EXPRND(0.8333,17077)))+ROUND(NORMAL(2,0.5,22717))
  OUTFLOWS:
   RM_input2 = MIN(WIP,M_DPR2)
UNATTACHED:
 M_DPR1 = ROUND(IF(PD1>0 OR WIP>=350 OR occurance_of_failure1<=365 OR lekage1>0 OR
 delay_DMF1>0)THEN(0)ELSE(IF(PRD_BTS<=5)THEN(NPR1)ELSE(IF(PRD_BTS>5 AND
 PRD_BTS<10)THEN(NPR1+.10*NPR1)ELSE(IF(PRD_BTS>=10 AND PRD_BTS<=25)THEN(NPR1+.20*NPR1)ELSE(NPR1+.30*NPR1)))))
UNATTACHED:
 M_DPR2 = ROUND(IF(PD2>0 OR WIP=0 OR occurance_of_failure2<=365 OR lekage2>0 OR
 delay_DMF2>0)THEN(0)ELSE(IF(PRD_BTS<=5)THEN(NPR2)ELSE(IF(PRD_BTS>5 AND
 PRD_BTS<=10)THEN(NPR2+.10*NPR2)ELSE(IF(PRD_BTS>10 AND PRD_BTS<=20)THEN(NPR2+.20*NPR2)ELSE(NPR2+.30*NPR2)))))
```

UNATTACHED:

M_POHS = (RM_in_transit+M_RM_INV)-RM_input1

UNATTACHED:

M_RM_order = IF(M_POHS<=M_RM_ROP)THEN(M_RM_Target_INV-M_POHS)ELSE(0)

UNATTACHED:

RM_order_BKLG = IF(M_RM_order>RM_dispatch)THEN(M_RM_order-RM_dispatch)ELSE(0)

UNATTACHED:

RM_Shortage = IF(M_DPR1>M_RM_INV)THEN(M_DPR1-M_RM_INV)ELSE(0)

UNATTACHED:

TPRD = PRD_BTS+PRD

M_RM_ROP = 200

M_RM_Target_INV = 350

NPR1 = 150

NPR2 = 150

occurance_of_failure1 = -(1/0.0001)*LOGN(1-(RANDOM(0,1,24697)))

occurance_of_failure2 = -(1/0.0001)*LOGN(1-(RANDOM(0,1,24137)))

PRD = ROUND(NORMAL(27,1,31051))

Appendix 7

Equations for stock-flow diagram shown in Figure 5.4

```
BPA(t) = BPA(t - dt) + (BPR - BTS) * dt
INIT BPA = 0
 INFLOWS:
    BPR = IF(TPD>SR)THEN(TPD-SR)ELSE(0)
 OUTFLOWS:
    BTS = BPA
BS_INV(t) = BS_INV(t - dt) + (BS_AR - BS_dispatch) * dt
INIT BS_INV = 500
 INFLOWS:
    BS_AR = (ROUND(NORMAL(28,1,18379)))
 OUTFLOWS:
    BS_dispatch = MIN(BS_INV,M_RM_order_to_BS)
delay_DMF1(t) = delay_DMF1(t - dt) + (lekage1 - CR11) * dt
INIT delay_DMF1 = 0
 TRANSIT TIME = 1
 INFLOW LIMIT = INF
 CAPACITY = INF
 INFLOWS:
    lekage1 = LEAKAGE OUTFLOW
     LEAKAGE FRACTION = IF(occurance_of_failure1<=365)THEN(PD1)ELSE(0)
     NO-LEAK ZONE = 1%
 OUTFLOWS:
    CR11 = CONVEYOR OUTFLOW
delay_DMF2(t) = delay_DMF2(t - dt) + (lekage2 - CR22) * dt
INIT delay_DMF2 = 0
 TRANSIT TIME = 1
 INFLOW LIMIT = INF
 CAPACITY = INF
 INFLOWS:
    lekage2 = LEAKAGE OUTFLOW
     LEAKAGE FRACTION = IF(occurance_of_failure2<=365 )THEN(PD2)ELSE(0)
     NO-LEAK ZONE = 1%
 OUTFLOWS:
    CR22 = CONVEYOR OUTFLOW
F_INV(t) = F_INV(t - dt) + (CR2 + CR22 - SR) * dt
INIT F_INV = 600
 INFLOWS:
    CR2 = CONVEYOR OUTFLOW
     TRANSIT TIME = ROUND(NORMAL(5,1,32411))
    CR22 = CONVEYOR OUTFLOW
 OUTFLOWS:
    SR = MIN(F_INV,TPD)
M_RM_INV(t) = M_RM_INV(t - dt) + (RMR_FRM_S + RMR_FRM_BS - RM_input1) * dt
INIT M_RM_INV = 500
 INFLOWS:
    RMR_FRM_S = CONVEYOR OUTFLOW
     TRANSIT TIME = ROUND(NORMAL(5,1,30013))
    RMR_FRM_BS = CONVEYOR OUTFLOW
     TRANSIT TIME = ROUND(NORMAL(5,1,30013))
 OUTFLOWS:
    RM_input1 = MIN(M_RM_INV,M_DPR1)
```

PD1(t) = PD1(t - dt) + (RM_input1 - CR1 - lekage1) * dt
INIT PD1 = 0
TRANSIT TIME = varies
INFLOW LIMIT = INF
CAPACITY = INF

INFLOWS:
RM_input1 = MIN(M_RM_INV,M_DPR1)
OUTFLOWS:
CR1 = CONVEYOR OUTFLOW
TRANSIT TIME = ROUND(NORMAL(5,1,22717))
lekage1 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = IF(occurance_of_failure1<=365)THEN(PD1)ELSE(0)
NO-LEAK ZONE = 1%

PD2(t) = PD2(t - dt) + (RM_input2 - CR2 - lekage2) * dt
INIT PD2 = 0
TRANSIT TIME = varies
INFLOW LIMIT = INF
CAPACITY = INF

INFLOWS:
RM_input2 = MIN(WIP,M_DPR2)
OUTFLOWS:
CR2 = CONVEYOR OUTFLOW
TRANSIT TIME = ROUND(NORMAL(5,1,32411))
lekage2 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = IF(occurance_of_failure2<=365)THEN(PD2)ELSE(0)
NO-LEAK ZONE = 1%

RM_in_transit1(t) = RM_in_transit1(t - dt) + (S_dispatch_rate - RMR_FRM_S) * dt
INIT RM_in_transit1 = 0
TRANSIT TIME = varies
INFLOW LIMIT = INF
CAPACITY = INF

INFLOWS:
S_dispatch_rate = MIN(S_INV,M_RM_order_to_s)
OUTFLOWS:
RMR_FRM_S = CONVEYOR OUTFLOW
TRANSIT TIME = ROUND(NORMAL(5,1,30013))

RM_in_transit2(t) = RM_in_transit2(t - dt) + (BS_dispatch - RMR_FRM_BS) * dt
INIT RM_in_transit2 = 0
TRANSIT TIME = varies
INFLOW LIMIT = INF
CAPACITY = INF

INFLOWS:
BS_dispatch = MIN(BS_INV,M_RM_order_to_BS)
OUTFLOWS:
RMR_FRM_BS = CONVEYOR OUTFLOW
TRANSIT TIME = ROUND(NORMAL(5,1,30013))

S_INV(t) = S_INV(t - dt) + (S_AR - S_dispatch_rate) * dt
INIT S_INV = 500
INFLOWS:

S_AR = IF(TIME>39 AND TIME <=45 OR TIME>=89 AND TIME<=96 OR TIME >=150 AND TIME<157 OR TIME>=200 AND TIME <=207 OR TIME>=300 AND TIME<=307) THEN(0) ELSE(ROUND(NORMAL(26,1,18379)))

OUTFLOWS:

S_dispatch_rate = MIN(S_INV,M_RM_order_to_s)

WIP(t) = WIP(t - dt) + (CR1 + CR11 - RM_input2) * dt

INIT WIP = 0

INFLOWS:

CR1 = CONVEYOR OUTFLOW

TRANSIT TIME = ROUND(NORMAL(5,1,22717))

CR11 = CONVEYOR OUTFLOW

OUTFLOWS:

RM_input2 = MIN(WIP,M_DPR2)

UNATTACHED:

M_DPR1 = ROUND(IF(PD1>0 OR WIP>=350 OR occurance_of_failure1<=365 OR lekage1>0 OR delay_DMF1>0)THEN(0)ELSE(IF(BTS<=5)THEN(NPR1)ELSE(IF(BTS>5 AND BTS<=10)THEN(NPR1+.10*NPR1)ELSE(IF(BTS>10 AND BTS<=20)THEN(NPR1+.20*NPR1)ELSE(NPR1+.30*NPR1)))))

UNATTACHED:

M_DPR2 = ROUND(IF(PD2>0 OR WIP=0 OR occurance_of_failure2<=365 OR lekage2>0 OR delay_DMF2>0)THEN(0)ELSE(IF(BTS<=5)THEN(NPR2)ELSE(IF(BTS>5 AND BTS<=10)THEN(NPR2+.10*NPR2)ELSE(IF(BTS>10 AND BTS<=20)THEN(NPR2+.20*NPR2)ELSE(NPR2+.30*NPR2)))))

UNATTACHED:

M_POHS = (RM_in_transit1+M_RM_INV+RM_in_transit2)-RM_input1

UNATTACHED:

M_RM_order_to_BS = IF(M_RM_order_to_s=0)THEN(M_RM_required)ELSE(0)

UNATTACHED:

M_RM_order_to_s = IF(S_INV< .85*M_RM_required)THEN(0) ELSE(M_RM_required)

UNATTACHED:

M_RM_required = IF(M_POHS<=M_RM_ROP)THEN(M_RM__TINV-M_POHS)ELSE(0)

UNATTACHED:

TPD = BTS+PRD

M_RM_ROP = 200

M_RM__TINV = 350

NPR1 = 150

NPR2 = 150

occurance_of_failure1 = -(1/0.0001)*LOGN(1-(RANDOM(0,1,24697)))

occurance_of_failure2 = -(1/0.0001)*LOGN(1-(RANDOM(0,1,9343)))

PRD = ROUND(NORMAL(28,1,31051))

List of Publications

International Journals Published

1. Sanjita Jaipuria and S.S. Mahapatra, (2014), An Improved Demand Forecasting Method to Reduce Bullwhip Effect in Supply Chains, **Expert System with Applications**, Vol. 41(5), 2395-2408.

2. Sanjita Jaipuria and S.S. Mahapatra (2015), Performance improvement of manufacturing supply chain using back-up supply strategy, **Benchmarking: An International Journal**, Vol. 22(3), 446-464.

International Journals Accepted

Sanjita Jaipuria and S.S. Mahapatra, A System Dynamic Approach to Study the Behaviour of Serial Supply Chain under Uncertain Environment, I**nternational Journal of Services and Operations Management.** (in press).

Internal Journals Communicated

Sanjita Jaipuria and S.S. Mahapatra, "A Hybrid Approach of WT and AI Techniques for Forecasting", **Engineering Application of Artificial Intelligence**. (under review).

National Journal Accepted

1. Sanjita Jaipuria and S.S. Mahapatra (2014)," Analysis of Manufacturing Supply Chain Performance under Uncertain Environment", **Industrial Engineering Journal**, 7(5), 17-24.

Book Chapter

1. Sanjita Jaipuria and S.S. Mahapatra (2013). Reduction of Bullwhip Effect in Supply Chain through Improved Forecasting Method: An Integrated DWT and SVM Approach. **In Swarm, Evolutionary, and Memetic Computing** (pp. 69-84). Springer International Publishing.

International Conferences

1. Sanjita Jaipuria and S.S. Mahapatra, Performance Evaluation of Supply Chain under Manufacturing Uncertainty. **The 12th Consortium of Students in Management Research (COSMAR-2012)**, at Indian Institute of Science Bangalore, during 16th-17th November 2012.

2. Sanjita Jaipuria and S.S. Mahapatra, Analysis of Manufacturing Supply Chain Performance under Uncertain Environment" (2012). **1st International Conference on Best Practices in supply chain management (BPSCM2012),** at **Institute of Technical Education and Research** Bhubaneswar, during 22nd– 23rd November 2012.

3. Sanjita Jaipuria and S.S. Mahapatra, Performance Analysis of Assemble-to-Stock Production System under Uncertain Environment using System Dynamic Approach. **16th Annual International Conference Society of Operations Management**

(SOM2012), at Indian Institute of Technology Delhi, during 21st – 23rd December 2012.

4. Sanjita Jaipuria and S.S. Mahapatra, Estimation of bullwhip effect and net-stock amplification in supply chain using ARIMA and GARCH process, **The 13th Consortium of Student in Management Research (COSMAR 2013)**, at Indian Institute of Science Bangalore Bangalore, during 15th -16th November 2013.

5. Sanjita Jaipuria and S.S. Mahapatra, Optimization of Backlog Quantity in Serial MTS System under Uncertain Environment, **4th NIRMA University International Conference on Engineering (NUICONE 2013)** at NIRMA university, Ahmedabad, during 28th-30th November 2013.

6. Sanjita Jaipuria and S.S. Mahapatra, Reduction of Bullwhip Effect in Supply Chain through Improved Forecasting Method: An Integrated DWT and SVM Approach", **4th Joint International Conference on Swarm, Evolutionary And Memetic Computing SEMCCO 2013 and FANCCO 2013** at Sri Ramaswamy Memorial University (SRM), Chennai, during 19th -21st December 2013.

7. Sanjita Jaipuria and S.S. Mahapatra, "A Hybrid Approach of Discrete Wavelet Transform and Genetic Programming for Improving Forecasting in Supply Chain Management". **17th Annual International Conference of Society of Operations Management (SOM 2013), Indian Institute of Technology, Chennai**, during 20th – 22nd December 2013.

8. Sanjita Jaipuria and S.S. Mahapatra, "A Hybrid Approach of Wavelet Theory and Adaptive Neuro-Fuzzy Inference System to Improve the Forecasting Accuracy", **1st International Conference on Mechanical Engineering: Emerging Trend for Sustainability (ICMEET 2014), at** Maulana Azad National Institute of Technology, Bhopal, during 29th - 31st January 2014.