SUPPLY CHAIN MODELING AND SIMULATION USING AGENTS

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DECLARATION

I hereby declare that this thesis is my original work and it has been written by me in its entirety. I have duly acknowledged all the sources of information which have been used in the thesis.

This thesis has also not been submitted for any degree in any university previously.

Sha Meng 16 Jan 2014

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Summary

Good supply chain management is crucial for business success in today's increasingly complex, global, and competitive business environment. Agent-based modeling and simulation (ABMS) is a natural fit to supply chains as it uses a bottom-up approach by modeling each supply chain entity as an agent which can interact with one another and response to changes based on its own interest. ABMS has been implemented to investigate, analyze, and diagnose supply chains. However, most of existing ABMS approaches are complex, and resulting models are hard coded and difficult for non-technical users to understand, manipulate and analyze.

This thesis proposes a business process modeling notation (BPMN) based framework for modeling and simulation of integrated supply chains. BPMN is a widely recognized unified graphical modeling notation for business processes. A key advantage of BPMN is its ability to transform documentation of process flows to executable process model with simple notation. The proposed framework combines the advantages of ABMS and BPMN and it is validated by replicating an existing multisite specialty chemicals supply chain model built in MATLAB SIMULINK. The built BPMN-based model has a more natural representation of the chemical supply chain and faster simulation. Various scenarios also demonstrate that a BPMN-based supply chain model is easier to understand, manipulate, and has high level of scalability and flexibility.

The strict safety and environmental regulation on chemical storage and transportation, expensive purchasing, leasing and maintenance charge of tank fleet, and the serious consequences from tank cars shortage make tank fleet sizing become an essential part of chemical supply chain management. This thesis builds an agent-based simulation model of a multisite chemical supply chain through BPMN-based framework

to address the tank fleet sizing problem. The simulation model explicitly takes into account of the independence of supply chain entities and their interactions across various supply chain operations such as replenishment planning and order assignment. Tank fleet is modeled as a set of objects that travel across the supply chain. The supply chain model is simulated with five tank fleet routing policies under different fleet sizes and various conditions. Optimal tank fleet routing policy and size are determined based on the comparison of the simulation results. This thesis also explores the impact of transportation disturbance on supply chain performance by introducing transportation delays into model, and studies the tank fleet switching problem involving multiple chemical products.

In conclusion, BPMN-based supply chain modeling and simulation framework make it easier to design, model, simulate and manipulate agent-based model of supply chains and it has high level of scalability and flexibility. BPMN-based model serves as a qualitative and quantitative tool to support decision making in chemical supply chains including handling chemical supply chain disturbances and policy evaluation.

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Chapter 1

Introduction

1.1 Background

A supply chain constitutes the various entities and activities involved in producing and delivering value to end customer in the form of product or service (Christopher., 1992; Ganeshan and Harrison, 1995; Lee and Billington, 1995). It is typically characterized by (1) material flows from the suppliers to the customers, (2) finance flows in the opposite direction, and (3) information flows in both directions. In reality, the organizations in most supply chains are not simply and sequentially linked; they can be cross-linked. For example, a plant might directly deliver products to retailers or customers. Thus, some researchers used “supply network” to describe the complex structure of supply chain (Harland and Knight, 2001). Through this whole thesis, “supply chain” is used as the standard term to describe this integrated system.

Supply chains commonly include operations for raw material procurement, storage, transportation, conversion, packaging, and distribution. These operations involve numerous heterogeneous entities with different (sometimes conflicting) interests, roles and dynamics with uncertainties, resulting in complex dynamics which in turn could lead to unforeseen domino effects. Management of these supply chain operations, termed supply chain management, is necessary to order to ensure that the supply chain performs smoothly and efficiently (Lummus and Vokurka, 1999). Supply chain management is achieved through a broad range of services, such as sourcing, contracting, planning, scheduling, monitoring, and financing. In today’s increasingly complex, global, and competitive environment, enterprises consider supply chain management to be a key factor for achieving better profitability, efficiency and sustainability. These motivate the development of simulation models of the supply chain that can capture the behavior of these entities, their interaction and the resulting dynamics. These models should also allow users to manipulate the policies of particular entities and disturbance so that they can be used to evaluate the impact of specific decision-making or disruption on supply chain performance, to identify the bottleneck of the supply chain, and further to serve as valuable quantitative tools in decision-making in supply chain management.

Agent-based modeling, a relatively new computational modeling paradigm, is a powerful simulation modeling technique for complex dynamic systems. For the past few years, it has been implemented in various areas including market simulation and flow simulation. In agent-based modeling, a system is modeled as a collection of autonomous entities called agents (Bonabeau, 2002). Each agent has its own state and interest, and makes decisions based on series of rules. Agents can execute various behaviors commensurate with the system they represent, such as producing, delivering, buying or consuming. Agents are also able to interact with each other, and to perceive their environment and respond to changes. They can be even designed to be proactive. These characteristics make Agent-based modeling a suitable technique to model supply chains.

1.2 Research Objectives

There are two specific objectives for this proposed research:

1) **To develop a new agent-based modeling approach for supply chains**

   Agent-based modeling of supply chain is challenging as entities in the supply chain have many complicated internal and external activities including pricing, bidding and negotiation, which are not easy to be described and analyzed. After an agent-based model is built, it is also very difficult to manipulate as a complex model might have hundreds of files and these files are poorly organized. If the modeler wants to make policy changes or introduce disturbances, it would not be straightforward to figure out which specific file(s) should be modified. Our approach is to implement Business Process Management Notation (BPMN) into agent-based modeling of supply chain so that the activities in the supply chain can be described as a collection of flow objects. These flow objects represent behaviors or events appropriate for the system, such as sending a request or receiving an order. Related flow objects are linked with each other by sequence flow or message flow, organized as a specific workflow. In such a way, a supply chain can be easily modeled, well organized and directly visualized in the model itself. Moreover, the policies of entities (agents) and disturbance could be easily manipulated in the corresponding workflows. The proposed modeling framework is validated by replicating an existing multisite specialty chemicals supply chain model presented in previous studies.

2) **To support tank fleet management through the developed new modeling approach**

The strict safety and environmental regulation on chemical storage and transportation, expensive purchasing, leasing and maintenance charge of tank fleet, and the serious consequences from tank car shortage make tank fleet sizing become an essential part of chemical supply chain management. Tank fleet sizing is not an isolated problem. It is closely related to tank fleet routing policy and other management policies and rules including inventory management policy. A complex chemical supply chain is presented and modeled through the proposed agent-based modeling framework. Subsequently, the developed agent-based model are used to formulate tank fleet management policies, study the performance of chemical supply chain under different scenarios and explore the effective strategies to manage tank fleet.

1.3 Outline of the Thesis

The rest of the thesis is organized as follows:

Chapter 2 discusses the supply chain management concept and provides a comprehensive literature review on agent-based modeling of supply chain and its applications. It also shows that agent-based modeling in chemical supply chain has not received adequate attention.

Chapter 3 describes BPMN and demonstrates how BPMN can be employed for development of agent-based models. Firstly, the advantages of BPMN and the possibility of implementing BPMN in agent-based model are discussed. Then the key elements of BPMN are introduced with simple supply chain operations as illustrations. The framework steps are described afterward.

Chapter 4 provides a case of multisite lube oil supply chain to illustrate the implementation of new agent-based modeling framework presented in previous chapter. It describes how supply chain entities, different policies, production operations, product transportation and also the supply chain conversations can be conceptualized into BPMN-based model.

Chapter 5 presents a new complex chemical supply chain model involving plants, warehouses, customers and market, as well as functional department such as order coordinator, replenishment coordinator and logistics department. Various tank fleet management policies are developed through case studies and implemented into the model. The performances of chemical supply chain under different scenarios are compared and discussed.

Chapter 6 demonstrates the advantages of the new ABMS framework by studying the ease of extension from the model developed in Chapter 5. The first section discusses the need for transportation disturbance studies in chemical supply chains, and compares the proposed tank fleet management strategies with two new local policies under the condition of transportation delays. The second section introduces the multi-product and tank fleet transition concept and demonstrates how tank fleet transition can be realized into the model described in the Chapter 5.

Chapter 7 presents the overall conclusion of this research thesis and a discussion of future research.

Chapter 2

Literature Review

2.1 Supply Chain Management

A supply chain is a network of organizations, people, resources and technology involved in the activities producing and delivering value to end customer in the form of products and services. Figure 2.1 shows an example of supply chain: raw material suppliers sell raw materials to tier suppliers that sell to primary manufacturers. Manufacturers produce products and send products to distribution warehouses that transport them to retailers. Finally, customers buy the products from retailers.

The Council of Supply Chain Management Professionals (CSCMP) defines supply chain management as follows:

> *"Supply chain management encompasses the planning and management of all activities involved in sourcing and procurement, conversion, and all logistics management activities. Importantly, it also includes coordination and collaboration with channel partners, which can be suppliers, intermediaries, third party service providers, and customers. In essence, supply chain management integrates supply and demand management within and across companies."*

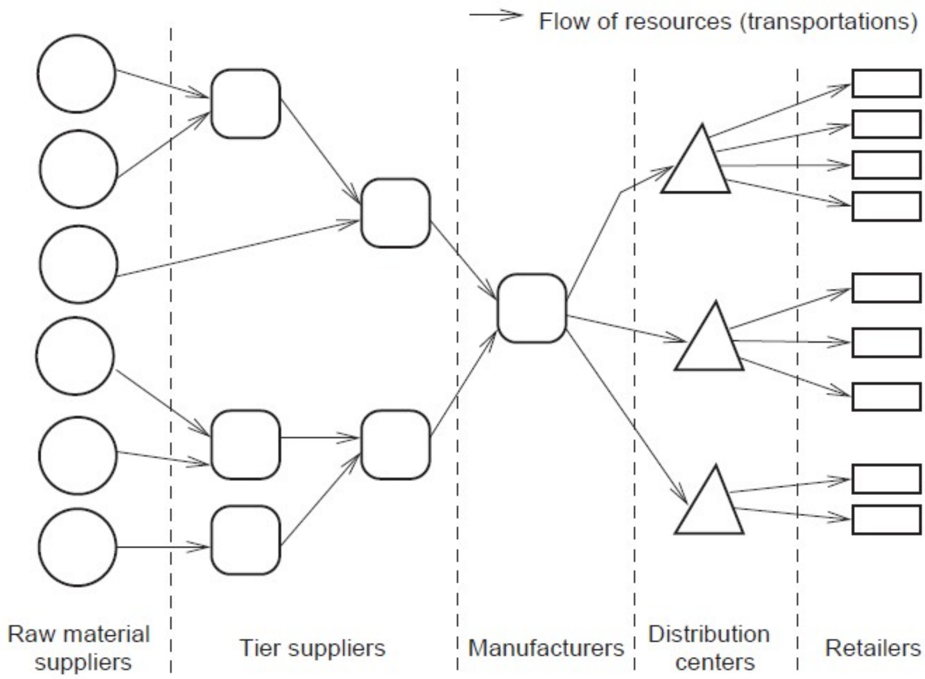


Figure 2.1: An example of supply chain (Moyaux et al., 2006)

Supply chain management involves decision making at different levels. At the long term level, companies have to decide about the structure of supply chains over the next few years, such as the location of warehouses and plants, production system, the composition of the products and raw material supplier selection. At the midterm level, decisions have to be made on inventory policies, distribution planning policies, production capacity planning and contracts of raw materials. At the operational level, various decisions are made at different departments to ensure the smoothness of the material flows so that the customer orders can be fulfilled at a satisfactory level. For instance, warehouses decide the transportation plans for accepted orders, plants decide daily or weekly production plans, and procurement department decides on raw material ordering. The decision making across different levels requests a comprehensive systemic view of the supply chains so that they can be coordinated to achieve higher profit and improve customer service level.

Supply chains consist of independent entities that operate autonomously with different objectives and subject to different sets of constraints. The flow of materials, information and allocation of resources result in strong connections among the entities which in turn determine customer service level, profit and costs. The welfare of any entity depends on the performance of the other entities and their willingness and ability to collaborate. Besides, lots of nonlinearities lie in the supply chains, such reliance on forecasts at each stage for base-stock decisions and differences in lot-sizing and transportation capacities. All these result in complexity and unpredictable domino effects. Hence, over the past decades, many scholars have studied supply chain dynamics from the perspective of complex systems (Choi et al. 2001; Peck, 2005; Surana et al., 2005; Datta et al., 2006).

For instance, increasing variability in market demand can get amplified along the supply chain due to bullwhip effect (shown in Figure 2.2), which increases uncertainty and results in the following consequences (Moyaux et al., 2006):

1) Excessive inventory investment: Since the bullwhip effect makes the demand more unpredictable, all upstream entities in the supply chain need to safeguard themselves with excessive inventory level to against the variations to avoid stock-out;
2) Poor customer service: In spite of having safety stocks there is still the hazard of stock-outs caused by the demand variance, resulting in a decrease in the customer service level;
3) Lost revenues and reduced productivity: In addition to the poor customer service level, stock-out may also cause lost revenues which in consequence would cause reduced productivity;
4) Ineffective planning and scheduling: Big variance in demand makes transportation planning, production planning and scheduling ineffective;
5) Difficult decision-making: Decision-makers have to react to demand fluctuations and adapt production and inventory capacities to meet peak demands;
6) High financial cost: The maintenance of higher safety stock and inventory level, and the ineffectiveness in production and transportation would induce a high financial cost.

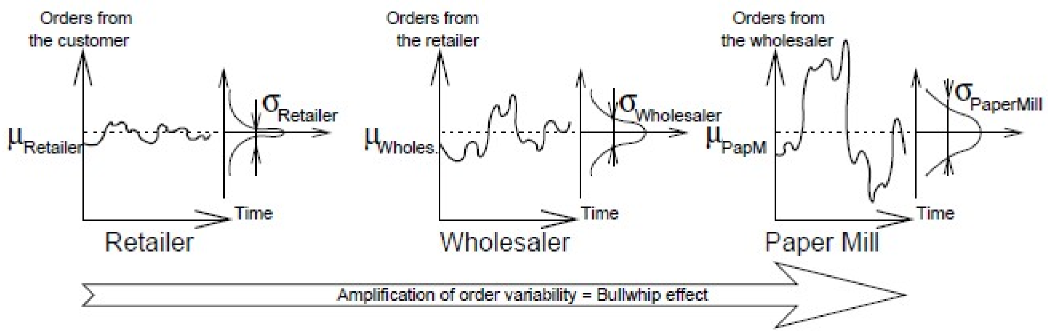


Figure 2.2: The bullwhip effect (Moyaux et al., 2006)

Managing supply chains also faces the challenge from present increasingly complex, global, and competitive environment. In the last two decades, companies started to outsource their non-core activities to third party so that the fixed capital investment and operating costs can be reduced and more resources can be invested on their core competence. Global sourcing is one type of the sourcing which exploits global efficiency in the delivery of products and services in terms of low cost resources, low cost labor, low tax and other economic factors, such as low cost trained labor in China and low cost programmers in India. These practices make supply chain more complex and sometimes put companies in a riskier situation because of political risks, long lead time and difficulties of product quality monitoring. For instance, Apple returned as many as eight million iPhones to its major manufacture Foxconn due to quality problems in 2013. 2011 Thailand floods hit the global production of hard disk drives, which caused a worldwide shortage and the prices of most hard disk drives almost doubled. Many global electronic and automobile supply chains were greatly impacted. All these complexities make supply chain management difficult, and motivate the development of quantitative models for system analysis.

2.2 Supply Chain Modeling Approach

Supply chain modeling approaches can be characterized into mathematical programming and simulation modeling. In mathematical programming approaches, supply chains are modeled as a set of mathematical equations of system observables such as flows and states, with objective(s) to be maximized or minimized and well-defined constraints which limit the solutions. These mathematical models are mix integer programming (MIP) based and require optimization algorithms to solve. Thus, mathematical programming approach requires:

1) A rigorous mathematical representation of the system
2) Solution/optimization algorithm

Therefore, a top-down methodology is implemented to formulate the problem. Objective(s) must be well quantified in the formulation of key state variables that define the system. The relationships between these state variables and those between state variables and local variables are also required. In order to make these variables mathematically tractable to construct the model, a number of assumptions have to be made to simplify the problems. For instance, multiple supplier or customers may be simplified and abstracted to one entity, the competition among entities may be ignored and the complexity of the supply chain architecture may be reduced. The simplification and the assumptions limit the extent to which the models reflect the reality of the complex relationships of supply chains, and the resulting optimal solution may be infeasible in the real supply chain.

Formulating the objective(s) to be optimized can be difficult, especially for modern supply chains composed of many independent elements. A clearly quantified objective(s) is not obvious in such systems. Take a multi-site manufacturing supply chain containing many plants for example. Each plant seeks to reduce its own costs and optimize individual profits, possibly at expense of the whole enterprise. In such situation, neither minimizing combined costs of all plants nor maximizing combined profits may be reasonable objectives.

The model formulation of mathematical programming approaches is brittle (North and Macal, 2007). A change in the formulation, e.g., continuous variable to discrete variable linear relation to nonlinear relation may require an entirely different solution algorithm. Besides, the solution of such models is also brittle. Some models may produce a highly optimal solution for a set of constrains and a static point in time, but these solutions may not prove to be robust in dynamic environments (Blackhurst et al., 2005). Optimal solution points are highly unstable once a slight change is made in the problem data. As a result, these models are very brittle (Davidsson and Wernstedt, 2002; North and Macal, 2007). In this regard, mathematical programming approach is not suitable to implement in decision support on complex supply chains. It is more suitable to be employed in the operational level, such as production planning and scheduling, where the problem structure is fairly static and brittleness of the model is not an important concern.

Modeling and simulation is a promising approach for decision support in supply chains (Petrovic et al., 1998; Julka et al., 2002; Thierry et al., 2008; van Dam et al., 2009; Longo, 2011). Simulations can help managers identify the various behaviors that the real system could exhibit, gain deep insights into key system variables and their interactions, and enhance their ability to extrapolate and foresee the effects of events. Terzi and Cavalieri (2004) did a comprehensive review on over 80 papers and showed the features and benefits of modeling and simulation in the supply chain context: it allows enterprises to conduct what-if analysis and evaluate consequences of operational alternatives quickly before real implementation (Chang and Makatsoris, 2001). The simulation result changes as the assumptions and data used in the model change. It can effectively explore a board range of managers' problems and situations that the enterprise may face (North and Macal, 2007)

Discrete event simulation is a common approach for supply chain modeling and simulation (Labarthe et al., 2007; Terzi and Cavalieri, 2004). It is a technique that models system processes as a chronological sequence of events (North and Macal, 2007). In discrete event simulation, time is represented only at discrete points, and each event (such as placing order) is scheduled to occur at these discrete time points. This in turn results in a sequence of events to be scheduled and processed. The state of the model changes over time which is triggered by these discrete events. No state change is assumed to occur between consecutive events, thus the simulation can directly jump from one event to the next.

Discrete event simulation focuses on fixed groups of entities that perform fixed sets of processes. The relationships between the entities and processes are typically defined at the start of simulation, rather than being generated or destroyed during the simulation. However, the system structure of supply chain varies over time. For example, enterprise may select new material suppliers; some customers may quit the marketing network of the enterprise; enterprise may set up a new plant or sell a plant at certain time point; plant may change the production process because of the implementation of certain new technology. In such situations, discrete event simulation may not be a suitable modeling framework.

From the review of the modeling approaches discussed above, the requirements of a comprehensive modeling framework for supply chain can be summarized as follows:

1) It has to capture the changing in the system structure of supply chains over time.
2) It has to account for the independence of the various elements comprising supply chains, their decision structure and the strategic structure.
3) It has to account for the complex interactions between the entities in both technical and social level by integration of the material structure and the information structure into the model.
4) It has to capture the dynamically changing supply chain environment through modeling of the market mechanisms, and other agents and phenomena which is outside the supply chain but influences the various internal entities.

2.3 Agent-Based Modeling

Agent-based modeling and simulation (ABMS) can fulfill the requirements summarized in previous section. It uses a bottom-up approach. It starts by identifying the most basic building blocks, termed agents (entities in the supply chain, e.g. customer, warehouse and etc.) of the supply chain; specifying their individual behaviors and decision making mechanisms; and identifying the interactions and relationships between the agents and the external environment. As a result, the structure of the supply chain model is determined by all its elements (agents) and their aggregation to more complex systems across a number of hierarchical layers. The behavior of the overall supply chain model emerges as a result of behaviors of all its agents connected with each other and the environment the system is embedded in.

The advantages of agent-based models can be summarized as follows:

1) Agent-based model is natural description of the systems: It is technically easy but conceptually deep. The behavior of the system is larger than the sum of the parts;
2) Agent-based model is flexible: Modeler can tune the level of complexity in terms of heterogeneous agents and the way they interact. Learning and adaption can also be added into agent;
3) Agent-based model is scalable: Modeler can manipulate the number of agents and the layers of system hierarchy, according to the size of the problem he is interested in;
4) Agent-based model captures emergent phenomena: Agents behavior discontinuously and their interactions are heterogeneous, and thus can generate network effects.

As a new modeling and simulation technique, ABMS offers some advantages in the context of supply chains. Firstly, ABMS has a more natural fit to real industrial systems. The modeled elements are individuals in the supply chains, which leads to more realistic observations (Thierry et al., 2008). ABMS is not limited by process complexity and can deal with numerous interacting phenomena. It can capture the behavior of the entities in the system, their interactions and the resulting dynamics. Secondly, an agent-based model can be translated back to practice easily and thus supports direct experimentation (Parunak et al., 1998) since users can manipulate policies of particular entities in the model and evaluate the impact on the supply chain. Further, bottlenecks in the supply chain and possible solutions can be directly explored. Thirdly, information sharing is becoming crucial for efficient decision-making in today's industries. A large amount of operational information is available to decision-makers at low cost because of the recent rapid developments in information and communication technology (Longo, 2011). ABMS offers an effective tool to identify and examine information sharing strategies to achieve a better supply chain performance (Ye and Farley, 2006). Besides, information technology provides sufficient amount of real data to train and validate supply chain models, and also offers a possibility to do real time evaluation of plans and schedules. As a result, ABMS serves as a valuable quantitative tool in decision-making for real-world supply chain management. A number of companies, such as Procter & Gamble (Garcia, 2005) and Macy's (Bonabeau, 2002) have reported the use of ABMS in supply chain management.

The primary focus of agent-based modeling is the building block called agent. Agent is a discrete entity that has its own state and interest, and makes decisions based on series of rules. Agents can take independent behaviors commensurate with the system they represent. For instance, agents can perform behaviors as producing, delivering, buying or consuming in agent-based models of supply chain. Wooldridge and Jennings (1995) summarized the characteristics of agent:

(1) Autonomy: Agent operates without the direct intervention of humans or others, and has some kind of control over its actions and internal states;

(2) Social ability: Agent can interact with other agents via agent-communication language;

(3) Reactivity: Agent perceives environment and responds in a timely fashion to the changes that occur in it;

(4) Pro-activeness: Agents do not simply act in response to other agents and their environment; they are able to exhibit goal-directed behavior by taking the initiative.

There is no rule to define or restrict the entity that should be modeled as an agent in agent-based models of supply chain. It is dependent on the size of the problem and the level of details that modeler is trying to capture in the model. Take the supply chain shown in Figure 2.3 for example. If the modeler is interested on the global supply chain of a specific chemical, he can model each enterprise involved as an agent as well as the logistics provider. Then he can build up the model by specifying the internal functions of each enterprise and logistics provider and their interactions (e.g. mass flow and information transactions). However, if the modeler is interested in the performance or decision-making process of a specific enterprise in the global environment, he can model this enterprise as a collection of agents. In this situation, for the particular enterprise, an agent could represent a single department or a combination of departments such as sales agent and production agent; for the other enterprises, they can either be modeled as a collection of agents or modeled as a single agent.

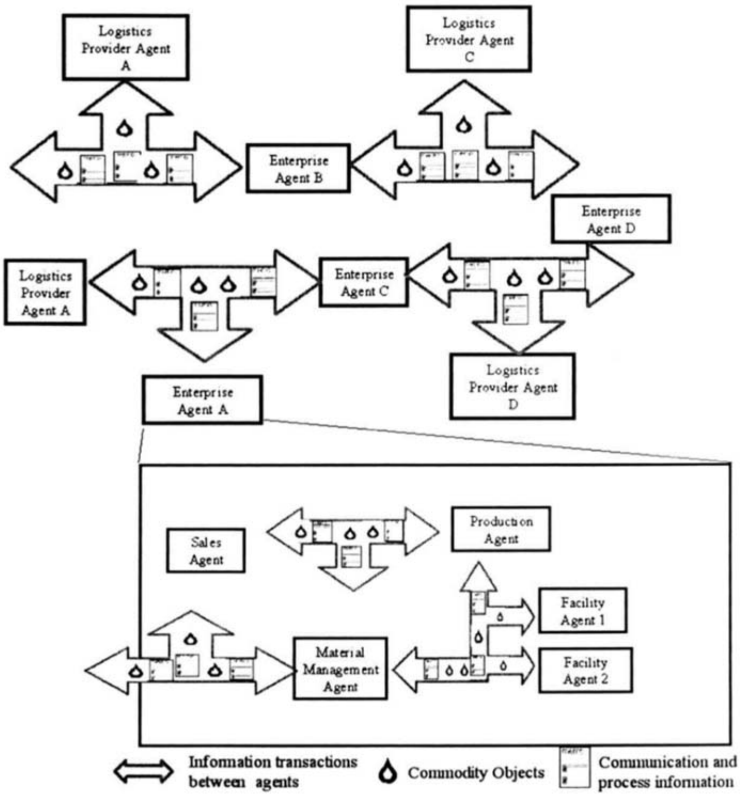


Figure 2.3: An example of agent-based model of supply chain (Julka et al., 2002)

2.4 Survey of Agent-Based Models of Supply Chain

We have done a literature survey on agent-based models of supply chain, covering over one hundred journal papers from Scopus published in the five years from 2006 to 2010, and continued monitoring the new papers till the time of thesis writing (i.e. 2013). From our survey, most of the researchers working on agent-based models of supply chain focused on the following three aspects:

1) To enhance the functionality or intelligence of supply chain agents through implementation of widely used techniques including machine learning, optimization algorithms and neural network;

2) To develop new approaches for more efficient and effective coordination and negotiation among supply chain agents in various problems such as order management and replenishment planning;

3) To provide decision support through modeling and simulation of supply chain for specific industry or product.

Shen et al. (2006) did a comprehensive review on agent-based models of manufacturing system and argued that most of the researchers focused on the fundamental research to enhance intelligence of agents and effective collaboration mechanism. From our survey, the research focus remains unchanged in the past few years as the majority of the papers in our survey still focus on the enhancement of agent functionality and the development of collaboration framework. Some examples are illustrated as follows:

1) Learning of supply chain agent:
    a. Kim et al. (2008) employed action-reward learning method and developed an asynchronous action-reward learning model which learned action cost faster than conventional action-reward leaning model. The authors built a simple two-stage serial supply chain model involving only supplier and retailer, and proposed two situation reactive inventory control models with non-stationary customer demand to study how the proposed learning model can be implemented to reduce average inventory cost.
    b. Jiang et al. (2009) proposed a case-based reinforcement learning (CRL) algorithm for dynamic inventory control in an agent-based model of two-echelon supply chain involving retailer and customer. The parameter values of two inventory review methods were learnt using the proposed algorithm to satisfy target service level under nonstationary customer demand.
    c. Valluri et al. (2009) applied agent-based modeling to investigate the comparative behavioral consequences of three simple reinforcement learning algorithms in a simple linear supply chain with five agents: customer, retailer, wholesaler, distributor and factory.

d. Chaharsooghi et al. (2008) addressed supply chain ordering management problem and implemented Q-learning algorithm to develop an effective reinforcement learning ordering mechanism for ordering management.

Majority of agent-based supply chain models in machine learning studies are simple sequential supply chains. Some even only have two echelons. Besides, the supply chain agents only have ordering and distribution functions. As a result, these developed algorithms might not be effective if they are implemented into a complex supply chain.

2) Optimization of supply chain operations:

a. Venkatadri et al. (2006) applied optimization in demand planning to help planner of the supplier make promise orders (price and due date) for the customers. The supply chain studied only have three entities (agents): one represents customers, one represents suppliers and the last represents centralized planner negotiating with customers.
b. Lin et al. (2008) employed genetic algorithm into supplier agent to plan quasi-optimal order fulfillment schedules to meet customers' demands. The supply chain in their study has two stages: supplier agent(s) and customer agent.
c. Mele et al. (2006) implemented genetic algorithm and simulation-based optimization to improve the operation of supplier under demand uncertainty. Each entity in the supply chain including plants, warehouses, distribution centers, and retailers, is represented as an agent. Beside, a central agent was employed to deal with the communication among the agents as well as the coordination through optimization and data analysis tools.
d. Ivanov et al. (2010) applied an optimization algorithm to solve the problem of planning and control in each agent along the supply chain and suggested a feed-back based, closed-loop adaptive supply chain optimization methodology for supply chain management. The agent-based model in their study contains enterprises and supply chain coordinator.

3) Decision making in supply chain agent:

    a. O'Leary (2008) did an overview of decision support applications for real-time enterprises and a detailed investigation into supporting real-time supply chain decisions. The agents in their study are intelligent agent dealing with monitoring and data analysis of the supply chain and further served in adaptive planning and scheduling.
    b. Wang et al. (2009) studied the mechanism of automatic decision making among software agents in service composition problem. Agents in their model deals with customer order services, procurement service, preprocess service, assembly service and prost-service.

    Agents in such kind of studies are not used to model the actual entities but the controllers that can be placed in the system.

4) Cooperation and negotiation among supply chain agents:

    a. Lin et al. (2006) integrated agent-based cooperative model and negotiation mechanism to resolve constraints in fulfilling supply chain orders by satisfying constraints. Intelligent agents were employed to model the supply chain entities: customer, manufacturers and supplier. Each agent has belief database, negotiation base, local scheduler, and coordination rules. Each agent communicated and cooperated with one another through coordination engine using proposals and counter-proposals.
    b. Chan et al. (2006) proposed a coordination mechanism on early order completion contract with demand uncertainty to minimize the negative impacts of demand uncertainty. An agent-based simulation model including one retailer and four suppliers is built to evaluate the performance of proposed approach.
    c. Zhang et al. (2010) identified and examined five information sharing strategies in B2B e-hubs. An agent-based E-Hub model was built which contained four types of agents: end customer, buyer, seller and supplier. Agents interacted with each other through orders, and their performances under different information sharing strategies were measured and analyzed.

d. Junga, et al. (2008) proposed a decentralized supply chain planning framework based on the minimal-information sharing between the manufacturer and the third party logistics provider. Manufacture and 3PL provider were modeled as agents that have their own database and planning systems.

The papers discussed above are related to various supply chain problems including order management and inventory management. Besides, planning strategy is also an essential topic in supply chain.

a. Frayret et al. (2007) combined agent-based technology and operation research tools, and proposed generic software architecture for the development of an experimentation environment to design and test distributed advanced planning and scheduling systems. The architecture was then configured into agent-based supply chain in lumber industry, which contains planning unit manager agent, source agent, deliver agent, make agent, and warehouse agent.
b. Forget et al. (2008) continued the work of Frayret et al. (2007), and developed a multi-behavior planning agent model using different planning strategies where decisions were supported by a distributed planning system by taking agility and synchronization into consideration.
c. Ivanov et al. (2010) introduced a new conceptual framework for multi-structural planning and operations of adaptive supply chains with structure dynamics considerations.

Some researchers are interested in the phenomenon of supply chain. For example, Fazel Zarandi et al. (2008) used a modified Hong Fuzzy Time Series with a genetic algorithm module to simulate the bullwhip effect and implemented a back propagation neural network for defuzzification and forecast the demand in fuzzy data. At last, an agent-based model of sequenced supply chain was developed to reduce the bullwhip effect. Their supply chain model contains manufacturer agent, distributor agent, wholesaler agent, retailer agent and other software agents that took in charge of information sharing and decision of best ordering policy through simulation module and genetic algorithm.

Among the papers in our survey, majority of them worked on simple sequenced generic supply chains, such as two-stage supply chain (e.g. supplier-customer or retailer-customer) and three-stage supply chain (e.g. supplier-retailer-customer). There are only ten papers working on specific industries or products: fashion industry, Canadian lumber industry, electricity supply chain, composite electronic products, chemical supply chain, and construction industry. As discussed above, Frayret et al. (2007) and Forget et al. (2008) worked on the planning strategy in Canadian lumber industry. In their model, some agents represent the core process operations while the others represent the control programs to coordinate the whole process. Lo et al. (2008) proposed an e-fashion supply chain management system with a web-based multi-agents design. Typical management information system development procedure was integrated into the system, making the system behavior more intelligent. There are two types of agents in this system: converting agents and application agents. Converting agents are acting on the interface between users and system. Their role is to manage the input and output information. Application agents are sitting on the layer between the database and conversation layer. Their role is to do scheduling and planning with the assistance of optimization tools. Xu et al. (2008) designed an agent-based model for simulating residential electricity consumption. The supply chain model contains consumer agent, power supply agent and policy maker agent. The author argued that the simulation model can serve as a useful tool to evaluate price policies.

From 2011 to 2013, there are two new journal papers studying on specific industries. One is working on the petroleum supply chain (Sinha, et al. 2011) and the other one is working on the pharmaceutical supply chain (Jetly et al., 2012). Sinha et al. (2011) applied agent based technology to model the petroleum supply chain from extraction till customer delivery. In their model, core operations rather than companies or departments are modeled as agents. Each operation agent also has subagents to represent their components. Negotiation framework was employed to ensure effective use of available resources so as to maintain sufficient inventory for processing at each stage of the supply chain. Jetly et al. (2012) developed a multi-agent simulation of the supply chains associated with the pharmaceutical industry. Manufacturers, suppliers and distributors were modeled as agents in their model, which interacted with each other to produce and distribute drugs. Their model was validated using real financial data.

2.4.1 Agent-Based Supply Chain Models of Chemical Supply Chains

Chemical industry is one of the world's largest manufacturing industries, producing thousands of chemicals and formulations. Compared with other industries, chemical industries supply chain is very complicated because it involves numerous intrinsically complex sub-systems and there exists many interactions among these sub-systems. It is influenced by lots of external factors including fluctuating oil price and demand uncertainties. Chemical supply chain also has some specific features such as longer chains, complex transportation process, large inventory, complex manufacturing process, etc. (Srinivasan et al. 2006). Agent-based models are ideal for simulation and analysis of chemical supply chain.

For the past ten years, agent-based modeling in chemical supply chains did not receive adequate attention. Only a few researchers have implemented agent-based modeling into chemical supply chains. Srinivasan et al. (2006) proposed a new environment called G2 Multi-Agent Development Environment for agent modeling chemical supply chains and one easy to use framework to model the functions and activities within a supply chain. The new framework was demonstrated through illustration on refinery supply chain studies. Zhang et al. (2008) presented an agent-based model of a global specialty chemicals supply chain which considered various supply chain entities from upstream raw material suppliers to downstream customers. The specialty chemicals company was modeled as a collection of agents including centralized sales department and numerous production sites located as different locations. A case study was done on global lubricant additive supply chain. Behdani et al. (2010) demonstrated how an agent-based model of chemical supply chain can be developed to evaluate the dynamic behavior of supply networks, considering both the system-level performance as well as the components' behavior particularly during disruptions. Later, they extended their work on the disruption management in chemical supply chains by developing an agent-based coordination framework (Behdani et al., 2011) to evaluate the effect of different coordination mechanisms, and a simulation-based approach for mitigating supply chain disruptions (Behdani et al., 2012). The model used in the three papers is an agent-based model of multi-site lube additives chemical supply chain, which consists of a global chemical enterprise that having a global sales department and three production plant, customers and suppliers. Agents were used to represent (model) customers, global sales department, plants and suppliers. Besides, Pepple et al. (2011) also used an agent-based chemical supply chain model to analyze how a short-term shutdown caused by earthquake would impact the upstream and downstream chemicals with the supply chain network. All these work have demonstrated the capability of agent-based modeling and simulation in the decision support for supply chain management.

2.5 Chapter Summary

In this chapter, we introduced the supply chain management concept and discussed the requirements for supply chain modeling framework and the advantage of agent-based modeling in supply chain studies. We have done a comprehensive literature review on agent-based modeling of supply chain and its applications from over one hundred journal papers, and also demonstrated the application of agent-based modeling in the domain of chemical supply chain.

Agent-based models are typically implemented in platforms such as Mason, NetLogo, Repast and Swarm. Allan (2010) did a very comprehensive survey of ABMS software packages and indicated that most of the platforms are difficult to use, especially for non-technical users. Thus it calls for a new framework for developing agent-based models of supply chains which can be easily implemented into real business domain. In the following chapters of this thesis, we present a new agent-based supply chain modeling framework and demonstrate its application in chemical supply chains.

Chapter 3

BPMN Based Specification of Agent-Based Models

3.1 Introduction

Good supply chain management is crucial for business success in today's increasingly complex, global, and competitive business environment. Modeling and simulation is a popular tool to handle the complexities and uncertainties of supply chain so as to observe, investigate, analyze, and diagnose the real industrial systems. However, most of existing supply chain modeling approaches are complex, and resulting models are hard coded and very difficult for non-technical users to understand, manipulate and analyze. Business Process Modeling Notation (BPMN) is a widely recognized graphical modeling notation for business processes. In this chapter, we propose a BPMN-based framework for supply chain modeling.

BPMN was first introduced by Business Process Management Initiative in 2002, and is currently maintained by Object Management Group. It is a language for constructing business process models. A BPMN model reveals the order of activities, when they happen, and under what conditions. It is based on concepts similar to flowcharting, hence, it is considered business-friendly. Several versions of BPMN have been released. In this thesis, we follow version 1.2.

BPMN is an increasingly important standard for business process modeling, and has been widely adopted today and attracted high levels of attention (Recker, 2010). Nowadays, BPMN is broadly supported both freely and commercially, and there have been more than seventy companies and organizations that offer products and services supporting BPMN. As a visual modeling language, BPMN provides a standardized notation similar to traditional flowcharting, and makes it easy to understand and employ by both technical and non-technical users, allowing them to draft, document and communicate business process with their internal and external business partners. The role of BPMN is to serve as a business-friendly communication language to minimize the misunderstanding among the users having different technical skills or business knowledge during the business process design and implementation. Besides, BPMN is designed as “executable” oriented (Silver, 2009). The specifications of BPMN allows for automated execution of processes, which implies that BPMN models can be designed to control business processes. This ability to transform documentation of process flows to executable process model with simple notation makes BPMN unique.

3.2 BPMN Elements

Business process modeling in BPMN is made by process diagrams with graphical elements. There are four basic categories of elements in BPMN: Flow Objects, Connectors, Artifacts and Swimlanes.

BPMN has three primary shapes – activities, gateways, and events – as shown in Figure 3.1. These primary shapes have several subtypes distinguished by border style, symbols inside, and placement in the diagram.

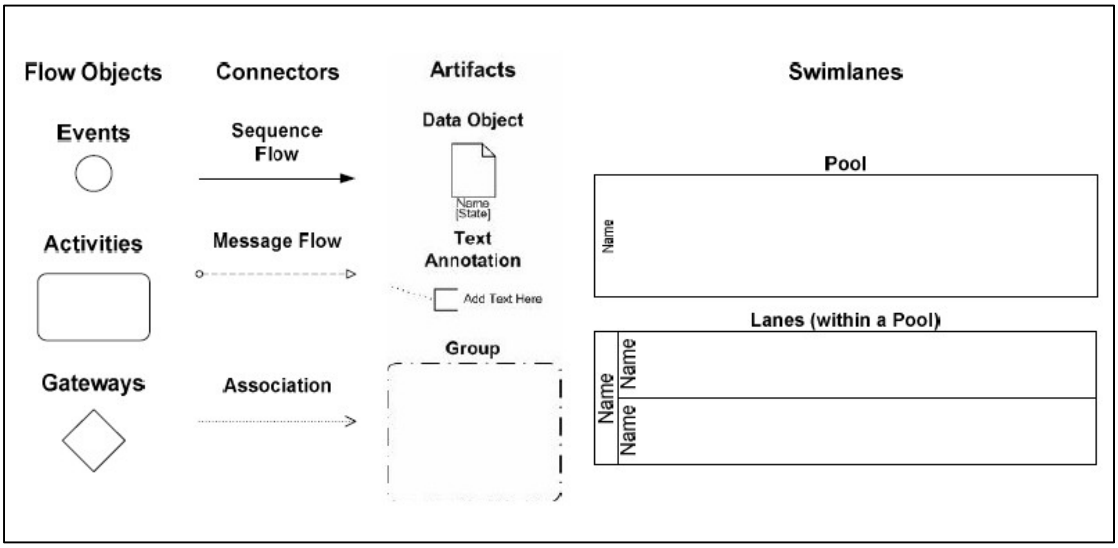


Figure 3.1: Elements of BPMN

Flow Objects are core elements and consist of three types: Event, Activity and Gateway. An Event is something that “happens” during the course of a process including message sending, message receiving and timer. Events affect the flow of the process and usually have a trigger or a result. They can start, interrupt, or end the process. Event is represented by a circle with open centers to allow internal markers that distinguish different triggers and results. The trigger and result can be empty, message or timer. There exist three kinds of events in BPMN based on when they affect the flow: Start Event, Intermediate Event, and End Event (see Figure 3.2). In particular, Start Event acts as the trigger of a process; End Event represents the result of a process.

An Activity is a generic term for work that is performed within a business process. It is represented by a rounded-corner rectangle. An Activity can be atomic or compound. There are two types of Activities: Task and Sub-Process (see Figure 3.2). A Task is an atomic activity and is used when the work in the process is not or cannot be broken down into subparts. A Sub-Process is a compound activity that is included within a process. It can be represented in a finer level of details through a set of sub-activities, which enables hierarchical process development. Sub-Process has a “plus” sign in the lower-center of the shape indicates that this activity has a lower level of detail. A Sub-Process has an event holder which can attach Intermediate Event for the purpose of exception handling, exception handling and compensation.

Gateways are control elements used to manipulate the convergence and divergence of the paths within a process. Thus, they will determine the forking, merging, and joining of paths. A Gateway is represented by a diamond shape with internal marker which indicates the type of behavior control, including Exclusive Gateway, Inclusive Gateway, Parallel Gateway and Complex Gateway. All gateways can split and merge the paths. Among these gateways, exclusive gateways are used where the sequence flow can take two or more alternative paths. There are two types of exclusive gateways based on decision mechanism, exclusive data-based gateway and exclusive event-based gateway. Exclusive gateways (see Figure 3.2) are also used to merge sequence flow. Parallel gateways are employed in a process where multiple parallel branches are defined.

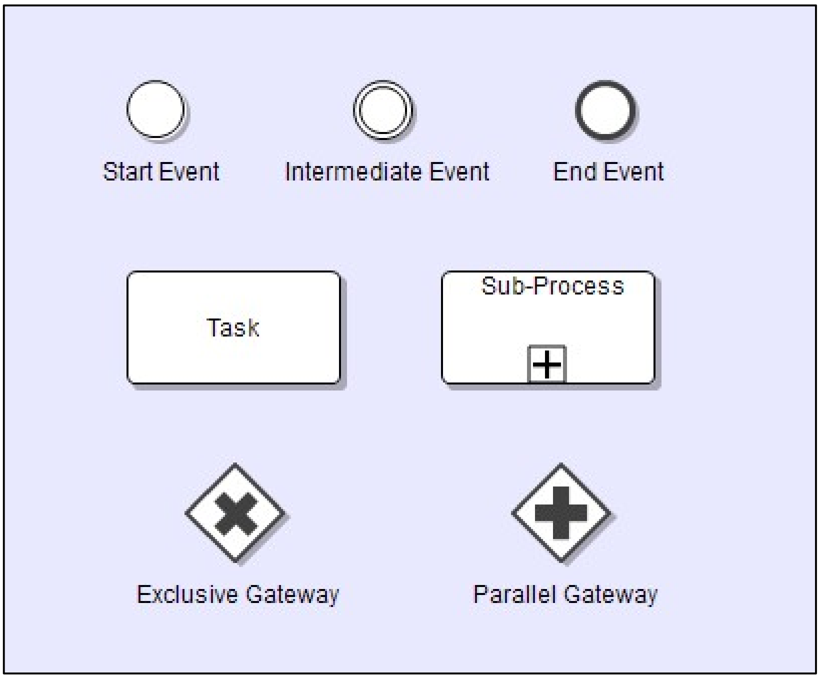


Figure 3.2: Legend of Flow Objects

Flow Objects are connected together in a process diagram by Connecting Objects, which are of three types: Sequence Flow, Message Flow and Association. A

Sequence Flow is represented with a solid line with arrow and shows the order that activities will be performed in a Process. Conditional argument can be added to a Sequence Flow to make it Conditional Sequence Flow, which is employed following Exclusive Gateway where a selection of path is required. A Message Flow is represented as a dash line with an open circle at the beginning and an open arrow at the end. It is used to show the flow of message between two entities that are prepared to send and receive it. An Association is represented with a dotted line and is used to associate data, information and artifacts with Flow Objects.

Figure 3.3 presents a simple Process Diagram of (S, s) inventory control. (S, s) inventory control is a typical inventory management policy. S represents the order level and s represents the reorder point. Under this inventory policy, the inventory position of material/product is observed at a given time point. Once the inventory position (I) is below s, a quantity of S - I is ordered in order to bring the inventory position back to S. In Figure 3.3, the process model starts with a Task to attain inventory position I and reorder point s. An Exclusive Data-based Gateway with conditional argument is then employed to compare the value of I and s, and split the course of the process into two possible branches. If the inventory level is higher than reorder point, the process would end with Empty End Event. Otherwise, an order with quantity of S – I is initiated and the process ends up with sending out the order.

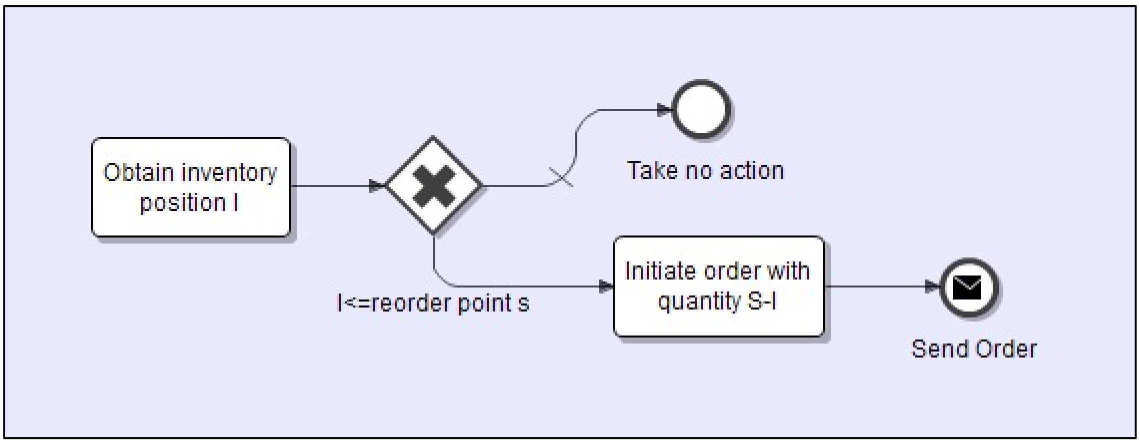


Figure 3.3: Process Diagram of (S,s) inventory control

For business processes involving multiple entities, Swimlanes are employed to help partition and organize elements into separate visual categories in order to represent different responsibilities, roles or functions. They include two types in BPMN, i.e. Pools and Lanes. A Pool acts as a container of a business process. It could also represent as a major participant in a process. A lane is a sub-partition of a process. It is used to represent subdivision for the objects within a Pool. A pool contains one or more lanes. Pools are used to contain the individual business process of each participant. Lanes may be employed if a participant can be further divided into subparts.

Artifacts provide the additional capability to show more information beyond the basic flow-chart structure of the process in process diagram. There are currently three types of Artifacts in BPMN: Data Objects, Groups, and Text Annotations. Data Objects show which data or documents are required in a process; Groups are represented with a rounded dash rectangle and used to highlight certain sections of process diagram; and Text Annotations are used to provide additional information about a process.

Figure 3.4 illustrates a Process Diagram of periodical review (S, s) inventory control developed from the previous simple process. In this example, there are two major participants in the process: Retailer and Supplier. Retailer periodically reviews the inventory position of product under (S, s) policy and places order to Supplier. Two Pools are implemented to represent Supplier and Retailer respectively. As shown in the figure, the process of Retailer starts with an Empty Start Event, crosses the first Exclusive Data-based Gateway and proceeds to a Sub-Process which represents the product inventory control process. The process shown inside the Sub-Process executes every periodical time interval. It starts with obtaining inventory position I of the product based on the inventory level and outstanding orders. If the inventory position is higher than reorder point s, the Sub-Process would end. Otherwise, Retailer initiates an order with quantity of S – I, sends order to Supplier, and waits for the response. Once Retailer receives the reply, it saves the order information and ends the Sub-Process. After that, the process continues to a Timer Intermediate Event representing the time interval for periodical review, and links back to the first Exclusive Data-based Gateway, allowing periodical execution of the Sub-Process.

Supplier Starts with a Message Start Event which is the order sent from Retailer. Therefore the process of Supplier is triggered whenever an order (message) is received from Retailer. Upon receiving the order, Supplier checks the product inventory. If there is adequate stock, Supplier informs Retailer and initiates product delivery. Otherwise, Supplier informs Retailer of delayed delivery, start manufacturing product and initiates delivery once the order can be fulfilled. The details of the production and delivery Sub-Process are not included in this example. In this Figure, Message Flows are also employed in the model to represent the information flows between Retailer and Supplier.

In conclusion, in the implementation of BPMN in supply chain modeling, Tasks and Sub-Processes represent supply chain plans and activities. Sequence Flows connect Activities and present the linkage of different tasks and plans in supply chain operations. Message Flows construct and display the information flows, material flows and financial flows among supply chain entities. Gateways visualize the decision-making process and control the paths in supply chain process diagrams. Sub-rocesses present the hierarchy of large processes. Artifacts explain the process diagram in forms of data and text. In this way, supply chain model would have a better vision and organization compared with many other supply chain simulation models that contains hundreds of files without intuitive expression.

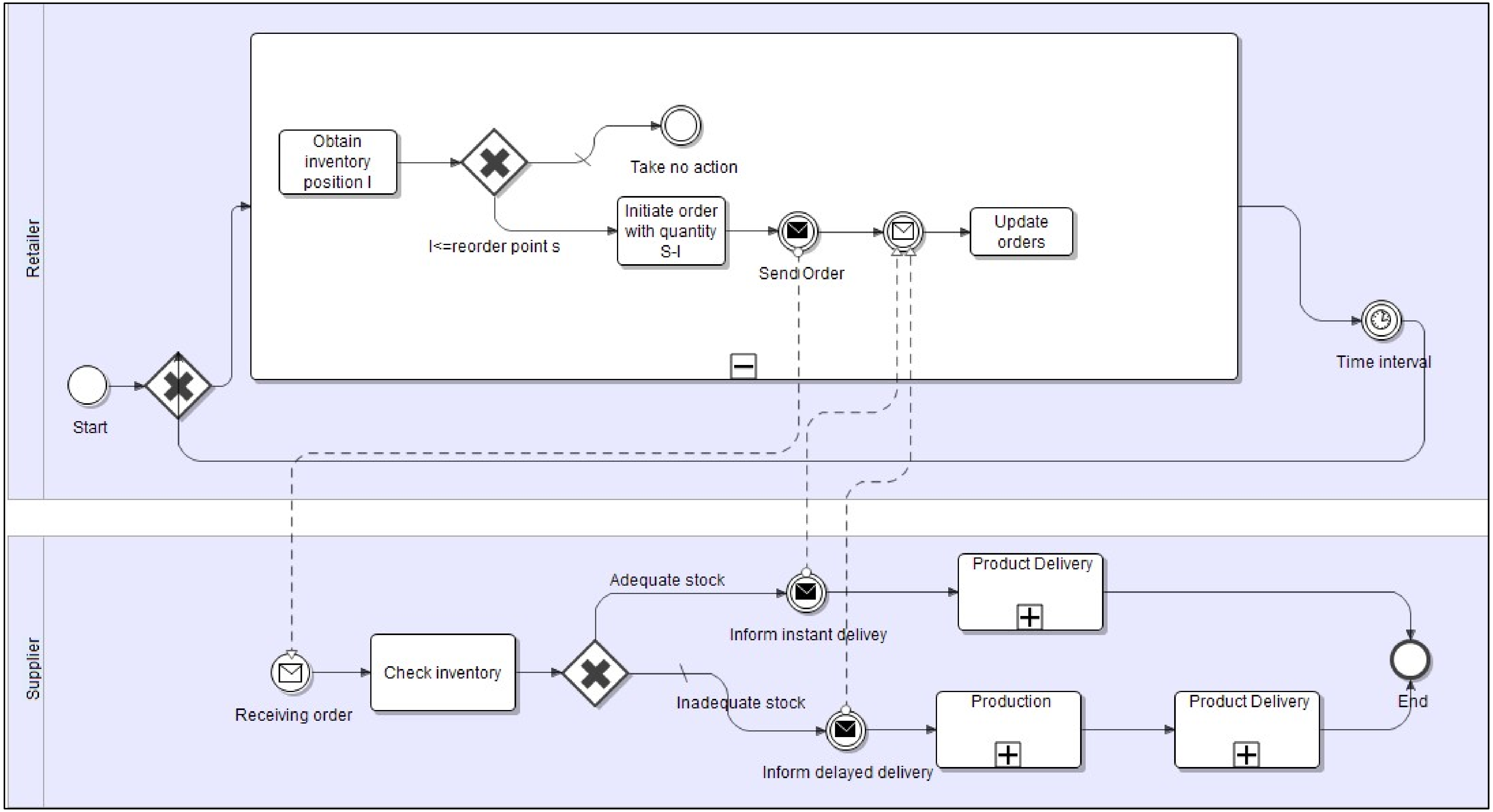
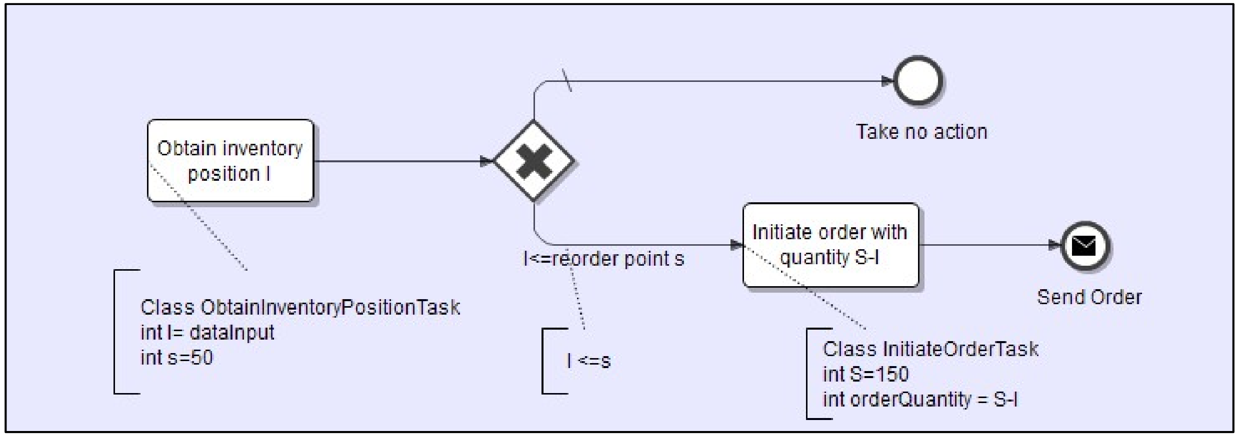


Figure 3.4: Process Diagram for periodical review (S,s) inventory control

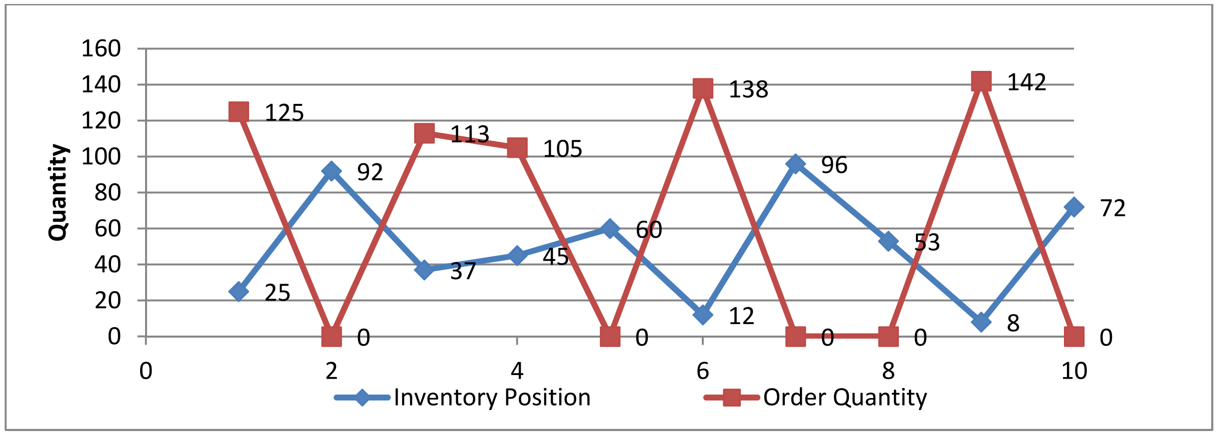
3.3 Execution of BPMN Models

BPMN is “executable oriented” designed. A BPMN model contains information that does not show in the diagram itself but is very important for model execution. The information mainly involves the properties (i.e. class and parameter value) of Activities, Sequence Flows, Message Events and Timer Events.

Figure 3.5(a) presents the property information in Text Annotations for (S, s) inventory control model in Figure 3.3. We assume that reorder point s is 50 units; order level S is 150 units and Inventory Position I is data input from user. As shown in the figure, the first task is associated with a function which assigns data input to inventory position I and attains the value of reorder point s. A conditional argument is added to the Condition Sequence Flow following the Exclusive Gateway so as to decide whether to place an order. If I is not larger than s, another function, which is attached to the second Task, is executed to attain the value order level S and compute the order quantity. After that, a Message Event is employed to send out the order. Figure 3.5(b) shows the inventory position and responding order quantity for 10 execution trails of (S, s) inventory control model. In this figure, order quantity of zero indicates that inventory position is higher than reorder point and there is no need to place an order.



(a)



(b)

Figure 3.5: (a) Details of Tasks and Connectors in (S, s) inventory control model; (b) Execution trails for (S,s) inventory control

3.4 BPMN Application

Over the past few years, a number of researches have been carried out to investigate the suitability of BPMN in process modeling, and to develop conceptual modeling framework using BPMN. Silver (2009) classified the use of BPMN in real business into three levels: descriptive modeling, analytical modeling and executable modeling. Descriptive modeling is to use the graphical elements of BPMN to document the order of activities and main structure of business process flows, which is similar as traditional flowcharting. Analytical modeling refines descriptive modeling by adding detailed control rules and exception paths to describe process flows more precisely for the purpose of process analysis. Analytical modeling also includes another user case that is to build process model underlying executable design without technical details. In this case, BPMN is employed only to provide descriptive view of process model and the hidden execution related details and complexity is handled by vendors' software. Executable modeling transforms the elements of BPMN from graphical notations to an XML language for direct executable process modeling. All the execution details such as messages and services are directly captured in BPMN attributes rather than through other software.

Birkmeier and Overhage (2010) conducted an empirical study on the application of BPMN by business users during a model creation task. The presented results indicated that BPMN performs satisfactory in efficient communication and user effectiveness. Recker (2010) did a three-year survey study on user acceptance of BPMN which involves 590 process modelers all over the world. The statistical results of the survey research showed the great attention gained by BPMN in both large organizations and small private sectors. The author also showed that BPMN has created a massive demand for education and training on business process modeling, which implies the spreading implementation of BPMN in real business.

Guizzardi and Wagner (2011) evaluated the suitability of BPMN against a foundational ontology for agent-based discrete event simulation from the perspective of business simulation language. The comparison results indicated that the BPMN core elements are well chosen but these still exists some "ambiguous elements, missing concepts, and redundant elements" according to the authors' criteria. However, this study was done only in the level of abstract concept without doing empirical study on real implementation. Silver (2009) argued that BPMN has already covers all the necessaries for business process modeling and those “missing concepts” are not essential to BPMN and could be described by other models that linked to it. Dubani et al. (2010) investigated the use of BPMN and Business Process Execution Language (BPEL) in executable business process modeling. The authors proposed a business process modeling framework and implemented it to model a typical manufacturing process in the automotive industry. However, their case study only involved two participants in a simple process, and only a few modeling elements were employed. As a result, it could not prove the capability and advantages of BPMN in supply chain modeling when handling complex industrial systems.

As a result, although BPMN has been recognized by more and more business organizations and it has been designed executable oriented, many business users still employ BPMN only for the purpose of documentation (Schnabel et al., 2010; Recker, 2010). Some have utilized it in modeling and simulation of simple supply chain operations. None has implemented BPMN in complex supply chain modeling and simulation yet. In this thesis, one of our main goals is to propose a BPMN-based supply chain modeling and simulation framework to construct complex supply chain models of real industrial operations using graphical elements of BPMN.

3.5 Guidelines for Modeling Complex Supply Chain Systems

We propose guidelines for BPMN-based modeling complex supply chain systems that consist of four steps: (1) Identify main activities and key supply chain entities, (2) Identify information flows and material flows, (3) Model supply chain operations of each entity using BPMN graphical elements, (4) Implement and Deploy BPMN-based model.

Step 1: Identify main activities and key supply chain entities

The modeling of complex supply chain system starts with identifying main activities and key supply chain entities. This step allows for two approaches. One is to choose supply chain processes or phenomenon needed to be modeled first, and then to ascertain the key entities involved and individual roles. The other approach starts from known supply chain organization (a group of supply chain entities), followed by the selection of main supply chain operations occur within the organization. In this step, the whole supply chain activities should be simplified for the convenience of modeling and further studies. Minor entities can be grouped into key entities and side operations can be cut down and even ignored.

Step 2: Construct information flows and material flows

After ascertaining the main activities and major supply chain entities, it is very important to identify and construct the information flows and material flows among these supply chain entities. In supply chain models, both information flows and material flows are considered as information sharing in forms of messages sending and receiving, which ensures the availability of tractable data and information necessary for the execution of all supply chain operations. As a result, information flows are modeled as instant message sending and receiving, while mass flows are modeled as message sending and receiving associated with a time delay. The benefits of this step are to divide supply chain activities into separate subparts for each entity and to recognize the triggers of these subparts. Ontology of these information and mass flows can also be created to classify the content of each information and material flow, which benefits Step 4.

Step 3: Model supply chain operations of each entity using BPMN graphical elements

This is the most important and complicated step. After first two steps, complex supply chain system has been divided into key entities with individual roles (operations) in supply chain activities. As a result, complex supply chain system is simplified into a bunch of supply chain processes exchanging information with each other through messages.

In this step, BPMN is employed to adequately convert the supply chain processes through natural language into process diagrams with graphical elements. Tasks and Sub-Processes are used to demonstrate simple supply chain plans and tasks. Sequence Flows are utilized to connect Activities and present the linkage and path of tasks and plans. Gateways are applied to control the convergence and divergence of the paths in supply chain process diagrams. Message Flows display the information flows and material flows between supply chain entities if necessary. Section 3.2 has already provided all necessary information and examples that supports the BPMN-based modeling of simple supply chain processes.

In addition, a Pool acts as a container of a business process. It was utilized to represent as a major Participant in a collaboration diagram in the example of Section 3.2. For complex supply chain, it would be very difficult and messy to use Pools to organize all supply chain entities into one process diagram as it may involve multiple types of entities with massive conversations. As a result, it is better to separate it into different process diagrams. Each process diagram represents the supply chain operations operated by each supply chain entity. There is another benefit when doing this. As a process container, Pools can be used to represent different configurations for entities, e.g. different policies, different set-ups. It allows multiple configurations of same class of entity in single simulation. In this way, the capability of BPMN has been greatly enlarged in supply chain modeling.

Step 4: Implement and deploy BPMN-based model

After all the supply chain processes are represented in process diagrams using BPMN graphical elements, in order to execute and validate the BPMN-based model, Jadex and Jadex BPMN editor are employed to refine the supply chain model and serve as simulation platform. Java functions have to be written and assigned to corresponding Tasks. Local parameters have to be mapped into Tasks, Sequence Flows and Control Elements to realize information passing and control functions. Java Beans have to be modified for message content for information exchange. Data structure has to be created and utilized adequately for data access, storage and calculation. An Application XML file is also used to manage all the configuration of the whole model. Upon the completion of the coding, Jadex Platform can be employed to run the simulation of the supply chain model.

3.6 Chapter Summary

This chapter introduced BPMN with the key elements, and demonstrated how BPMN can be employed to model supply chain operations. Firstly, the advantages of BPMN were discussed and the key elements of BPMN were introduced with simple supply chain operations as illustrations. Then, the supply chain operation model was simulated to demonstrate the excitability of BPMN followed by a discussion on its application. Lastly, the framework steps to model a complex supply chain were described. The rest of the thesis explores how simulation models of supply chains can be developed from this new modeling framework and used to support decision making in supply chain management.

Chapter 4

A BPMN-Based Model of Integrated Supply Chains

4.1 System Description

In this chapter, an existing multisite specialty chemicals supply chain model developed by Adhitya et al. (2010) through MATLAB Simulink is replicated through our proposed modeling approach. As shown in Figure 4.1, this supply chain is a multisite lube additive supply chain which contains raw material suppliers, third-party logistics (3PL), lube additive enterprise, and customers. The lube additive enterprise comprises a global sales department and three lube additive plants located in Singapore, Houston and Japan respectively (only two plants shown in Figure 4.1). Each plant is further divided into procurement department, storage department, scheduling department, packaging department and production department. Each entity is functioning on certain rules and policies, together with the information flows (dotted arrows in Figure 4.1), material flows (solid arrows in Figure 4.1) and financial flows among them, integrating the overall supply chain performance.

It is assumed that all plants can produce three types of product: A, B and C. Each type of product has five grades: 1, 2, 3, 4 and 5. These products are made from eight types of raw materials. There are three main activities that constitute the whole supply chain operation: enterprise-level collaboration, plant production operation and inventory management. The enterprise-level collaboration involves customers, global

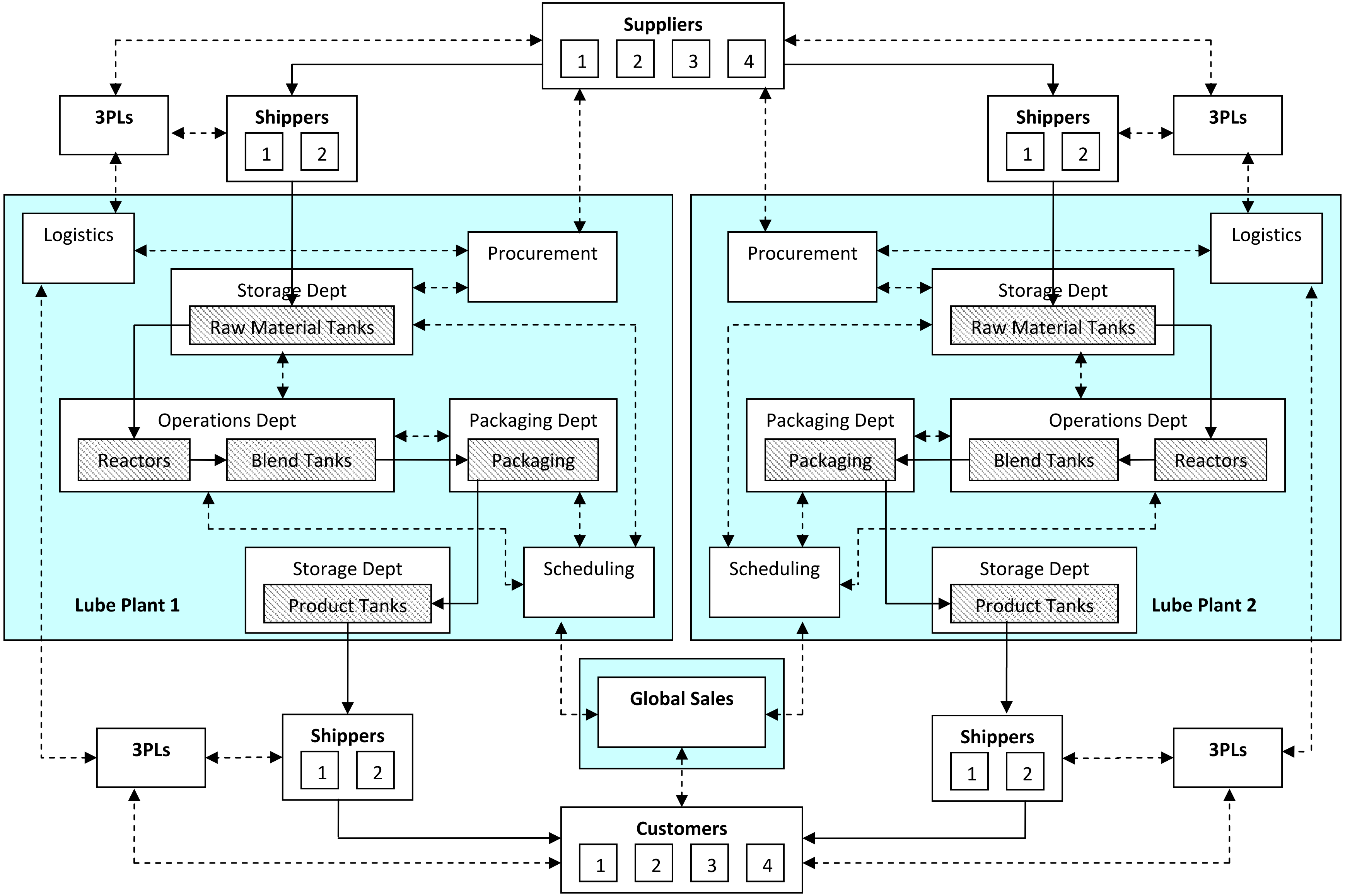
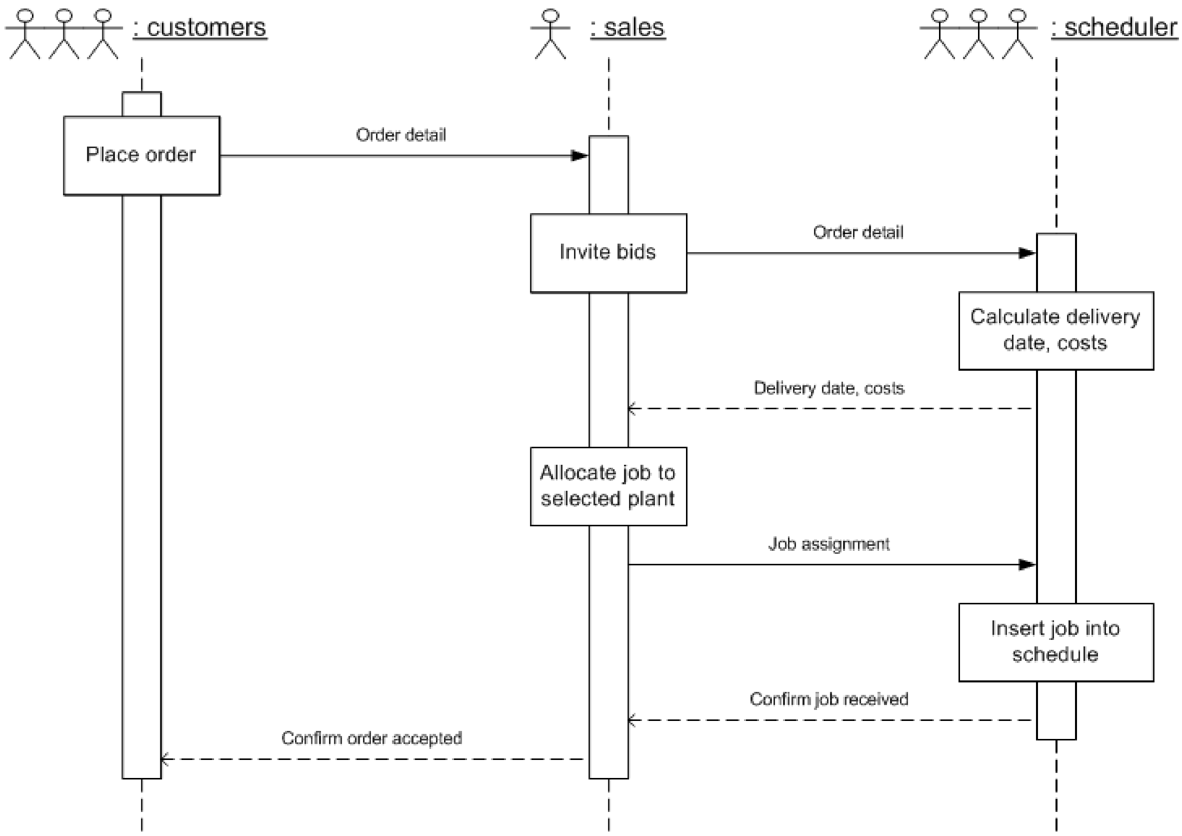


Figure 4.1: Schematic of multi-site lube additive supply chain (Adhitya et al. 2010)

sales department, and the scheduling department of each plant. As shown in Figure 4.2(a), the whole collaboration starts with a customer placing an order to the global sales department who then calls for bid by forwarding the order details to the scheduling department of different plants. The scheduling department in each plant estimates the delivery date and costs of the potential order and sends a proposal/bid back to the global sales. After collecting the proposals/bids, sales department decides which plant the order should be assigned to following a predefined order assignment policy, such as nearest to customer's location or earliest estimated delivery date. The scheduling department of the chosen plant accepts the order and inserts it as a job into the production schedule following a scheduling policy, e.g. earliest Production Due Date (PDD). If the order requires a due date by when all the plants are not able to fulfill, the order would be rejected and accounted as missed order.



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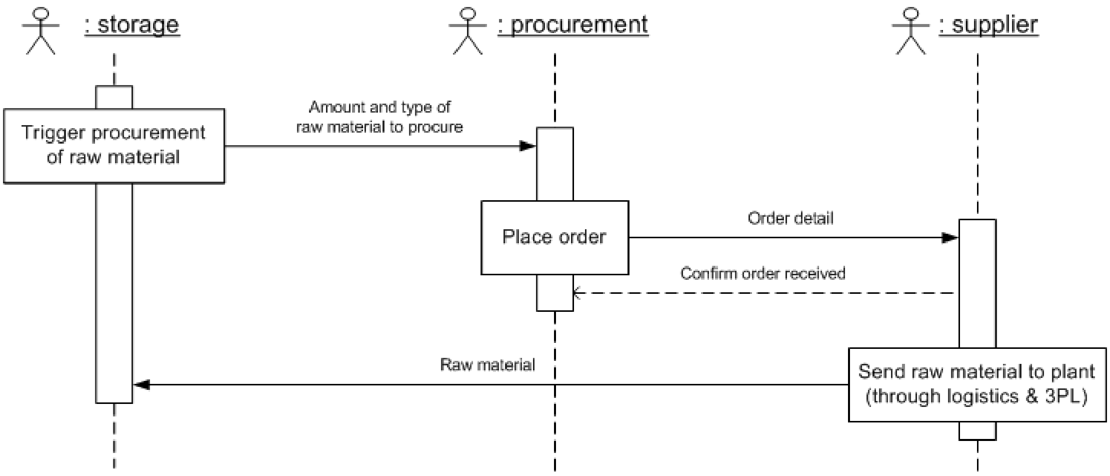

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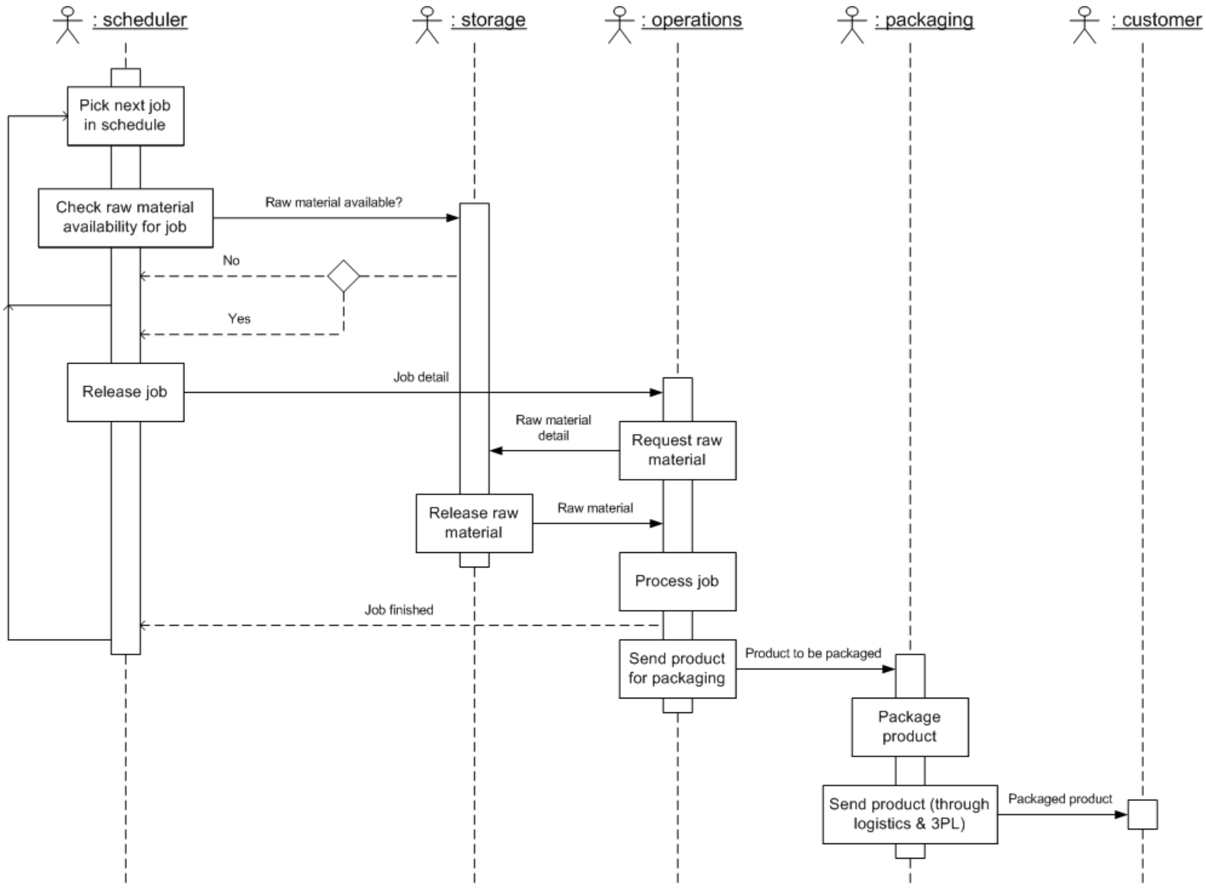


(c)

Figure 4.2: (a) Sequence diagram of enterprise-level collaboration; (b) Sequence diagram of raw material inventory management; (c) Sequence diagram of plant production operation (Adhitya et al. 2010)

Production operation is a series of activities performed only at the plant level, which is accomplished through the cooperation of different departments inside the plant. As shown in Figure 4.2(c), production operation starts from the scheduling department that releases job (one job corresponding to one order) from the production schedule. Before assigning the job to the operations department, the scheduling department first contacts the storage department to check for the availability of raw materials in the inventory. If there are not sufficient materials for the current job, the whole production operation would suspend. Otherwise, the job would be handed over to the operations department that takes charge of the whole manufacture of the corresponding product. Afterwards, the production operation splits into two branches. One is that the manufactured product is transferred to packaging department for wrapping and then shipped to the customers through logistics. The other one is that the scheduling department is notified once the operations department completes the current job, and releases the next job in the production schedule, making production operation perform in a cycle.

In order to avoid the interruption of production operation caused by raw material shortage, the storage department and procurement department of each plant continuously monitor and manage the inventory of all materials. The inventory is controlled through procurement policy, which is similar as the illustrative models in Chapter 3. Taking (S, s) policy as an example (shown in Figure 4.2(b)), once the inventory position of a particular raw material falls to or below the corresponding reorder point s, a procurement is triggered and an order is placed to raw material supplier with details of material type and order quantity so as to raise the inventory position back to order point S. The ordered raw material will be delivered to the storage through logistics and 3PLs.

4.2 BPMN-Based Model for Multisite Specialty Chemical Supply Chain

In this section, we implemented our modeling approach to develop BPMN-based model according the system description and detailed configuration of the multisite specialty chemicals supply chain model developed by Adhitya et al. (2010).

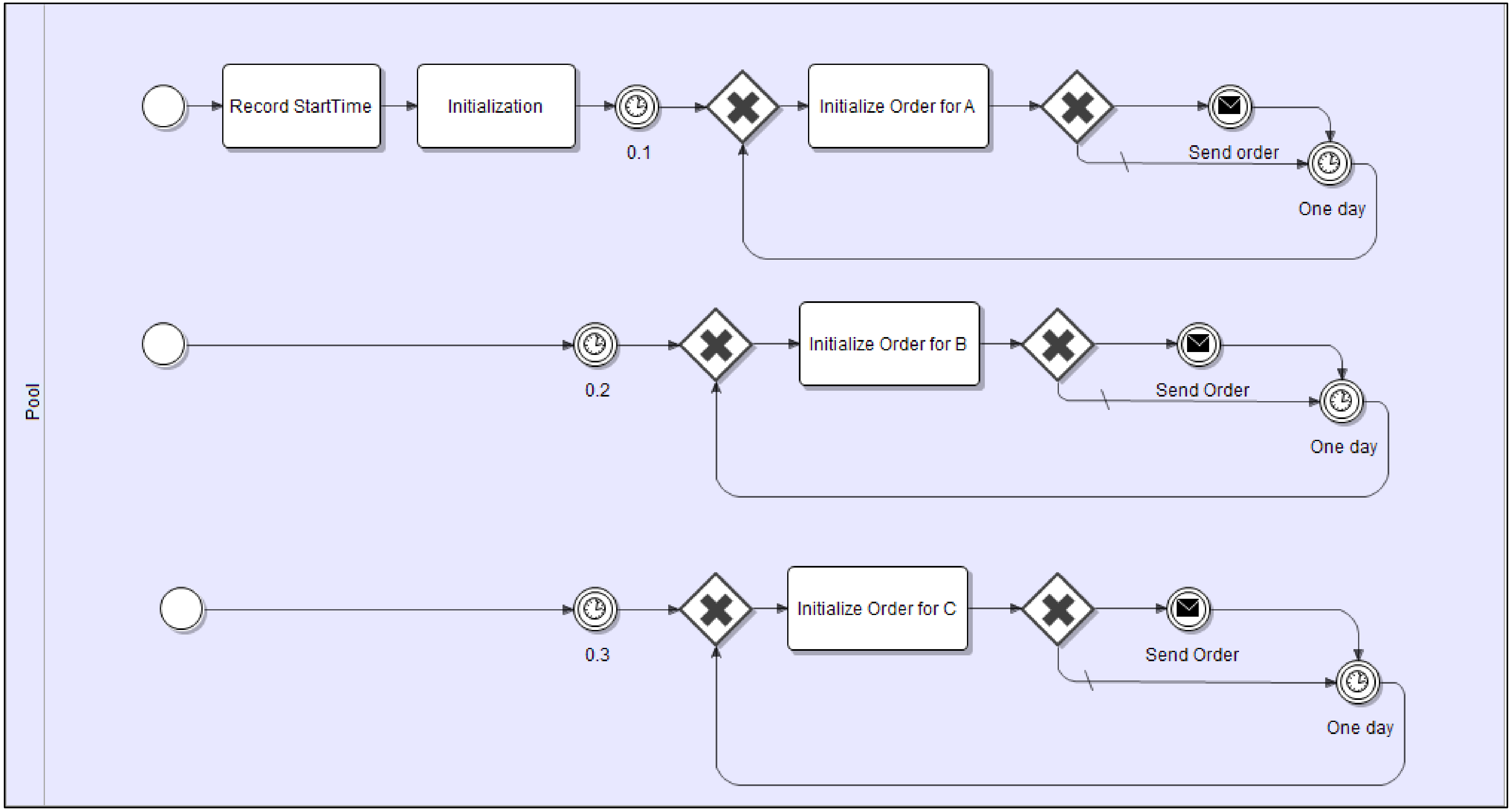


Figure 4.3: Process Diagram for Customers

The whole network contains raw material suppliers, 3PL, lube additive plants, a global sales department and customers. Each plant is further divided into procurement department, storage department, scheduling department, packaging department and production department. And as described in Section 4.1, there are three main activities to be modeled: enterprise-level collaboration, plant production operation and inventory management. From the details of supply chain activities in system description, the variations among the customers and raw material suppliers are not concerned, and 3PL is only doing simple job. As a result, the key supply chain entities are identified as customers (all customers as one entity), global sales department, each plant, logistics, and raw material suppliers (all raw material suppliers as one entity). Adhitya et al. (2010) already provided a schematic of the supply chain. As shown in Figure 4.1, the information flows and material flows among these supply chain entities have already been identified and constructed.

The remaining of this section follows Step 3 of the proposed guidelines. The whole supply chain models consists of five process diagrams for Customers, Global Sales, Logistics, Suppliers (raw material) and Plants.

As discussed above, since the function of customers is only to generate and send orders, only one entity is created for the group of customers: Customers. Figure 4.3 shows the process diagram for Customers, which involves three similar operations: making order for product A, making order for product B and making order for product C. The supply chain operations of Customers start from recording simulation starting time for the convenience of date calculation, followed by an initialization function which generates all the orders of three types products for the whole simulation horizon based on the market demand model developed in the original paper. After initialization, an Intermediate Timer Event labeled as “0.1” ensures the first making order process start at the time point 10% of first simulation day, which is to replicate the same setting in the MATLAB Simulink model. An Exclusive Data-based Gateway and an Intermediate Timer Event with attribute of one day integrate the daily order making process for product A. For every simulation day, the cycle of making order process starts from order initialization to check whether an order for product A is scheduled. If it is, other order details including packaging type, customer location, due date and grade are randomly generated, and sent to the Global Sales together with

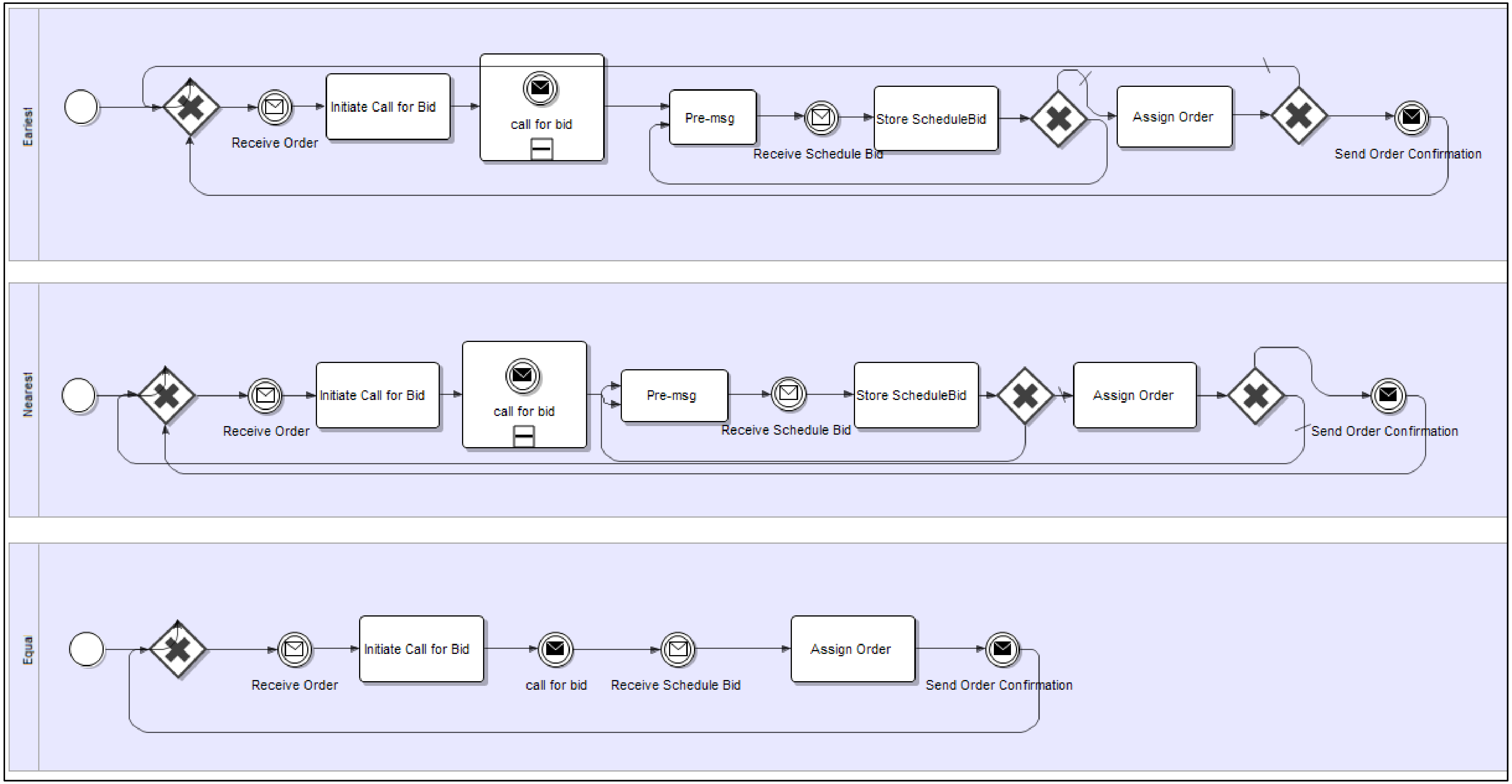


Figure 4.4: Process Diagram for Global Sales

order quantity. Otherwise, it bypasses the sending order operation and waits for the next simulation day through Intermediate Timer Event. Similar processes in BPMN are created for product B and C.

As shown in Figure 4.4, the Global Sales has three Pools. Each Pool represents one different configuration of Global Sales. In this case, the three Pools correspond to three different order assignment policies: Earliest Completion Date, Nearest Plant Location and Equal Assignment (shown in Figure 4.4). Take Earliest Completion Date policy as example. After receiving an order from Customers, Global Sales initiates a call for bid and sends it to all plants through a simple Sub-Process (shown as the first Pool in Figure 4.4). Afterwards, Global Sales waits for the response from plants and stores all the proposals (Schedule Bids). A “Pre-msg” Task and an Exclusive Data-based Gateway are used to control the collection of the responses. If number of responses is less than expected, the Gateway would control the path go back to Receive Schedule Bid to wait for the next response. Upon the collection of all the responses, the Task “Assign Order” would be executed to choose the plant which proposes the earliest completion date for that order. If the earliest completion date is not later than the due date plus tolerance window, the order would be assigned to the plant. Or else, the order would be accounted as missed order. Nearest Plant Location policy (shown as the second Pool in Figure 4.4) has the same configuration as the first policy except that the Task “Assign Order” is assigned with a different Java function. In this policy, the plant nearest to the customer location has the highest priority to get the order. If the order cannot be completed within the requesting date, the next nearest plant would have the highest priority. If all the plants cannot fulfill the order, the order would be considered as missed order. The third Pool in Figure 4.4 represents the Equal Assignment Policy in which orders are assigned to all plant equally. First plant gets the first order; second plant gets the second order and so on. Under this simple policy, the due date of the orders is not a concern. So there would be no missed order but the lube additive enterprise risks a lower customer satisfaction.

Logistics in this supply chain model is a combination of all logistics departments, shippers and 3PLs. The main function of Logistics is to account for the transportation of product delivery and raw material delivery with time delay. As shown in Figure 4.5, the two operations are the same as each other except for the calculation of transportation time. The transportation time of product delivery is calculated based on the distance between plant location and customer location. For raw material delivery, each plant is assumed to have its own specific raw material supplier, so the transportation time is set to a constant number. This process diagram also demonstrates the way to model material flows. Take raw material delivery for example. Upon receiving raw material delivery request from Suppliers, Logistics initiates raw material delivery and calculates the transportation time for this particular delivery. A Parallel Gateway follows to split the paths into two branches. One branch returns back to the message receiving to wait for the next request. The other one has an Intermediate Timer Event and Message Sending Event to model the raw material delivery. During simulation, message sending and receiving are instant events, so Intermediate Timer Event should be added either in message sending or receiving part to account the transportation time for material flows.

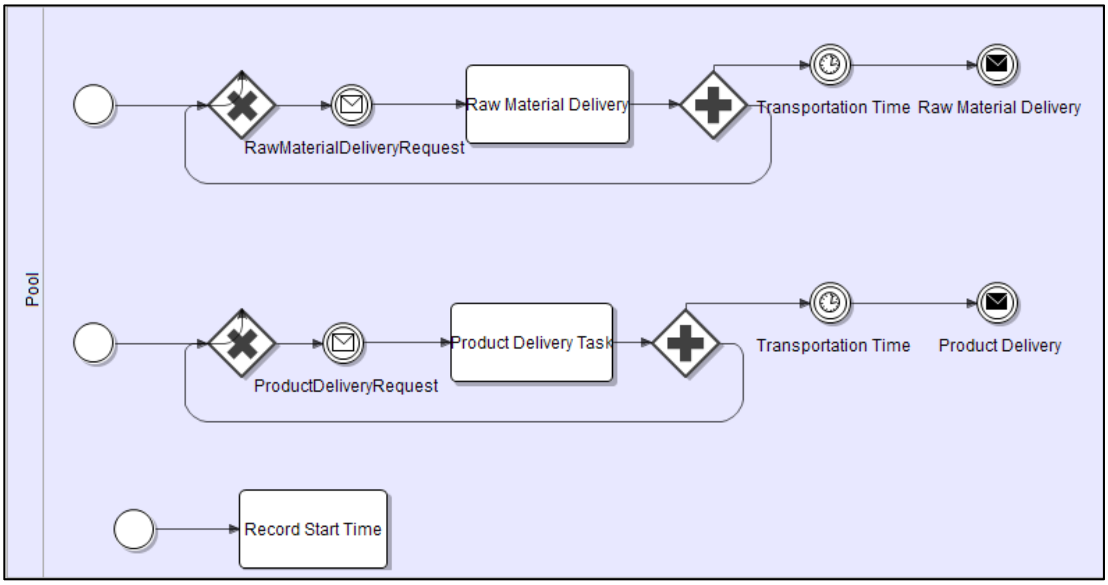


Figure 4.5: Process Diagram for Logistics

Figure 4.6 shows process diagram for Suppliers which receives raw material orders and requests Logistics to deliver raw materials. This simple process starts from a raw material order receiving, followed by a Task to initiate raw material delivery and followed by sending a raw material delivery request to Logistics. An Exclusive

Data-based Gateway is employed to ensure the process to be always reactive during simulation.

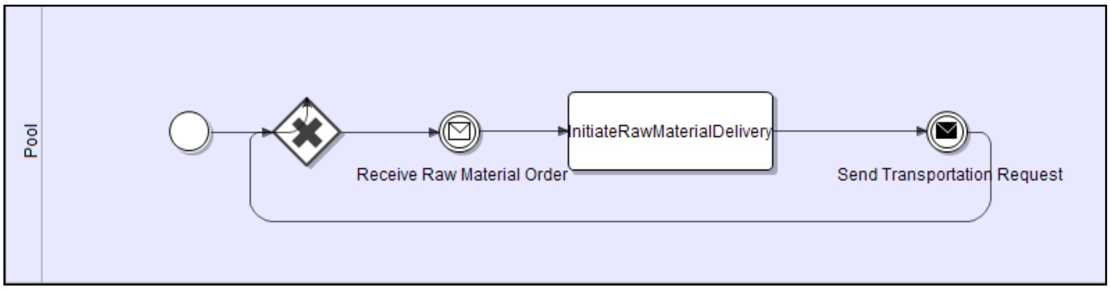
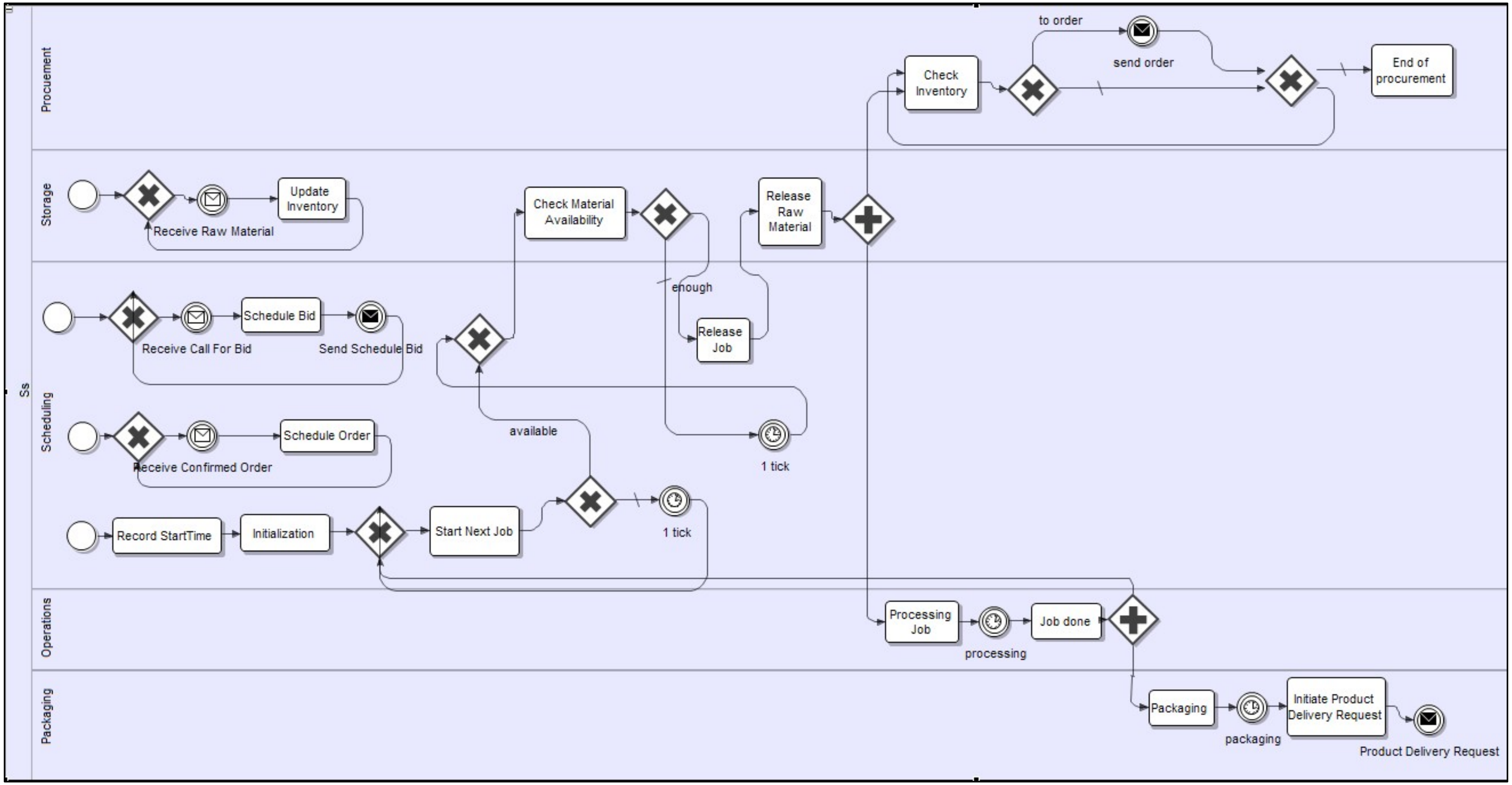


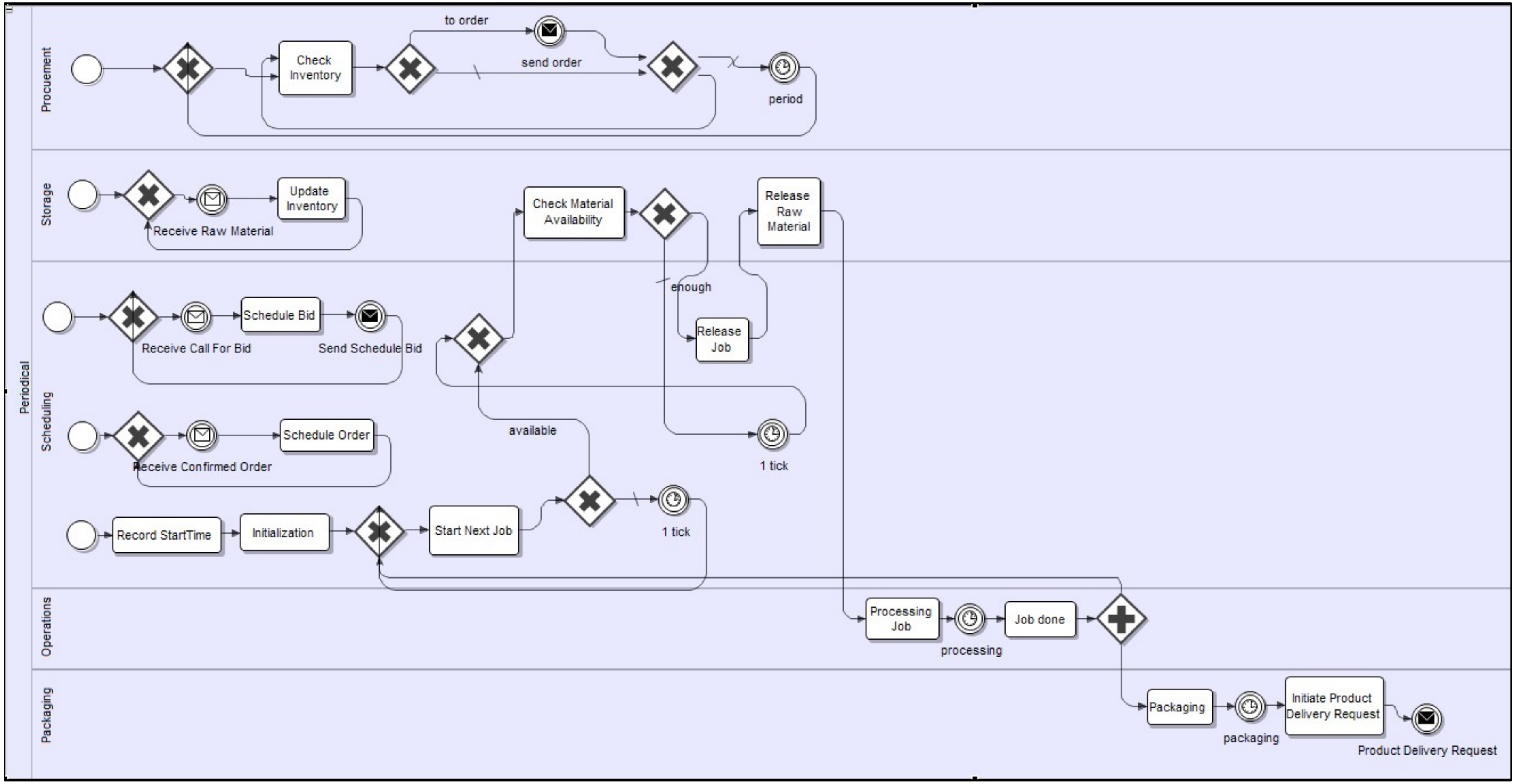
Figure 4.6: Process Diagram for Suppliers

In this supply chain model, each plant has five departments: procurement department, storage department, scheduling department, packaging department and production department. Considering the fact that the departments in the same plant are sharing plant historical data in reality and they have a very high level of cooperation in this case, each plant is treated as one entity to simplify the model. Besides, Lanes are used to represent different departments as sub-divisions. As shown in Figure 4.7, process diagram for Plant consists of two Pools to distinguish two procurement policies, one for (S, s) policy and the other for periodical review policy. Each Pool includes five Lanes; one Lane corresponds to one department. Scheduling department is the core of the plant, which has to handle three operations shown in Lane "Scheduling". Firstly, it has to make a proposal (schedule bid) and send it to Global Sales once a call for bid is received. Secondly, when the order is confirmed and assigned to the plant, scheduling department has to insert the order as a job into the production scheduling. Thirdly, it initiates and controls the production operations for the whole plant. After the initialization process, the production operation starts once the first job in the production schedule is available. If the schedule is empty, an Exclusive Gateway associated with Intermediate Timer Event constitutes a cycle that continuously monitors it. Once there is a new job, storage department examines the availability of raw materials for the current job. A similar controlling cycle is also designed to monitor the raw material inventory. If there are sufficient materials, scheduling department releases the job and storage department releases the raw materials to operations department. For (S, s) policy shown in Figure 4.7(a), the path splits into two parallel branches at this point. One branch proceeds to procurement department to examine the inventory positions of released raw materials. If the inventory position of any material falls to or below reorder point, a raw material order would initiate. Two Exclusive Gateways are placed to establish the procurement of each raw material involved. The other branch processes production in operation department by calculating the processing time and manipulating the attribute of Intermediate Timer Event so that the production is modeled as a time delay. For periodical review policy (shown in Figure 4.7(b)), the process path goes directly to production without splitting. Once the production is completed, the path divides into two ways in parallel. One way continues down to packaging department followed by sending product delivery request to Logistics. The other way informs the scheduling department of current job completion and starts a new one.

For periodical review policy shown in Figure 4.7(b), the procurement department periodically monitors the inventory position of each raw material. Any material inventory position falls to or below reorder point would trigger a raw material order and send it to Suppliers. It is similar as the procurement process shown in Figure 4.7(a). The only difference is that the former one has an Intermediate Timer Event that makes the procurement work periodically. In addition, storage department of plant takes charge of receiving raw material delivery from Suppliers and updating it into inventory.


Ss
Procurement
Storage
Scheduling
Operations
Packaging
to order
send order
Check Inventory
End of procurement
Update Inventory
Receive Raw Material
Check Material Availability
Release Raw Material
enough
Release Job
Schedule Bid
Receive Call For Bid
Send Schedule Bid
available
1 tick
Schedule Order
Receive Confirmed Order
Record StartTime
Initialization
Start Next Job
1 tick
Processing Job
processing
Job done
Packaging
packaging
Initiate Product Delivery Request
Product Delivery Request

(a)



(b)

Figure 4.7: Process Diagram for Plant: (a) Pool for (S, s) policy; (b) Poor for periodical review policy

4.3 Case Studies

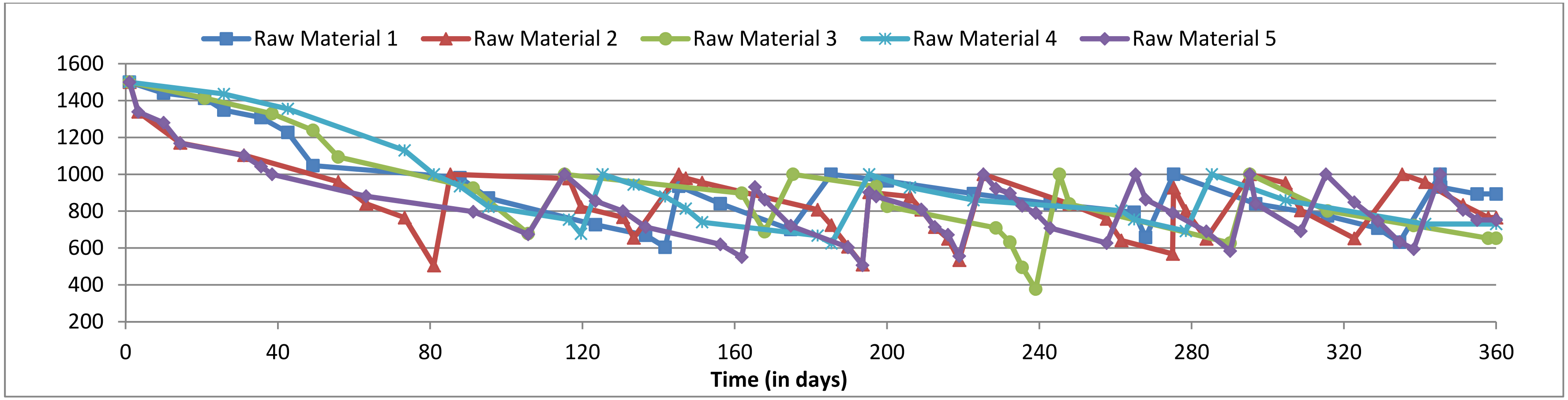
The BPMN-based supply chain model described above has been implemented in Eclipse with Jadex and Jadex BPMN editor. The simulation clock is set as event driven clock. The details of the model, such as product receipt, calculation of production processing time and packaging time, exactly follow the system configuration in original paper (Adhitya et al., 2010). The configuration of the model, i.e. BPMN diagram and model parameters are declared and modified in the Application XML file which is to be executed to simulate the model.

Table 4.1: Nominal values for entities' model parameters (adopted from Adhitya et al., 2010)

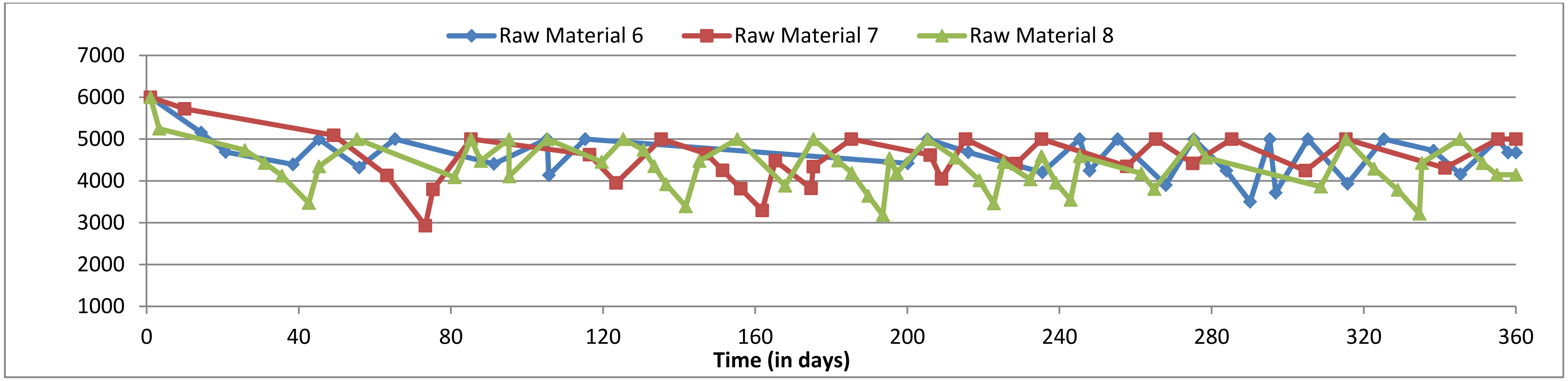
Entity	Parameter Description	Value
Customers	Frequency index	[0.3 0.4 0.6]
	Minimum order size (unit)	350
	Maximum order size (unit)	3500
	Demand random seed	varies
	Number of cycles in 360 days	[2 2 2]
	Amplitude of cycles (unit)	[4 4 4]
	Demand growth factor	$\frac{[8\ 8\ 8]}{37000}$
	Base daily demand (unit)	[200 250 300]
	Daily uncertainty limit ± (unit)	[5 5 5]
	Product grade range	1 to 5
	Due date range (days)	15 to 25
	Packaging type range	1, 2
	Customer location x-coordinate range	0 to 10
	Customer location y-coordinate range	0 to 10
Plant S	Location coordinates	[3 3]
Plant H	Location coordinates	[7 3]
Plant J	Location coordinates	[5 8]
Global Sales	Job assignment policy	Earliest Completion Date
	Customer tolerance (days)	5

Table 4.2: Nominal values for plant's model parameters (adopted from Adhitya et al., 2010)

Function	Parameter Description	Value
Operations	Processing time per unit product (days)	[0.005 0.002 0.003]
	Batch size (unit)	1000
	Processing time per batch (days)	[2 2 2]
	Scheduling policy	PDD with late jobs consideration
	Maximum processing delay (%)	10
	Plant disruption start time	0
	Plant disruption end time	0
Packaging	Packaging size (unit)	[100 500]
	Packaging time per package (days)	[0.1 0.1]
	Maximum packaging delay (%)	0
	Transportation speed (days/unit distance)	1
Procuremen t	Procurement policy	Periodical review policy
	Procurement cycle time (days)	10
	Reorder point (unit)	[700 700 700 700 700 4500 4500 4500]
	Topup point (unit)	[1000 1000 1000 1000 1000 5000 5000 5000]
Supplier	Raw material lead time (days)	[4.3 4.3 4.3 4.3 4.3 4.3 4.3 4.3]
	Maximum raw material delivery delay (%)	0
Economics	Product price ($/unit)	[100 110 120 130 140; 200 210 220 230 240; 300 310 320 330 340]
	Raw material price ($/unit)	[30 60 90 70 50 35 130 25]
	Processing cost ($/tick)	120
	Fixed operating cost ($/tick)	20
	Packaging cost ($/package)	[100 200]
	Raw material inventory cost ($/unit/tick)	0.001
	Late penalty ($/day)	500
	Delivery cost ($/unit/unit distance)	5
Storage	Initial raw material inventory (unit)	[1500 1500 1500 1500 1500 6000 6000 6000]



(a)



(b)

Figure 4.8: (a) Plant S Inventory profile for Raw Material 1, 2, 3, 4 and 5; (b) Plant S Inventory profile for Raw Material 6, 7 and 8

In nominal case, there are three plants: Plant S, Plant H and Plant J. Table 4.1 and 4.2 present the nominal values of model parameters of key entities, and each department or function of plant respectively. A trial run of the BPMN-based model in nominal case was done with simulation horizon of 360-day and 100 ticks per day. And the inventory profile for eight types of raw materials in Plant S is shown in Figure 4.8. As seen from the figure, the inventory levels of all eight raw materials are periodically maintained around the individual reorder point and top-up point.

4.3.1 Validation

The BPMN-based model is validated by comparing the simulation results of BPMN-based model with the original model developed in MATLAB Simulink. Model parameters of BPMN-based model and MATLAB Simulink model exactly follows the nominal values shown in Table 4.1 and 4.2. The simulation horizon is 180-day with 100 ticks per day. A simulation run of the MATLAB Simulink model requires ~600 s on an Intel Xeon, 3.0. GHz processor, while the BPMN-based model requires less than 30 s in the same computer. We performed 100 simulation runs for both models and reported the mean and standard deviations for simulation results of performance indices in Table 4.3. Considering the stochastic variations in customer order generation, i.e. quantity distribution and customer locations, and production processing time calculation, the simulation results, namely, transportation costs, plant revenues and other performance indices were quite different from one simulation run to another. However, from the mean and standard deviation of performance indices shown in Table 4.3, two modes generated statistically the same results (unpaired t-test). As a result, the BPMN-based model is validated from the comparison of the simulation results.

Various case studies have already been done in the model developed in MATLAB Simulink, including comparison on procurement policies, order assignment policies and scheduling policies. And the BPMN-based model has been validated through the comparison of simulation results between the two models, so it is not necessary to replicate these case studies in the BPMN-based model. Instead, we would like to do some scenario studies to investigate the benefits and shortcomings of BPMN in supply chain modeling.

Table 4.3: Comparison of performance indexes for validation

Performance Index	BPMN-based	MATLAB Simulink
Overall Profit (M$)	5.72 (0.53)	5.71 (0.52)
Customer Satisfaction	86.4% (3.6%)	86.7% (4.0%)
Total Transportation Cost (M$)	1.36 (0.06)	1.34 (0.05)
Overall Plant Utilization	98.3% (0.7%)	98.3% (0.8%)
Total Tardiness (days)	16.3 (4.2)	16.5 (4.6)
Number of Missed Orders	36.4 (4.0)	36.7 (4.1)

```xml
<configurations>
    <configuration name="default">
        <components>
            <component type="Customers" name="Customers" />
            <component type="GlobalSales" name="GlobalSales" configuration="Eariest"/>
            <component type="Logistics" name="Logistics"/>
            <component type="Suppliers" name="Suppliers"/>
            <component type="Plant" name="S" configuration="NonPeriod" />
            <component type="Plant" name="H" configuration="NonPeriod" />
            <component type="Plant" name="J" configuration="NonPeriod" />
        </components>
    </configuration>
    <configuration name="Nearest">
        <components>
            <component type="Customers" name="Customers" />
            <component type="GlobalSales" name="GlobalSales" configuration="Nearest"/>
            <component type="Logistics" name="Logistics"/>
            <component type="Suppliers" name="Suppliers"/>
            <component type="Plant" name="S" configuration="NonPeriod" />
            <component type="Plant" name="H" configuration="NonPeriod" />
            <component type="Plant" name="J" configuration="NonPeriod" />
        </components>
```

Figure 4.9: Configuration of BPMN-based model shown in Application XML file

4.3.2 Scenario 1

The first scenario studies the difficulties when manipulating BPMN-based model and MATLAB Simulink Model. For BPMN-based model, the structure of the whole model is mainly controlled through the Application XML file (Figure 4.9) which is capable to display the details of model in terms of configuration of each type of entities, i.e. number, entity name and model parameters such as location coordinates. If one wants to switch the policies of Global Sales and certain Plant, one can directly change the corresponding configuration in the Application XML file easily. And different configuration of model can be saved and easily switched. But for MATLAB Simulink model, one has to modify the parameters of all related blocks (entities) individually if there is any modification in model configuration.

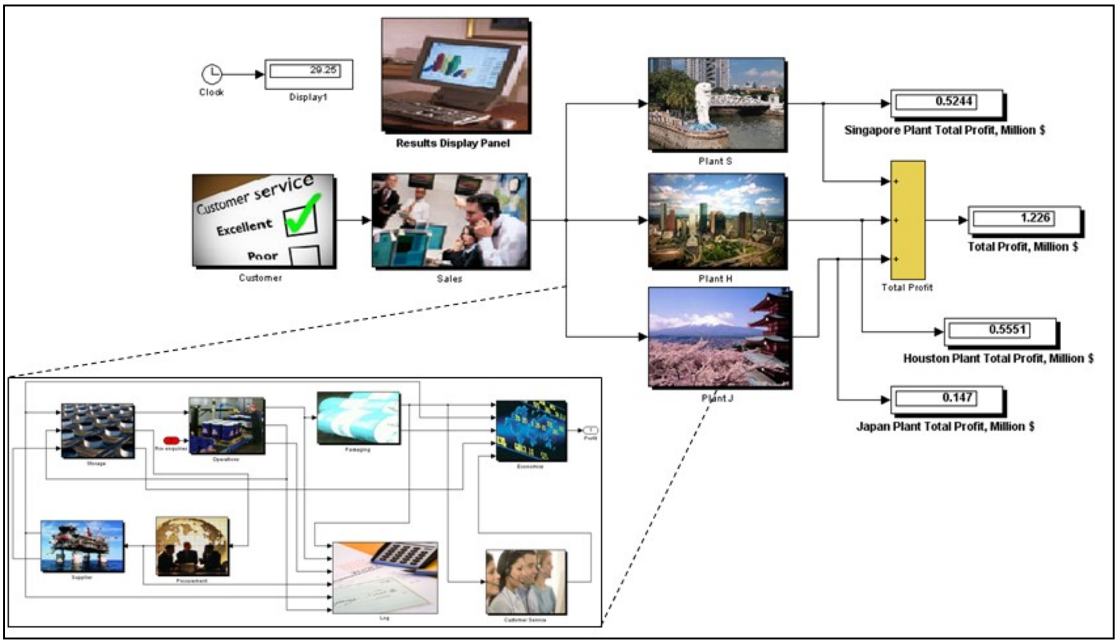


Figure 4.10: Schematic of MATLAB Simulink model of Multisite Specialty Chemicals Supply Chain (Adhitya et al. 2010)

Secondly, each entity is shown as one single Simulink block in MATLAB Simulink model (Figure 4.10). All the tasks flows, control functions and decision making process of each entity are hidden and hard coded, and each Simulink block has multiple signal lines indicating different inputs and outputs. As a result, the MATLAB Simulink model is not able to provide a comprehensive descriptive and analytical view of the supply chain. It would be difficult for users other than developers to understand and manipulate.

4.3.3 Scenario 2

In today's world, facing the drastic changes of economic development, political crisis, energy crisis and great opportunities offered by globalization, many enterprises come across a situation to decide whether to open more sectors/plants or quit certain regional markets. As a decision support tool, supply chain model should have a high level of scalability.

In this scenario, since BPMN diagram works a class of entities, it is very easy to upgrade or downgrade the scale of enterprise by just manipulating the number of entities declared in the application XML file. For MATLAB Simulink model shown in Figure 4.10, each entity has to be shown as single block or combination of blocks in the Simulink window. Upgrading or downgrading the model scale can only be achieved by creating or deleting blocks (entities) and modifying all the signal lines that representing the information and material flows of these simulation blocks. If the number of entities of the model, e.g., the number of plants, has altered so large that it would be messy and even impossible to make it in the Simulink window as all the entities should be shown up and all information and material flows should be created as signal lines connecting these entities(blocks).

4.3.4 Scenario 3

Modern supply chain is increasing complex and decision makers are interested to investigate all possible aspects of supply chains that could reduce the cost and increase the profitability. As a result, supply chain models should have high capability for further development and use.

For example, the enterprise is interested in customer relation management. He wants to choose certain pattern of customers that has higher priority to satisfy during product shortage and study the influence to the inventory management and customer satisfaction. As a result, in both models, customers should be modeled as a group of entities instead of a single entity. According to Scenario 2, MATLAB Simulink model would have a disadvantage compared with BPMN-based model if the number of customers goes large. Moreover, a new Task for decision making should also be added to Global Sales to decide the priority for both models. If this decision making process is very complicated and a fine level of graphical form is required, BPMN-based model can accomplish it through hierarchy development using Sub-Process, and MATLAB Simulink model can only add codes in corresponding block to achieve this. However, in the new framework, technical developers can ask business user to draft the decision making process in BPMN and directly enhance the BPMN-based model from the drawing, while MATLAB Simulink model does not has this benefit.

Figure 4.11 shows the enhanced Process Diagram for Global Sales. Comparing with Figure 4.4, the Task “Assign order” is replaced with a Sub-Process to show a finer level of a more complex decision making process. It starts with a task to examine whether the product is in shortage season or not. If it is in shortage season, Global Sales evaluates the priority of the customer. If the customer has a higher priority, Global Sales would confirm the order if possible. Otherwise, it would reject the order. The priority of customers can be predefined or decided and updated based on the ordering pattern of customers.

Taking logistics for another example, the enterprise wants to evaluate whether it is profitable to own its own transportation sector instead of buying services from third party. In BPMN-based model, it achieved by creating a Java class for transportation tools and adding the object of this class as an attribute to the product delivery. Afterwards, the number and lot size of transportation tools can be estimated and optimized through simulation runs with certain algorithms. And the profitability can be evaluated. In this case, MATLAB Simulink model can also achieve this by creating matrix for storing and updating status of transportation tools whenever a mass transfer is made.

4.4 Conclusions and Discussion

Natural fit to real systems, easy translation between practice and experiment, and increasing reliability and profitability make ABMS a promising tool to handle the complexities and uncertainties of supply chain systems. But most agent-based models are hard-coded and the concept of current ABMS methodologies is abstract and academic, making it difficult to employ in the business area. BPMN is gaining widespread acceptance in today's business organizations as it provides a more standardized graphical notations to unify the concept of business process (Dubani et al., 2010) and minimizes the gap in business process modeling between business users and technical developers. The combination of ABMS and BPMN can bypass the disadvantages of present ABMS methodologies and make it realizable in real industrial implementation.

Guidelines for modeling complex supply chain system were employed and validated by replicating an existing multisite specialty chemicals supply chain model from BPMN approach and comparing the simulation results between the two models. Scenario studies demonstrated the key benefits of BPMN in supply chain modeling. BPMN-based model is easier to understand, manipulate and has high level of scalability. It is capable to study various supply chain problems in an easy fashion. There also exists a tradeoff between graphical notations and hard codes. A complex decision making process can be difficult and messy to model with notations, in which case, it would be better to hard coded in custom function and shown as a Task in the thread.

Our proposed guidelines have a high potential in real business implementation. Business users can easily follow the first three steps of the guidelines to create a draft with text notations for the complex supply chains using BPMN graphical elements as what they have been doing using other flowcharting tools. Afterwards, the draft and can be handed over to technical developers to complete into executable supply chain models following the last step of the guidelines and returned to business users for real implementation. Since business users and technical developers are communicating with each other using the same modeling language, the efficiency is greatly improved and the misunderstanding can be minimized. As a result, the advantages of modeling and simulation can significantly benefit the real industry.

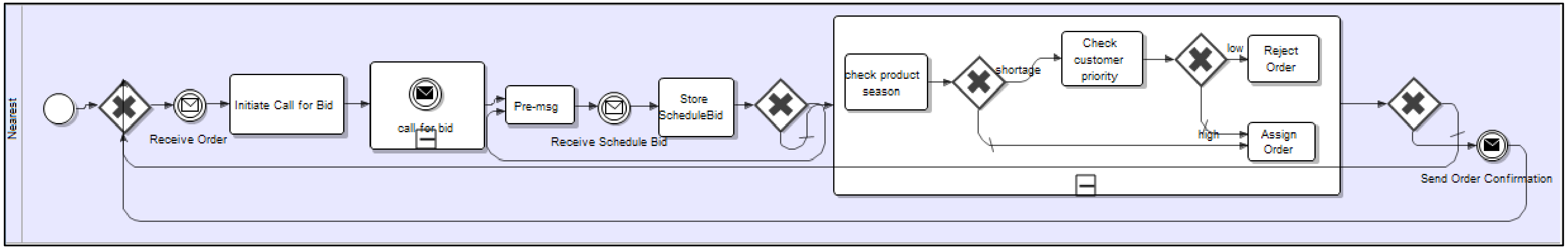


Figure 4.11: Process Diagram for Global Sales in Scenario 3

Chapter 5

Optimizing Tank Fleet in Chemical Supply Chains Using Agent Based Simulation

5.1 Introduction

Logistics is central to the chemical industry. Transporting chemical substances holds together the numerous entities of the chemical supply chains from the upstream processing facilities in major production centers in the Middle East, Europe and the US to downstream manufacturers worldwide and further to most sectors of the global economy (Jetlund and Karimi, 2003). Effectiveness of logistics is crucial for the performance of the supply chain, especially due to recent trends such as just-in time (JIT) manufacturing, outsourcing and global sourcing. The logistics costs of chemical industry are considerable and can be as high as 20% of the purchase costs (Karimi et.al, 2002). Effective logistics decisions and policies are therefore essential in terms of both logistics expenditure and supply chain performance.

Chemicals are commonly toxic, explosive or otherwise hazardous. As a result, special purpose assets are needed to transport them. Various types of assets are used depending on the mode of transportation, including rail cars, intermodal tanks, ISO tanks and road tankers. In order to avoid any possible cross contamination problem, each tank is often dedicated to a single product. A typical cycle of such an asset (henceforth called a tank) starts from the manufacturer's plant where it is filled with the chemical and transported to a distribution center. From the distribution center it is delivered to a customer based on existing orders. The customer uses the chemical product directly from the tank and therefore holds it until it become empty. The empty tank is returned to the distribution center or manufacturer's plant. In order to ensure high customer satisfaction, chemical enterprises must maintain sufficient number of tank cars in the right locations across plants, depots, distribution centers, warehouses and ports to meet the day-to-day operational needs. Shortage of tank cars can cause production disruption, leading to massive financial losses and low customer satisfaction level. Therefore in practice, chemical enterprises hold a large number of tanks at hand. As a result, purchasing and leasing of tanks account for large expenses for the chemical industry as does maintenance costs (Cheon et al., 2012). These motivate studies of optimizing tank fleet size and tank fleet routing problem.

Fleet sizing is a widely studied topic as reviewed in Section 5.2. Coarse models have been widely used along with mathematical programming based solution strategies. These approaches suffer from a number of disadvantages. In this chapter, we demonstrate the need for detailed operational models for making fleet sizing decisions. Specifically, we focus on a complex chemical supply chain consisting of an end product market, multiple customers and a chemical enterprise comprising multiple departments, as described in Section 5.3. A detailed agent-based simulation for this supply chain is developed in Section 5.4. The various supply chain entities function based on certain policies and interests. They communicate and collaborate with each other across various activities including end product sale, order placement, order assignment, inventory management and replenishment planning. These activities drive the plants to manufacture chemical products, transfer them to warehouses, deliver to customers and ultimately meet the market demand. The dynamics of the supply chain is therefore reproduced by this bottom-up model. We illustrate the effect of logistics decisions on the dynamics of the supply chain in Section 5.5. In Section 5.6, using this detailed supply chain model, we derive the logistics related policies and optimize fleet size for optimal performance.

5.2 Literature Review

Tank fleet management requires various decisions making at strategic decisions such as fleet size and composition, and operational decisions such as routing strategy and empty repositioning (Cheon et al., 2012). Strategic decisions are long range planning decisions that enterprises have to make to maximize their projected profit in a long term, e.g. one year or even longer, which includes fleet size, fleet type and the ratio of purchasing and leasing of tank fleet. Operational decisions deal with routing problem to serve a given day's customers, involving optimization on the routing of tank cars delivering products to customers and the reallocation of empty tank cars returned from customers so that the chemical enterprises can satisfy the customers' demand with a low cost.

Table 5.1: Classification of fleet sizing models (Turnquist and Jordan, 1986)

		Traffic Pattern		
		One-To-One	One-To-Many	Many-To-Many
Shipment Size	Full Vehicle Loads	Cyclic Queuing Models	Fleet Allocation Models	
	Partial Loads	Dispatching Models	Vehicle Routing Models	Scheduled Operations

Tank fleet sizing has been widely studied in literature (Turnquist and Jordan, 1983; Klincewicz et al., 1990; White, 1996; Lesyna, 1999; List et al. 2003; Cheon et al., 2012). The traditional way of estimating fleet size only involves average demand, tank capacity and average roundtrip time for one tank vehicle to complete one cycle of route (Anderson, 1982):

$$\text{fleet size}= \frac{\text{average demand} \times \text{average roundtrip time}}{\text{tank capacity}}$$

But this calculation always underestimates the fleet size as it ignores the dynamics in the system. A large number of researchers have therefore proposed various methodologies that rely on a more detailed representation of system. Turnquist and Jordan (1986) considered traffic pattern (determined by number of origins to number of destinations) and shipment size (relative to single vehicle capacity) as two important characteristics of fleet sizing problem and hence classified fleet size models into different categories (see Table 5.1). For instance, fleet allocation model is employed "One-To-Many" the fleet sizing problem involves one component plant shipping full loaded containers to many warehouses or customers.

These methodologies can be categorized into mathematical programming, heuristic approach and simulation modeling. Among these, simulation modeling captures the complex system dynamics and enjoys high credibility.

Many researchers have employed mathematical programming to capture the intricate relationships between decisions on fleet composition and repositioning and the resulting profits, market satisfaction and customer service level. Turnquist and Jordan (1983) underlined the importance of empty car redistribution on financial health of railroads, and developed a dynamic optimization model of empty car redistribution to improve the fleet utilization and further to maximize the revenue. The failure of satisfying demands and the holding the empty cars were accounted as costs in their model. Klincewicz et al. (1990) introduced a mathematical model to address a fleet size planning problem of a warehouse serving local customers with a combination of private delivery fleet and outside carrier service. A "single-source capacitated facility location formulation" was implemented in their solution approach where each vehicle was considered as a facility to serve multiple customers. Their model is a vehicle routing model according to Turnquist and Jordan (1986). Wu et al. (2002) integrated a mathematical model to solve a rental fleet sizing problem with heterogeneous trucks that vary in ages and types, and proposed a two-phase solution strategy approach. Phase I allocates customer demand among available trucks based on their types and capacities, and Phase II further improves the solution quality through Lagrangian relaxation. In their model, time and space are simplified as series of time-space nodes. Klosterhalfen et al. (2003) developed a MILP model to optimize the structure of a rail car fleet for a chemical company by minimizing direct rail car cost, and further determined the optimal size by using an approximation from inventory theory. Researchers also incorporated uncertainties related to transportation time and demand in mathematical models and developed stochastic models. Turnquist and Jordan (1986) proposed a fleet sizing model with stochastic tank cars travel time and analyzed its impact on the probability of tank car shortage. List et al. (2003) formulated and solved a fleet planning optimization model by accounting for uncertainties in future demand and productivity of individual vehicles. Uncertainties in customer demand and travel time were also taken into account in Wu et al. (2002)'s truck-rental fleet sizing model and Klosterhalfen et al. (2013)'s model.

In these papers, there are a lot of assumptions that must be made to simplify the problems. The planning time periods may be abstracted to time points. Only state variables such as avenues and costs are considered in the equations, while the system dynamics in the detailed level is not captured, for instance, the inventory control of warehouses or customers. Also, the interactions among the supply chain entities are ignored. The discrete mass transfer may be simplified to continuous flow and some nonlinear relations are simplified to be linear in order to make the model mathematically tractable. These assumptions and simplifications limit the extent to which these models truly represent the dynamics of the supply chain. Moreover, the model formulation of the mathematical programming approaches is brittle. A change in the formulation, e.g., continuous variable to discrete variable linear relation to nonlinear relation may require an entirely different solution algorithm. Besides, the solution of such models is also brittle. Some models may produce a highly optimal solution for a set of constrains and a static point in time, but these solutions may not prove to be robust in dynamic environments (Blackhurst et al., 2005). Optimal solution points are highly unstable once a slight change is made in the problem data. As a result, mathematical programming is quite limited in dealing with such kind of large-scale, complex, dynamic, nonlinear problems (Wan et al., 2005; Mele et al., 2007).

Researchers have also focused on routing efficiency for improving fleet management and reducing fleet size and costs. It has been much discussed in recent literature through heuristic approaches. Golden et al. (1984) addressed the fleet size and mix vehicle routing problem involved a central depot and customers with consideration of heterogeneous fleet. The authors described several efficient heuristic procedures to approach optimal fleet size by minimizing the sum of fixed cost and variable costs. Sherali and Tuncbilek (1997) proposed a dynamic model based on time-space network to solve a rail car fleet management problem. The authors solved the model through a heuristic that decomposed the problem into a sequence of time-space sub-problems and achieved reduced empty repositioning travel and improved routing efficiency. Renaud and Boctor (2002) presented a new sweep-based heuristic for fleet size and mix routing problem which involved decisions on both fleet composition and fleet routing. Koo et al. (2004) proposed a two-phase heuristic procedure for fleet sizing and routing of static container transportation. In this procedure, an optimization model was first introduced to determine lower bound of fleet size and then a heuristic tabu search algorithm was employed to solve the transportation problem with minimum fleet size.

These heuristic approaches provide search algorithms that were only proved efficient in the specific problems or models which involved a number of simplifications and assumptions. They may be inefficient and even impractical for systems with different configurations, but still they offer basis for the development of specialized algorithms to solve such problems within a reasonable time for complex systems.

Simulation modeling has proven to be a valuable approach to understand complex dynamics of supply chain and logistics system (Petrovic et al., 1998; Julka et al., 2002; Thierry et al., 2008; van Dam et al., 2009; Longo, 2011). A simulation model not only considers the various sources of variability and uncertainty that affect the system performance, but also takes into account individual behaviors and heterogeneities as well as their interactions. Therefore, it has a more detailed representation of the system (Lesyna, 1999). Moreover, the rules for operating the both system components and their interactions can be easily integrated into simulation models while it is unfeasible to comprise these essential features in mathematical programming models. Based on this perspective, the fleet size and management problem can be studied taking into account its effect across the entire system rather than in an isolated way. Lesyna (1999) reported a discrete-event simulation model used in DuPont to optimally size the rail car fleet deployed to deliver products to end customers. Various management policies were evaluated through simulation model and the study showed that a policy that was initially thought as appropriate in the company was actually counterproductive. Song and Dong (2008) modeled the movements of containers between ports and used a simulation model to evaluate the performance of different empty container management policies for a cyclic shipping route under different demand patterns. White (1996) underlined the importance of railcars to chemical enterprises and discussed the complexity and challenges on current railcar management. The author illustrated two case studies in different situations when simulation modeling can be used as a valuable tool to achieve significant savings on investment and operating cost. In the two case studies, simulation models were able to quickly and objectively compare alternatives in different scenarios so that optimal policies were determined to improve the system efficiency and avoid unnecessary capital investment.

Most of the literature focuses on the fleet sizing and management problem in general industries, while the work specially for chemical industry is limited. In chemical industry, tank cars are normally dedicated to single product to avoid any possible cross contamination problem. In many cases, tank cars are the only place to store newly produced products and maintain inventory (Cheon et al., 2012). Customers also hold tank cars as temporary storage and return them when they use up the products. Shortage in tank car will cause production disruption, which leads to massive financial losses and customer service level decrease. Therefore, the local policies and rules of supply chain entities and their interactions have strong impact on tank fleet sizing and management. All these factors have to be taken into account.

In this chapter, we propose an agent-based simulation model of a multisite chemical supply chain to address the tank fleet management problem.

5.3 A Multisite Chemical Supply Chain

Figure 5.1 shows a multisite supply chain of a chemical product. The product is used as feedstock by customers who further process it into a compound that is sold in the market. The entire supply chain of interest thus consists of a market, multiple customers, and the focal chemical enterprise that produces the product. The enterprise has multiple plants where the product is produced as well as multiple warehouses from where it is supplied to the customers. The various entities – customers, warehouses, and plants – are spatially distributed. A key characteristic of the product is that it is stored and transported in special-purpose tank cars. There is no separate storage tanks in the plant, warehouse, or in the customers facility.

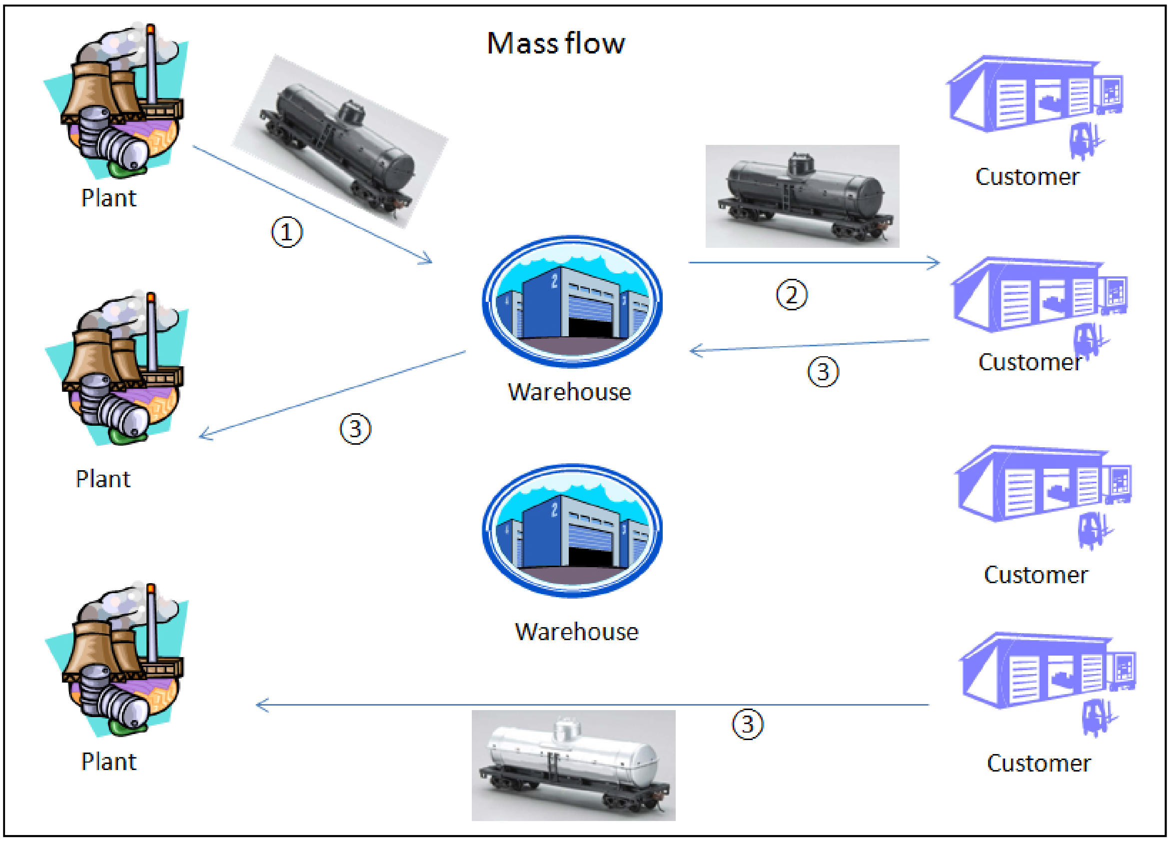


Figure 5.1: Schematic of a chemical supply chain: mass flow

The material flow in the supply chain (see Figure 5.1) starts from the plants which manufacture the product and load it into tank cars. Filled tank cars are then transported to a warehouse. Warehouses retain the filled tank cars as their inventory and deliver them to customers based on their orders. The customers use the product directly from the tank cars. Once the product in a tank car is used up by the customer, the empty tank car is released back to the enterprise which then arranges for it to be transported back. Thus the movement of the tank cars is synchronous with the production, flow, and usage of products in the supply chain. Further, since the number of tank cars in the system, i.e., fleet size, is fixed, it is a significant factor that determines the dynamic behavior of the supply chain.

The operation of this supply chain relies on three different information flows that facilitate the material flows in the system: order assignment, replenishment planning, and logistics as shown in Figure 5.2. Each of these is coordinated by a distinct functional department – order coordinator, replenishment coordinator, and logistics coordinator.

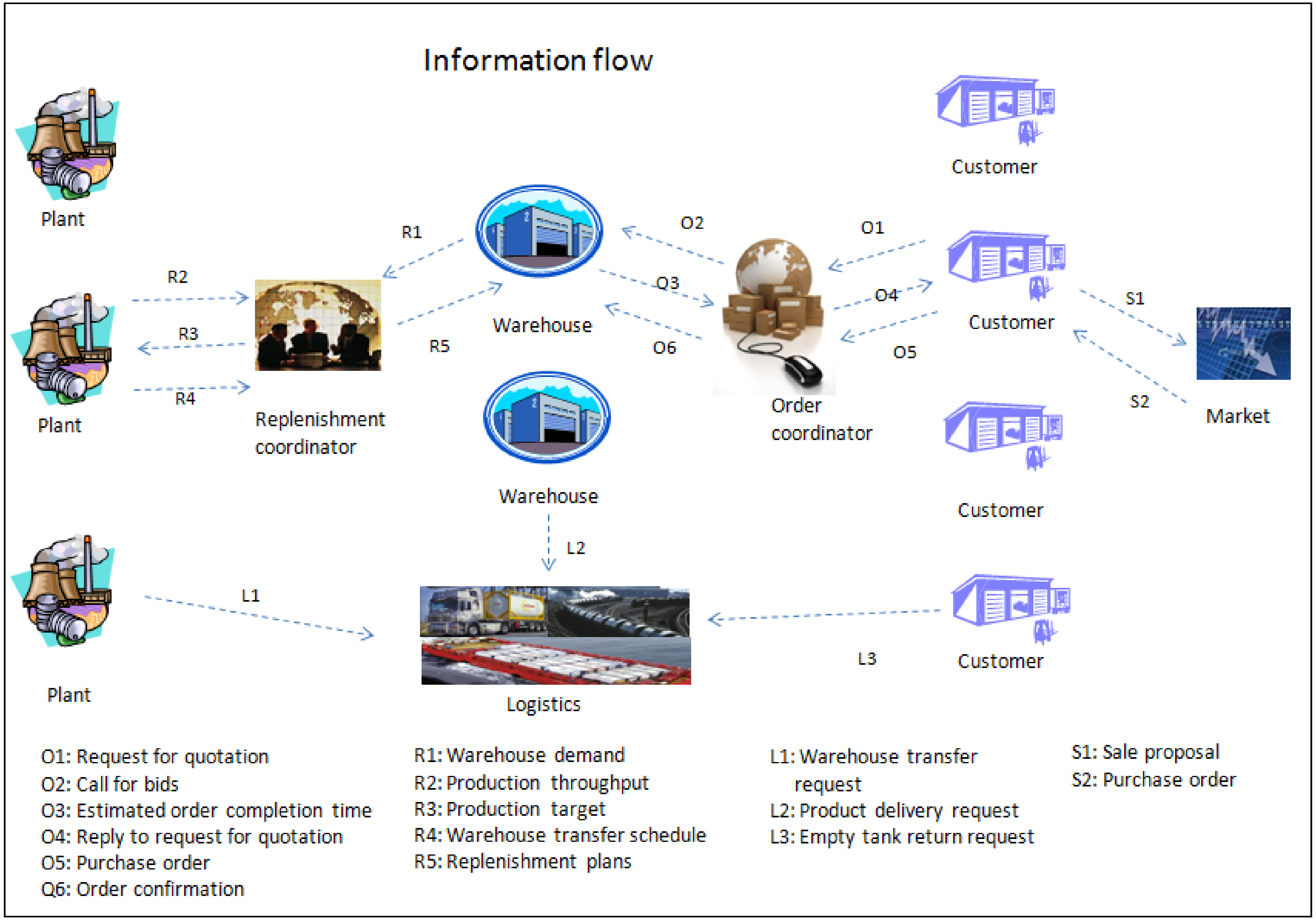


Figure 5.2: Schematic of a chemical supply chain: information flow

The order assignment process seeks to allocate each customer order to a warehouse from where it would be fulfilled in a timely and cost-effective manner. Based on geographic locations and warehouse capacities, each customer is pre-assigned a specific warehouse, called the *primary warehouse,* from which fulfillment would occur, if possible. The other warehouses in the system are considered to be *reserve warehouses* for that customer and would be called on only if the primary warehouse is unable to fulfill the customer's orders. Once a customer initiates an order, it is routed to the order coordinator who has to decide if the order can be accepted and if so the warehouse from which to fulfill it. These decisions are not made immediately as soon as the order is received; instead all orders received within an *order-processing window* (typically 1 day) are processed in batches. Each batch of orders is handled in two stages. In the first stage, for each order, the order coordinator first consults the primary warehouse to obtain an estimate of the earliest delivery date. If the order can be fulfilled by the primary warehouse before the due date required by the customer, the order coordinator will assign the order to the primary warehouse and inform the warehouse and customer accordingly. Any order that *cannot* be fulfilled by the primary warehouse within the due date is set aside and will be processed in the second stage. All orders in the batch are processed in this fashion. In the second stage, all the orders that could not be fulfilled by the primary warehouses are sent to their reserve warehouses and an earliest delivery date estimate obtained. An order that can be fulfilled before its due date is assigned to that warehouse that can deliver it the earliest. If no warehouse expects to fulfill the order before its due date, the order coordinator rejects the order – such orders are called *missed orders*. The customer (and the concerned warehouse in the former case) is informed accordingly. This two stage order assignment process followed by the order coordinator thus seeks to minimize the warehouse-to-customer transportation time and costs since order fulfillment from primary warehouses are given priority over others.

The role of the replenishment coordinator is to enable the warehouses to maintain adequate inventory in order to meet customer orders. It achieves this by coordinating the production of the product in the plants as well as the transfer from the plants to the warehouses. Replenishment planning is performed periodically (typically, once every 10 days) and caters to the need of the warehouses over a *replenishment planning horizon.* As shown in Figure 5.2, it is initiated when the coordinator seeks the cumulative demand over the replenishment planning horizon from each warehouse. Warehouses use a periodic replenishment policy; hence they can estimate the amount of products they would require based on their current inventory level, expected product deliveries from the plants, and their confirmed customer orders until the end of the replenishment planning horizon. In parallel, the replenishment coordinator also seeks the plants' production capabilities (expected minimum and maximum throughputs). The replenishment coordinator then solves a resource allocation problem to match the warehouses demands and the plants capabilities, and assigns production targets to the various plants. The plants use these targets to make their own production plans and calculate the schedule at which product can be transferred to the warehouses. The warehouses use this transfer schedule to schedule their deliveries to the customer.

Tank cars are a limited resource in this system. Once a customer is ready to release an empty tank car, a tank return request is sent to the logistics department which decides the destination (specific warehouse or plant) to which it should be transported to. This in turn determines the availability of empty tank cars in plants. Thus, the movement of the tank cars through the supply chain, starting from availability of empty tanks for storing products as soon as they are produced in the plant, to warehouse transfer, product delivery to customer, and finally return of the empty tank cars back to the plants is *not* managed holistically by one entity, rather it emerges based on the interplay of the decisions by the customers, logistics coordinator, plants, replenishment coordinator, and warehouses.

As in other supply chains, demand for the product is exogenous to the enterprise and also plays a crucial role in determining the performance of the supply chain. Product demand emerges in this supply chain from the competition between customers in a price-sensitive market. Customers produce a compound and sell it in the market. The total size of the market (daily demand for compound) is constant, however since customers may offer a different sale price on each day, the total sales for each customer is time-varying. Customers in turn require the product to produce the compound and maintain their own inventories; therefore the set of customers placing orders from the enterprise varies continuously as does the size of their orders. Every day, each customer sends a sale proposal to the market with information on their offered sale price and the maximum quantity for sale. The market first ranks the various sales proposals based on ascending price and confirms sales offers to customers, starting from the top of the ladder (i.e., low price to high price) until the entire market demand is fully satisfied. Once a customer receives a sales offer, products are immediately released from inventory for transformation into compound.

The various interactions, decisions and the resultant material flow and tank car movement determine the dynamics of the supply chain. Each supply chain entity functions based on certain rules and policies and makes decisions to pursue its own interests. The performance of the supply chain emerges from the interactions among the entities. We have developed a dynamic agent-based model of the supply chain to analyze and optimize this system, as described in the next section.

5.4 Dynamic Simulation Model of the Chemical Supply Chain

We use Agent-based Modeling and Simulation (ABMS) to capture the intricate dynamics between logistics and the other elements that form the chemical supply chain. Agent-based modeling uses a bottom-up modeling approach and is widely considered as a valuable approach for decision support in supply chains (Julka et al., 2002 a; Julka et al., 2002 b; Mele et al., 2007; van Dam et al., 2009). Each entity in the system is modeled as an "agent" that has its own states and interests, and makes decisions based on a series of rules (Bonabeau, 2002). Agents are also able to interact with each other, perceive their environment, and respond to changes. Agent based models are flexible and scalable. The complexities of models can be manipulated by modifying the number of agents and the rules for their actions and/or reactions, learning, and interaction. These important features make ABMS a natural fit to the study of fleet sizing in chemical supply chains.

The proposed simulation model uses a discrete-time representation, where each day d is divided into T time ticks. We define seven classes of agents to represent the key entities in the supply chain: market, customer, order coordinator, warehouse, replenishment coordinator, plant and logistics. The geographical location of each customer, warehouse, and plant is represented through a pair of coordinates (*xloc*, *yloc*), which is an attribute of the agent. We assume that products are sold in units of full tank cars.

5.4.1 Market Agent

The market agent represents the market for the compound. Different customers offer different quantities of compound for sale daily at different prices. The responsibility of the market agent is to partition the daily total market demand into customer-specific demands. For this, it identifies the equilibrium price at which supply matches demand.

The sale of compound starts with customers offering sales proposals to the market. Each sale proposal is modeled as a class with four attributes: (1) SP^{id} its unique id; (2) SP^{c} the customer id; (3) SP^{MaxAmt} the maximum amount that the customer is willing to sell; and (4) SP^{Price} the offer price. Every day, the market agent receives sales proposals from various customers, collates them in a list, $SPList$, which is then sorted by the offer price.

$$SPList \leftarrow sort(SPList, SP^{Price}, ascending)$$

The role of the market agent then is to create purchase orders for the successful sales proposals. Let *MPO* denote the purchase order, MPO^{SPID} the id of the corresponding sales proposal to which this purchase order is the reply to, MPO^{BuyAmt} the confirmed amount of purchase. Further, let *SM(t)* be the amount of sales in response to that day's total market demand, denoted as *MD(t)*.

```
INIT BalanceAmt as MD(t)
INIT SM(t) as 0
WHILE BalanceAmt > 0 AND SPList is not empty
        Set SP to the first sales proposal in SPList
        Create a new purchase order MPO
        Set MPO^SPID to SP^id
        IF BalanceAmt ≥ SP^MaxAmt THEN
                SET MPO^BuyAmt to SP^MaxAmt
        ELSE
                SET MPO^BuyAmt to BalanceAmt
        ENDIF
        Remove SP from SPList
        Update BalanceAmt as BalanceAmt – MPO^BuyAmt
        Update SM(t) as SM(t) + MPO^BuyAmt
ENDWHILE
```

If the total amount of the compound that customers all together offer to the market is less than the market demand, all the proposals will be accepted, otherwise only the lower priced ones that can adequately meet the market demand. Finally, all purchase orders are dispatched to the respective customers.

Market satisfaction, *MS,* is employed as a metric to measure the overall system performance. It is determined as the ratio of compound sold by the customers to the market demand, both on a daily and cumulative basis.

$$MS(t) = \frac{MS(t)}{MD(t)} \times 100\%$$

The cumulative market satisfaction, *CMS,* is calculated as:

$$CMS = \frac{\sum_t MS(t)}{\sum_t MD(t)} \times 100\%$$

5.4.2 Customer Agents

Customers buy product from the enterprise and process it further to make the compound that is sold in the market. For simplicity, we assume that each unit of product is transformed into one unit of compound. Batches of compound are produced by the customer only when a market demand is realized, i.e., a MPO is received. Further, there is no separate inventory of compound. Every day, customers offer a sales proposal SP to the market specifying the offer price SP^{Price} and maximum quantity SP^{MaxAmt}. We assume that customers are willing to sell the entire amount of compound that can be produced from their inventory of product at hand:

$$SP^{MaxAmt} = IL_c(t)$$

where $IL_c(t)$ denotes the product inventory level of customer c at time t. The offer price is calculated using a sliding scale based on the inventory at hand:

$$SP^{Price} = BP_c - FP_c \times IL_c(t)$$

where BPc is the base price and FP_c a pricing factor.

Upon receiving a purchase order MPO from the market, customers offload the product from tank cars and transform it to $\text{MPO}^{\text{BuyAmt}}$ amount of compound. Therefore the new inventory of product is given by:

$$IL_c(t) \leftarrow IL_c(t) - MPO^{BuyAmt}$$

Customers hold their inventory of product in tank cars. Each tank car is modeled as a class with three attributes: (1) TC^{id} is a unique id; (2) TC^{Cap} the capacity of the tank car; and (3) TC^{Amt} the current inventory of product in the tank car. We assume all tank cars have the same capacity. Customers manage the set of tank cars holding their inventory based on a First-In-First-Out (FIFO) policy. Each customer has a list of tank cars, $TCList_c$. When a new tank car carrying product arrives from the enterprise, it is inserted at the end of the list. Product will be consumed first from the tank car in the front of the $TCList_c$. Once the product in a tank car is used up, the customer will release it back to the enterprise and remove it from $TCList_c$.

```
INIT ProcessingAmt as MPO^BuyAmt
WHILE ProcessingAmt > 0
        Set TC to the first tank car in TCList
        IF TC^Amt > ProcessingAmt THEN
                Set TC^Amt to TC^Amt – ProcessingAmt
                Set ProcessingAmt to 0
        ELSE
                Update ProcessingAmt as MPO^BuyAmt - TC^Amt
                Set TC^Amt to 0
                Remove TC from TCList
        ENDIF
ENDWHILE
```

Customers manage their inventory of product using the (S, s) policy. If the inventory position falls below the reorder point s, procurement is triggered, and an order is placed to the enterprise. The ordering process starts with the customer sending a request for quotation to the enterprise (specifically the order coordinator). The Request for Quotation, RFQ, is modeled as a class with five attributes: (1) RFQ^{id} is a unique id number; (2) RFQ^{C} the customer id number; (3) RFQ^{Amt} the ordered amount; (4) RFQ^{DD} the due date; and (5) RFQ^{Tol} the tolerance days defined as the maximum number of days after the due date by which the order must be delivered. The amount of product ordered (in number of tank cars, each of capacity $\mathrm{TC}^{\mathrm{Cap}}$) can be calculated as:

$$RFQ^{Amt} = round\left(\frac{S_c - IP_c(t)}{\mathrm{TC}^{\mathrm{Cap}}}\right)$$

The reply from the enterprise, $RRFQ$, contains three attributes: (1) $\mathrm{RRFQ}^{\mathrm{id}}$ its id which matches the corresponding RFQ^{id}; (2) $RRFQ^{Cmf}$ is the enterprise's confirmed acceptance (=1) or rejection (=0) of the order; and (3) $RRFQ^{CmfDD}$ the confirmed due date on acceptance. If the enterprise can fulfill the *RFQ*, the customer will create a purchase order, CPO which has four attributes: (1) CPO^{id} is the id of the corresponding *RFQ*; (2) CPO^{c} the customer id; (3) CPO^{Amt} the ordered amount; (4) CPO^{CmfDD} the confirmed due date; and (5) CPO^{Cmplt} which is its completion status that is set to 1 when the order has been delivered. These purchase orders are stored by the customer in a $CPOList_c$ for tracking. The inventory position at time t, $IP_c(t)$ is given by the sum of the inventory at hand and on order.

$$IP_c(t) = IL_c(t) + \sum_{CPO \in CPOList, CPO^{Cmplt}=0} CPO^{Amt}$$

Purchase orders are fulfilled when the customer receives a product delivery. Let $PD^{OrderID}$ denote the id of the order based on which the delivery is initiated, PD^{Amt} the total amount delivered, and PD^{TCList} the list of tank cars carrying the product. The tank cars delivered are inserted at the back of the customer tank list $TCList_c$ and the product inventory, $ILc(t)$ updated.

$$IL_c(t) = IL_c(t) + PD^{Amt}$$

The customer updates the completion status of the corresponding order in the *CPOList* and other statistics regarding the enterprise's performance including the number of customer orders delivered delayed, CDD_c, and the number of customer orders delivered on-time, CDO_c.

```
Set CPO^Cmplt to 1
IF CPO^Cmfdd ≥ t THEN
        Update CDOc as CDOc + 1
ELSE
        Update  CDDc as  CDDc +1
ENDIF
Insert PD^TCList at the end of TCList_c
```

At the end of the simulation, these statistics can be used to calculate a customer satisfaction metric, CS_c, for customer *c* defined as the percentage of orders delivered on-time as well as the cumulative satisfaction for all the customers, *CCS*.

$$CS_c = \frac{CDO_c}{CDO_c + CDD_c} \times 100\%$$

$$CCS = \frac{\sum_{c} CDO_c}{\sum_{c} CDO_c + \sum_{c} CDD_c} \times 100\%$$

5.4.3 Order Coordinator Agent

The order coordinator is a functional department, which receives the Request for Quotation, RFQ, from customers, and then decides if it can be accepted and which warehouse would fulfill the order. Order assignment is done in batches every day. The order coordinator forwards the first request for quotation, RFQ, to the primary warehouse and asks for the projected completion date. The primary warehouse estimates the order completion date, $SchOrder_w^{cmplt}$, based on its order delivery scheduling policy, and replies to the order coordinator with this information. If the customer order can be fulfilled by the due date, the order will be accepted and the coordinator will send a Reply to Request for Quotation RRFQ, to the customer.

$RRFQ^{id} = RFQ^{id}$
$RRFQ^{cmf} = 1$
$RRFQ^{CmfDD} = RFQ^{DD}$

Otherwise, the order coordinator puts that RFQ aside and proceeds to the next one. After the conversation with the respective primary warehouse of each RFQ, if any RFQ remains unaccepted, the order coordinator will proceed to the second stage and initiate a call for bids from all warehouses except the primary warehouse. Each warehouse replies with their $SchOrder_w^{cmplt}$. The order coordinator then finds the earliest completion date from all the responses including the primary warehouse. If this is within the order due date plus tolerance days, the order coordinator will confirm the RFQ. The confirmed due date $RRFQ^{CmfDD}$ is set as the order due date or the earliest completion date as follows:

$$RRFQ^{CmfDD} = \begin{cases} RFQ^{DD} & \text{if } SchOrder_{w,\min}^{cmplt} \le RFQ^{DD} \\ \min\limits_{w}\left(SchOrder_w^{cmplt}\right) & \text{otherwise} \end{cases}$$

If the earliest completion date is beyond even the allowed tolerance RFQ^{Tol}, then the order is rejected. The number of such missed orders, *OM*, is used as a KPI of the enterprise's performance.

$RRFQ^{id} = RFQ^{id}$

$RRFQ^{cmf}$ =0
Update OM as OM + 1

Upon receiving the confirmation, customer initiates a purchase order CPO and sends it to the order coordinator which forwards it to the corresponding warehouse.

5.4.4 Warehouse Agents

The warehouse receives filled tank cars from plants, holds them as inventory, and delivers them to customers based on their purchase order *CPO*. When a warehouse *w* receives WT^{Am} of products in tank cars WT^{TCList}, the list of tank cars are appended to its $TCList_w$ and the product inventory, $IL_w(t)$, updated as:

$$IL_w(t) \leftarrow IL_w(t) + WT^{Amt}$$

Each warehouse maintains an order delivery schedule ODS_w sorted based on its scheduling policy DSP_w. The warehouse then delivers products according to this order delivery schedule. We assume that customers are willing to accept delivery earlier than the due date. Every day, the warehouse monitors its inventory. If the on-hand inventory level, $IL_w(t)$, is sufficient to satisfy the first order in the order delivery schedule, the warehouse will initiate delivery.

```
INIT InventoryAdequate as true
WHILE the size of ODS_w>0 AND InventoryAdequate
        Set CPO as the first order in ODS_w
        IF IL_w(t) ≥ CPO^Amt
                Set PD^OrderID as CPO^id
                Set PD^Amt as CPO^Amt
                Set N to PD^Amt/ TC^Cap
                Insert the first N elements in TCList to
        PD^TCList
                Remove the first N elements from TCList
                Update IL_w(t) as IL_w(t) - PD^amt
                Remove CPO from ODS_w
        ELSE
                Set InventoryAdequate as false
        ENDIF
ENDWHILE
```

As a simple shipment policy, we use the Shipment-due-date CPO^{ShipDT} to sequence orders. The shipment-due-date which represents the latest time by which the warehouse should initiate product delivery for the order to be delivered to the customer on-time.

$$CPO^{ShipDT} = CPD^{DD} - TT_{c,w}$$

where $TT_{c,w}$ denotes the transportation time between warehouse and customer. This shipment policy also has a role to play during order assignment process described above. Upon receiving a Request for Quotation, *RFQ*, from the order coordinator, the warehouse has to reply with the order completion date. This estimate of the completion date $ProjSch_w$ is based on the scheduling policy DSP_w.

$$\mathrm{ProjSch_w = DSP_w(RFQ,\ ODS_w)}$$

In the Shipment-due-date policy, $ProjSch_w$ is calculated as the earliest date that the potential order can be scheduled (i.e., the earliest place it can be inserted in ODS_w) without causing any previously confirmed orders to be delayed beyond their due-date. During this calculation, the current inventory position and the replenishment plans are also taken into account.

During replenishment planning, each warehouse estimates its demand over the replenishment cycle. Warehouses use a periodic review policy to maintain inventory. Let TL_w be the target level for inventory. The estimated demand WD_w is then calculated based on the inventory position $IP_w(t)$ which in turn is calculated using on-hand inventory and the outstanding replenishment transfers RT_w and customer purchase orders CPO_w.

$$IP_w(t) = IL_w(t) + \sum RT_w^{Amt} - \sum CPO_w^{Amt}$$

$$WD_w = TL_w - IP_w(t)$$

This estimate is sent to the replenishment coordinator. As explained below, the replenishment coordinator collects and reconciles the estimates from the various warehouses to the plants' throughput and confirms the replenishment amount and transfer schedule.

5.4.5 Replenishment Coordinator Agent

In any multi-plant, multi-warehouse system, each warehouse could be replenished from various plants. The goal of replenishment planning is to optimally allocate the replenishment to the plants. This would translate to production targets for the plants in each replenishment cycle which would then fulfill them through warehouse transfers. The replenishment coordinator is the initiator and central entity in replenishment planning. We assume that replenishment cycles have a fixed length and the start time of the i+1th replenishment cycle coincides with the end time of the ith cycle.

$$RC_i^{ET} - RC_i^{ST} = RC_{i+1}^{ET} - RC_{i+1}^{ST}$$
$$RC_i^{ET} = RC_{i+1}^{ST}$$

where RC_i^{ST} and RC_i^{ET} represents the start and end times of the ith replenishment cycle, respectively. At the beginning of replenishment planning, the coordinator seeks the estimated demands from the various warehouses and the limits on the production rates of each plant. After that, replenishment coordinator allocates the production target and decides the warehouse transfer based on a replenishment policy. In one policy, the replenishment coordinator seeks to assign production targets for each plant so as to optimize the transportation distance for the replenishment transfers.

$$Min \quad \sum_p \sum_w D_{p,w} T_{p,w}$$

where $D_{p,w}$ is the transportation distance between plant p and warehouse w, and $T_{p,w}$ the production sub-target assigned to plant p for warehouse w in that cycle. Three different situations can be differentiated:

a. The total warehouse demand $\sum_w WD_w$ is less than the minimum production throughput $\sum_p PT_p^{Min}$ (explained below) of the plants for that cycle: In this situation, in the interest of keeping all the plants running even if that requires producing more than the actual demand, the constraints become:

$$\sum_p T_{p,m}(RC_i) \geq WD_w(RC_i), \forall\ w$$
$$\sum_w T_{p,m}(RC_i) = PT_p^{Min}(RC_i), \forall\ p$$

b. The total warehouse demand is between the minimum and maximum production throughput of the plants. Here, we seek to balance the demand exactly while ensuring that all plants are running within their limits.

$$\sum_p T_{p,w}(RC_i) = WD_w(RC_i), \forall\ w$$
$$\sum_w T_{p,w}(RC_i) \geq PT_p^{Min}(RC_i), \forall\ p$$
$$\sum_w T_{p,w}(RC_i) \leq PT_p^{Max}(RC_i), \forall\ p$$

c. The total warehouse demand is higher than the cumulative production throughputs of all the plants. Here, we replenish as much of the demand as possible while running the plants at their full throughputs.

$$\sum_p T_{p,w}(RC_i) \leq WD_w(RC_i), \forall\ w$$
$$\sum_w T_{p,w}(RC_i) = PT_p^{Max}(RC_i), \forall\ p$$

Based on the situation in each replenishment cycle, the corresponding LP is solved and the optimal replenishment targets for each plant-warehouse combination $T_{p,w}$ allocated. The plants then plan their operations as described next.

5.4.6 Plant Agents

The role of the plants is to manufacture products and replenish the warehouses. During replenishment planning, the coordinator requests plants for their minimum and maximum production throughputs over a planning replenishment cycle RC_i defined by its starting and ending times, RC_i^{ST} and RC_i^{ET} . Let PR_p^{Min} and PR_p^{Max} denote the plant's minimum and maximum production rates per unit time and $BL_{p,i-1}$ any backlog from the (i – 1)th cycle (as explained below). The maximum and minimum production throughput of plant p, $PT_{p,i}^{Max}$ and $PT_{p,i}^{Min}$ during replenishment cycle RC_i can then be calculated as:

$$PT_{p,i}^{Max} = PR_p^{Max} \times (RC_i^{ET} - RC_i^{ST}) - BL_{p,i-1}$$
$$PT_{p,i}^{Min} = PR_p^{Min} \times (RC_i^{ET} - RC_i^{ST}) - BL_{p,i-1}$$

Based on these, the replenishment coordinator calculates the production target (as described in Section 4.5) and informs the plants. Using the total production targets and its production throughput limits, each plant determines its production profile over the course of the cycle. There are several ways of determining the production profile. In one policy that we term 'simple production policy', the plants maintain the same throughput throughout the horizon, calculated as:

$$PR_{p,i}^{Ave} = \frac{\sum_{w} T_{p,w,i} + BL_{p,i-1}}{RC_i^{ET} - RC_I^{ST}}$$

Next, the plant determines the replenishment plans for each warehouse. Each replenishment plan specifies the time ordered set of replenishment transfers for the various warehouses accounting for the transportation time. For simplicity, it is assumed that transfers are done in batches of one filled tank car. The replenishment plans are then sent to the replenishment coordinator who further forwards them to the respective warehouses. The plant's production schedule PS_p is derived by collating all the replenishment transfers.

The ultimate goal of each plant is the timely manufacture of products and their transfer to the warehouses. Each plant maintains a list of empty tank cars $TCList_p$ and manages it using a First-In-First-Out policy. The real-time production rate of each plant is a function of its production policy and conditional on the availability of empty tank cars. For example, in the case of the 'simple production policy' the product inventory level of plant $IL_p(t)$ is updated at each time tick t based on the availability of tank cars:

```
IF size of TCList_p >0
        Set TC to the first tank car in TCList_p
        Set PR_p(t) to PR_{p,i}^{Ave}
        Update TC^{Amt} as TC^{Amt} + PR_p(t)
        Set IL_p(t) to IL_p(t-1) + PR_p(t)
        Set SD_p(t) to 0
        Update AP_{p,i} as AP_{p,i} + PR_p(t)
ELSE
        Set PR_p(t) to 0
        Set IL_p(t) to IL_p(t-1)
        Set SD_p(t) to 1
ENDIF
```

where $AP_{p,i}$ is the actual production in the ith replenishment cycle and $SD_p(t)$ the production status of plant p, with a value of zero indicating that the plant is under operation at t and a value one indicating that it is shutdown. Once a tank car is filled, a warehouse transfer is initiated to complete the first replenishment transfer in the production schedule.

```
IF TC^Amt = TC^Cap
        Set RT to the first replenishment transfer in PS_p
        Set WT^RTID to RT^id
        Set WT^amt to TC^Cap
        Add TC to WT^TCList
        Update IL_p(t) as IL_p(t) - TC^Cap
        Remove TC from TCList_p
        Remove RT from production schedule
        Dispatch TC
ENDIF
```

Backlogs arise when the actual production in a cycle falls below the production target assigned to the plant. In this ‘simple production policy’, if the plant undergoes a shutdown due to unavailability of empty tank cars, it would lead to a backlog since the production rate would be retained at $PR_{p,i}^{Ave}$ even after tank cars become available. This can be ameliorated by using the available production rate of the plant and increasing the throughput to PR^{Max} in order to catch-up with the original plan. We call this the ‘optimistic production policy’. If the shutdown is for an extended duration, even the ‘nominal production policy’ could lead to a backlog. The amount of backlog in replenishment cycle RC_i is calculated as:

$$BL_{p,i} = \sum_w T_{p,w,i} + BL_{p,i-1} - AP_{p,i}$$

We define two KPIs to measure the plants’ reliability, the plant shutdown rate, PSR_p and the cumulative shutdown rate CSR:

$$PSR_p = \frac{1}{SH} \sum_t SD_p(t) \times 100\%$$

$$CSR = \frac{1}{P} \sum_p PSR_p \times 100\%$$

where SH is the simulation horizon and P the total number of plants in the system.

5.4.7 Logistics Agent

In our agent-based simulation model, the fleet of tank cars is the only resource where products can be stored. It thus constrains the inventory for both the enterprise and the customers. The plants require empty tank cars to store newly produced product; the filled cars are transferred to the warehouses. The warehouses in turn hold the tank cars as their inventory and deliver them to customers to fulfill order. The tank cars are also used as storage by customers who hold them until all the products in the car is consumed. Finally, the empty tank cars are returned back to the enterprise. The logistics agent serves as the centralized department that manages the transportation of the tank cars. It receives transportation requests from plants, warehouses, and customers and arranges the transfer of tank cars from plant to warehouse, from warehouse to customer, and the empty tank back to the enterprise.

The transportation of tank cars is modeled as a pure time delay. Also, since the product transferred from plants to warehouses are all scheduled during replenishment planning, all the warehouses know the exact number of full tank cars that will be received from each plant in the near future (next cycle) if there are no disturbances. The plant, warehouse and customer all use the First-In-First-Out policy to manage their tank cars. So the only decision for the logistics agent is the assignment of empty tank cars released by customers. Here we propose a simple policy called the warehouse-centric policy first; other alternatives are analyzed in Section 6. In the warehouse-centric policy, a set of tanks are assigned for dedicated use by each warehouse. So when an empty tank car is returned by the customer, it is first transported back to the same warehouse from which product was originally shipped to the customer. The warehouse in turn may send the car to any plant from which it is receiving product in future replenishment cycles. Next, we illustrate the dynamics of this system.

5.5 Illustrative Simulation Results of the Chemical Supply Chain Model

In this section, we illustrate some of the key characteristics of the system. We consider a supply chain consisting of eight customers, four warehouses and six plants with geographical locations as shown in Figure 5.3. The system contains a total of (fleet size) 122 tank cars of capacity 500 units each. For simplicity, we assume that the total market demand is constant at 6000 units per day. Plants have a maximum production rate of 1000 units / day and a minimum of 300 units per day. The length of replenishment cycle is set at 10 days, and the replenishment plans for each cycle is decided on the first day of the previous cycle. The values of other parameters are shown in Table 5.2.

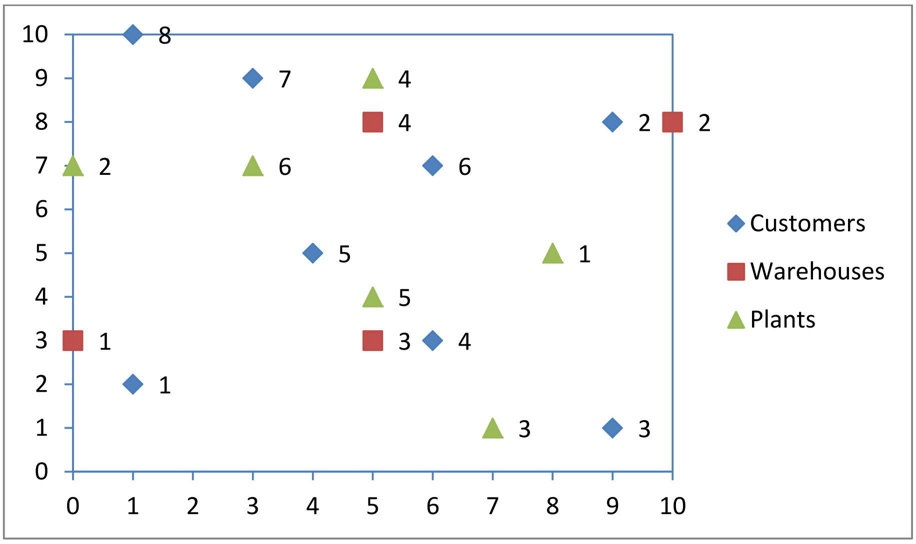


Figure 5.3: Geographical locations of customers, warehouses and plants

Table 5.2: Values of system parameters

Customer Inventory Control, (S,s) Policy	(5000, 2500)
Replenishment Planning Horizon	10 days
Customer Locations	(1,2), (9,8), (9,1), (6,3), (4,5), (6,7), (3,9), (1,10)
Warehouse Locations	(0,3), (10,8), (5,3), (5,8)
Plant Locations	(8,5), (0,7), (7,1), (5,9), (5,4), (3,7)
Warehouse Top-up Level	$\frac{\text{Market Demand} \times \text{Replenishment Planning Horizon} \times 2}{\text{Number of warehouses}}$
Production Capacity	1000 units per day per plant
Transportation Speed	3 per day
Tank Car Capacity	500 units per tank car
Simulation Horizon	200 days

The model described in Section 5.4 has been implemented in Jadex and BPMN. Discrete event driven simulation clock with tick size of 0.01 day was used. Customers were created without any initial inventory of products. 80 out of 122 tank cars were initialized as full tank cars and distributed equally among the four warehouses. The other 42 tank cars were initialized as empty and equally distributed among the six plants. The first replenishment cycle is an initialization period during which there is no market sales and plant production. After the initialization period, simulation was performed for a horizon of 200 days (20 cycles).

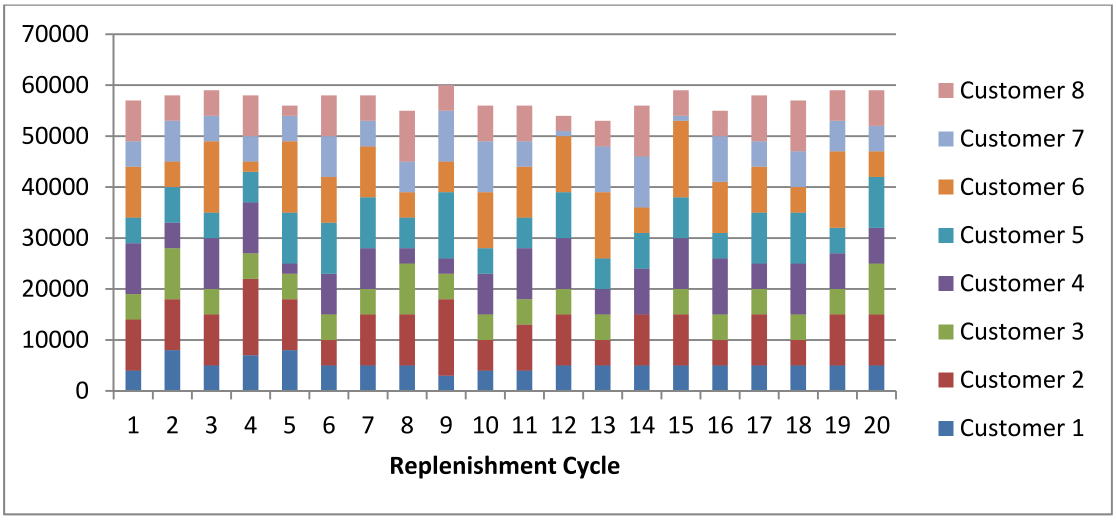
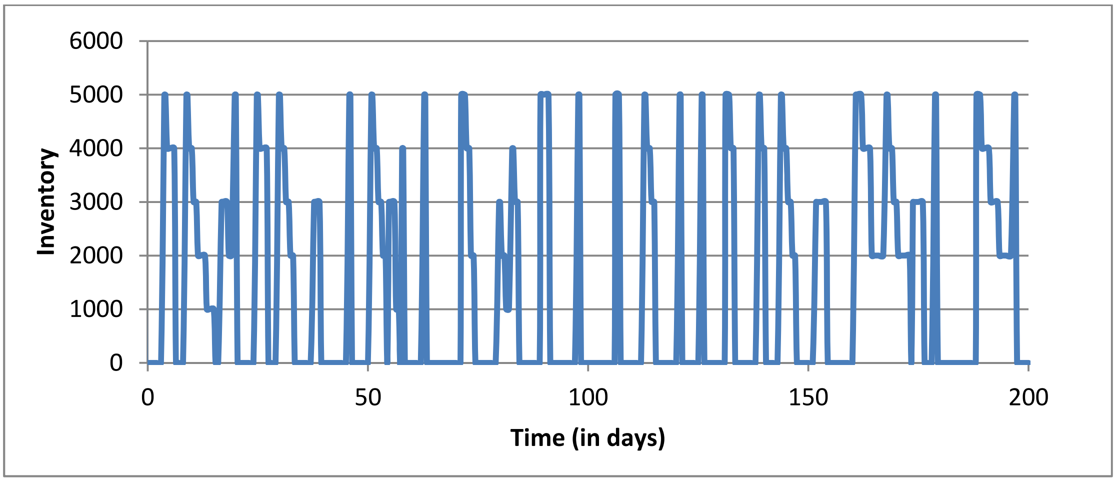
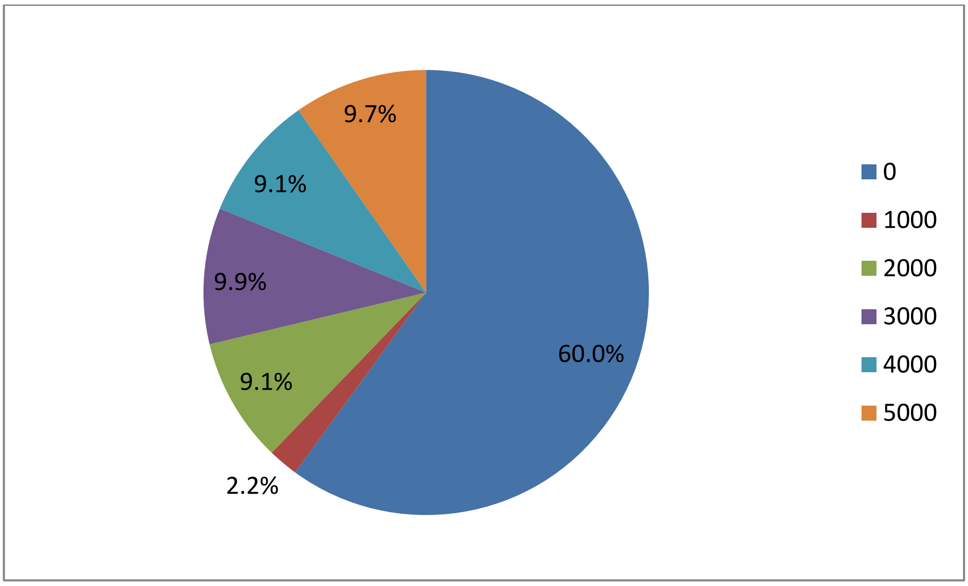


Figure 5.4: Customer sale of compound in a typical run

In contrast to common supply chains where storage capacity is limited at various parts of the supply chain, here there are no explicit limits at each part. Instead, the fleet size as a whole is limited which constrains the total inventory of the entire system and hence leads to interesting dynamics as shown below. Figure 5.4 depicts the quantity of sales by the customer over the 20 replenishment cycles. As can be seen from there, the eight customers share the whole market demand, and their relative portion varies across the cycles. The total market demand in every replenishment horizon is 60,000 units, which is equal to the total production capacity of all the plants. However, Figure 5.4 shows that market demand is fully satisfied in only 1 out of the 20 replenishment cycles. The average shortfall is about 2550 units per replenishment cycle, which is about 4.25%. Besides, the customer satisfaction level in this typical run is only about 89.3%, which mean more than 10% of the customer orders were delivered late to the customers.



(a)



(b)

Figure 5.5: Inventory profile of Customer 1 in a typical run: (a) inventory vs. time (b) time proportion of different inventory level

Next, we explain the dynamics of each constituent of the supply chain. Figure 5.5 shows the inventory profile of a typical customer. Compound sale and inventory management leads to the inventory level varying from 0 to 5000 units. There is no product inventory during 60.0% of the horizon while there is full inventory of product (i.e. 5000 units) during 9.7% of the time. The time-weighted average inventory level is about 1350 units. Figure 5.6 shows a typical customer purchase order size distribution. Due to the order being in units of full tank car (500 units), the inventory level in tanks take only discrete values – each customer manages inventory using the (S,s) policy with S = 5000 and s = 2500. Depending on the inventory position upon placing the order, the order size varies from 3000 to 5000. As seen from the figure, 64.5% of Customer 1 orders size is 5000 units and the rest is 3000 units except for one order at 4000 units. Other customers also have similar distributions in inventory profile and order sizes.

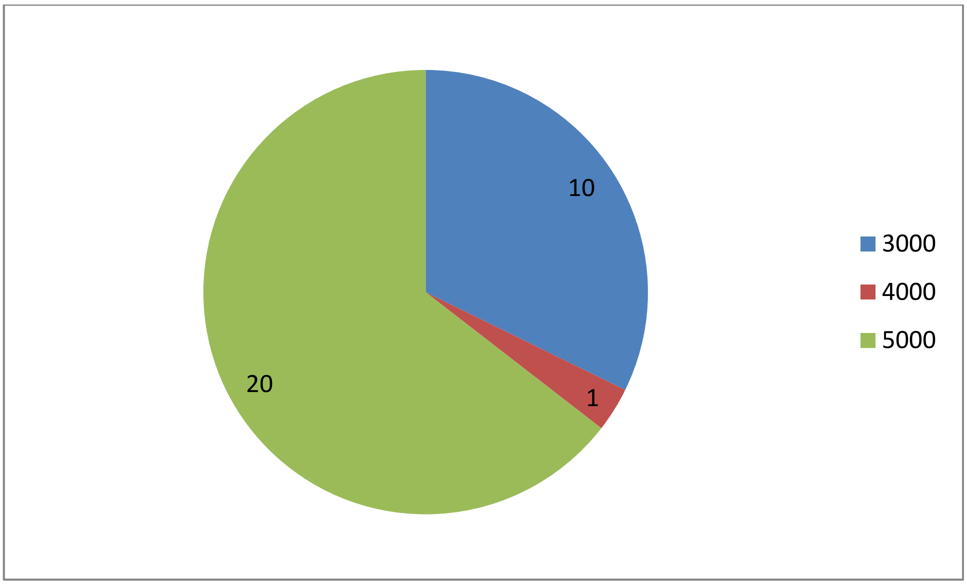


Figure 5.6: Customer 1 purchase order size distribution in a typical run

Figure 5.7 demonstrates the inventory profile of a single warehouse. The inventory of the warehouse never exceeds 5000 as once the inventory accumulates to the order size, e.g. 3000, 4000 or 5000, a product delivery is immediately initiated.

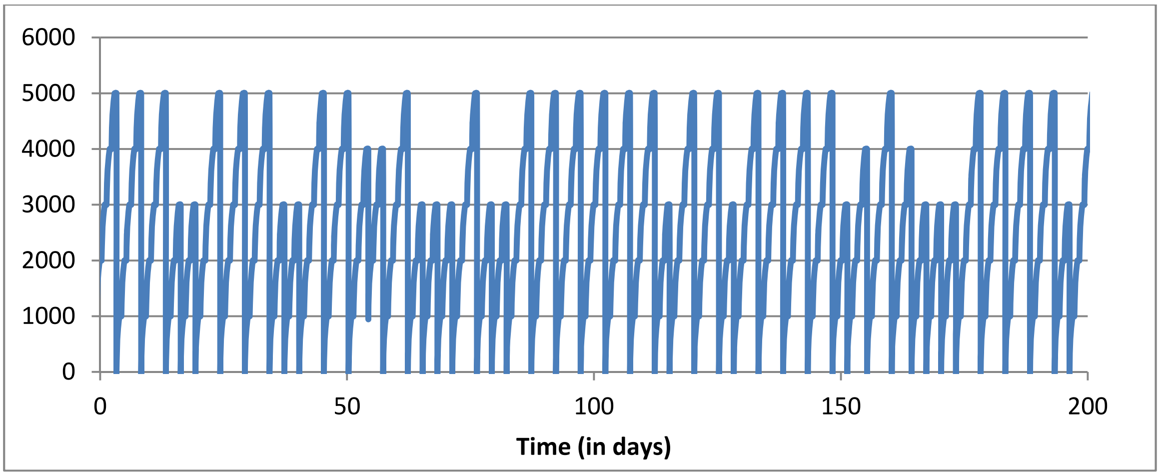


Figure 5.7: Warehouse 1 inventory profile in a typical run

Figure 5.8 shows the time profile of Plant 6's production rate. As seen from the figure, the plant kept production rate at highest level except during time when it was forced to shut down due to the shortage of empty tank cars. Eleven shutdowns with total duration of 8.6 days occurred in this plant, and 70 shutdowns with a total duration of 44.2 days occurred for all eight plants over the course of the simulation horizon.

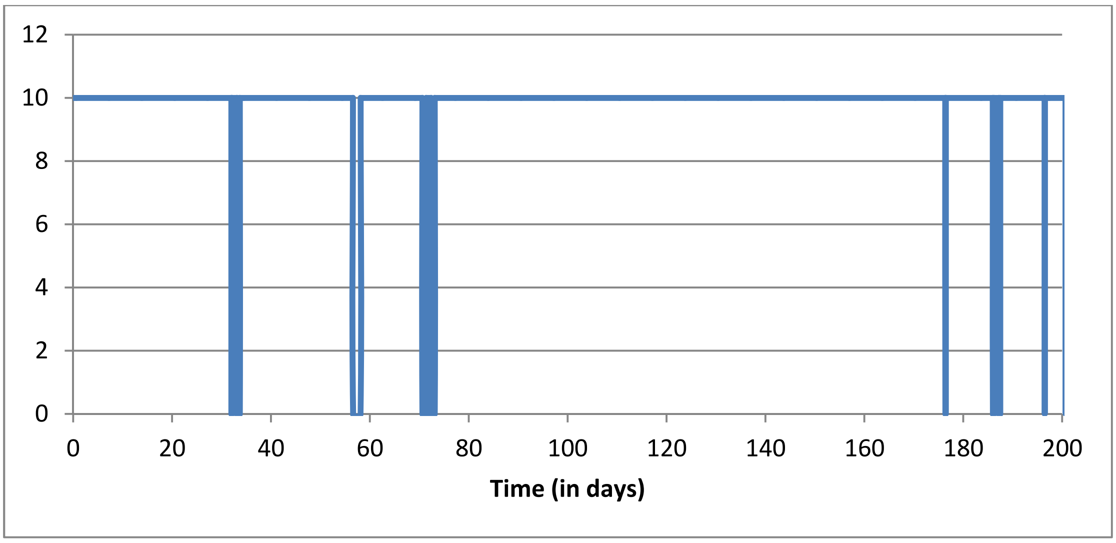
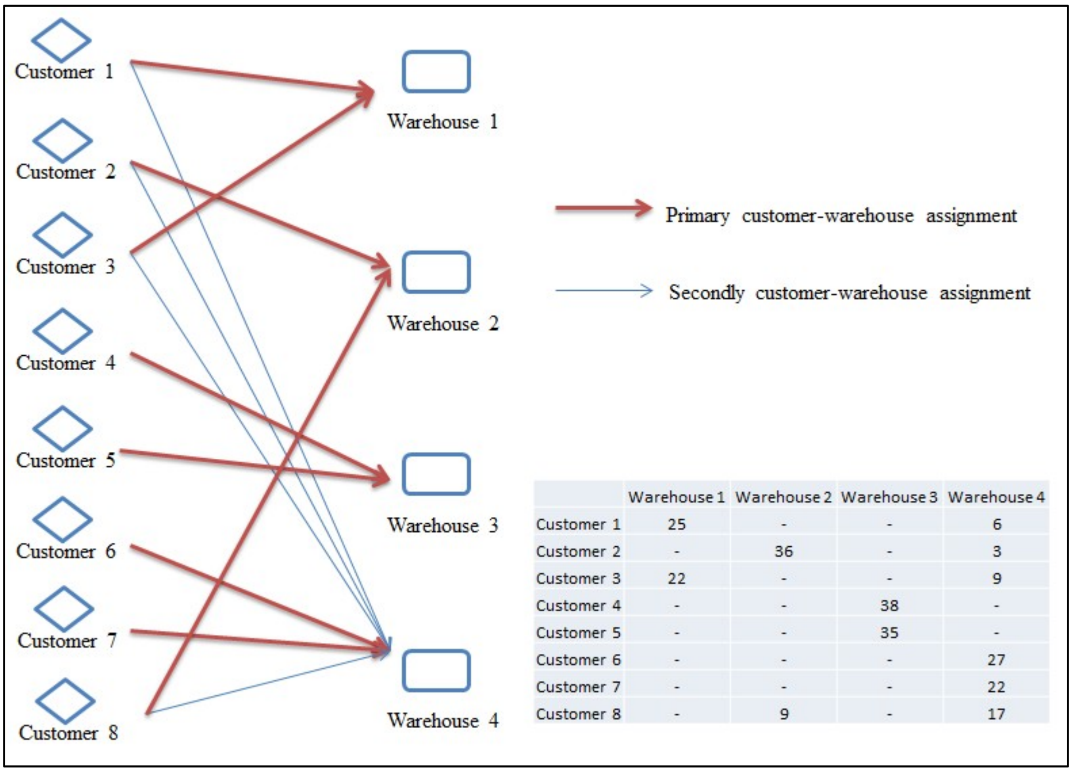


Figure 5.8: Plant 6 production rate in a typical run

Figure 5.9 depicts to which warehouse each customer order was assigned. 214 out of 249 orders were assigned to the primary warehouse, while the remaining 35 orders were assigned to a secondary warehouse. It is because the primary warehouses for Customer 1, 2 3 and 8 (see Figure 5.9) were not able to satisfy some orders before the due date while another warehouse (Warehouse 4 in the typical case) was able to fulfill them.



	Warehouse 1	Warehouse 2	Warehouse 3	Warehouse 4
Customer 1	25	-	-	6
Customer 2	-	36	-	3
Customer 3	22	-	-	9
Customer 4	-	-	38	-
Customer 5	-	-	35	-
Customer 6	-	-	-	27
Customer 7	-	-	-	22
Customer 8	-	9	-	17

Figure 5.9: Customer-warehouse order assignment in a typical run

Figure 5.10 shows the order assignment to all the warehouses. Most of the time, the total amount of the product ordered from the customers during the replenishment cycle is less than the quantity customers require to fully satisfy the market demand. The average shortfall is about 2250 units per replenishment cycle. As a result, the total amount of the production target assigned to the plants is less than the actual market demand in most of the replenishment cycles; thus not all the plants in the typical run were set to run at 100% production capacity although the market demand equaled to the total production capacity (see Figure 5.11). Figure 5.12 demonstrates the warehouse-plant production target assignment in the whole simulation horizon. The data shown in the figure are in unit of tank cars of capacity 500 units each. The warehouse-plant production target assignment is done through an optimization described in the previous section. Since the objective is to minimize the transportation distance, each plant mainly serves one warehouse.

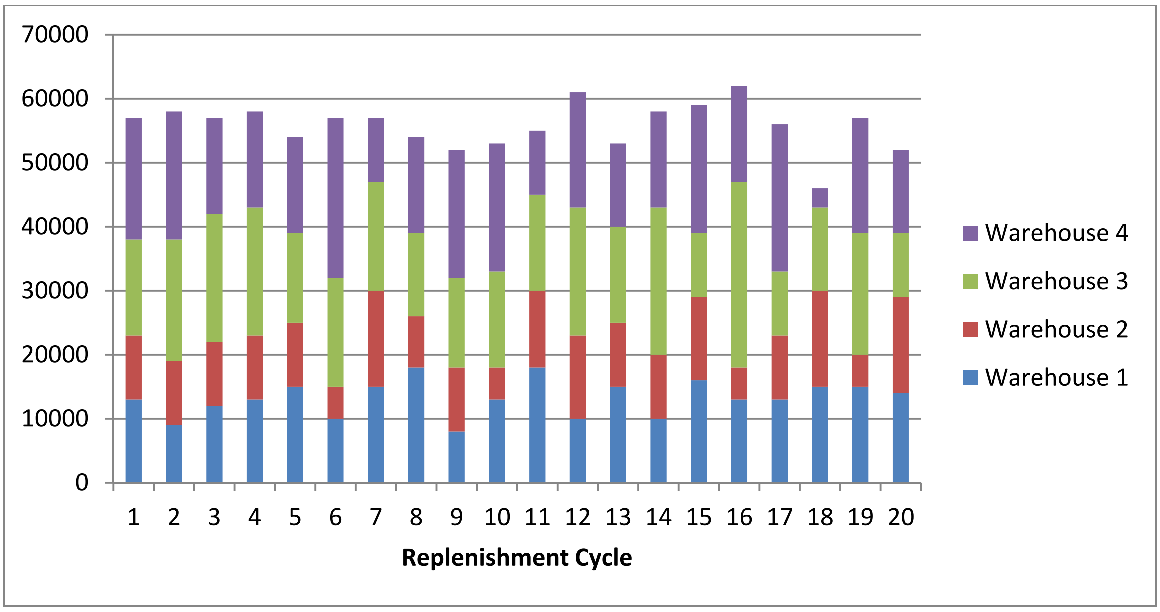


Figure 5.10: One run simulation result: order quantity assigned to warehouses

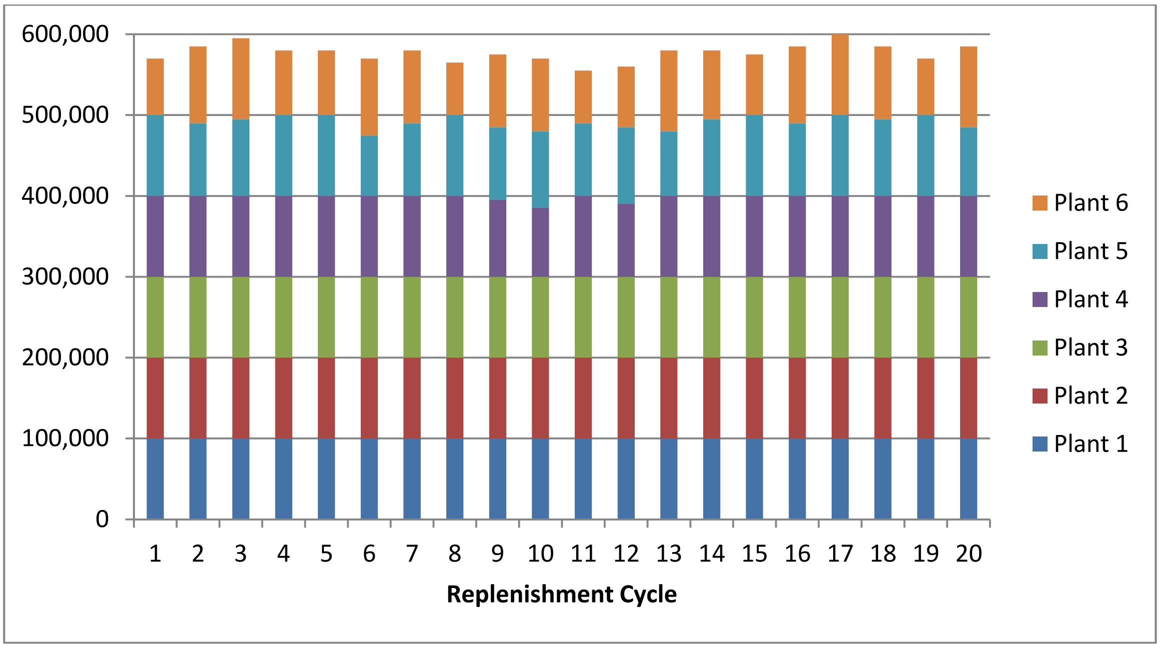
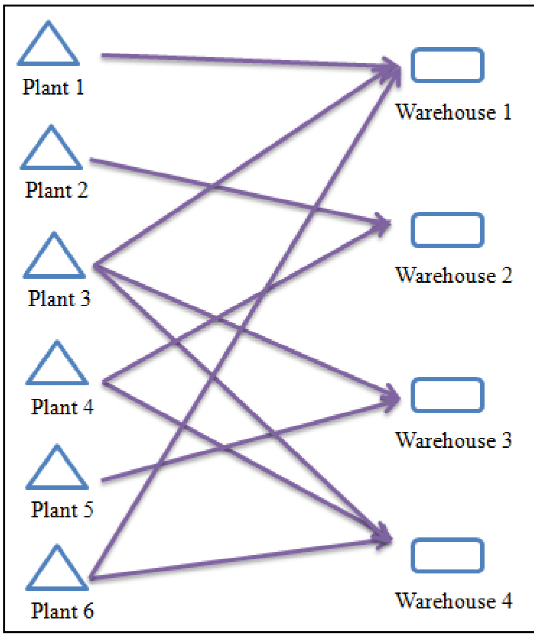


Figure 5.11: Plant production target in a typical run



	Warehouse 1	Warehouse 2	Warehouse 3	Warehouse 4
Plant 1	400	-	-	-
Plant 2	-	400	-	-
Plant 3	50	-	335	15
Plant 4	-	2	-	351
Plant 5	-	-	372	-
Plant 6	77	-	-	308

Note: In unit of tank cars (500 units of product per tank car)

Figure 5.12: Warehouse-plant production target assignment in a typical run

In order to track the movement of tank cars, we associate an attribute, called state, with each tank car which specifies its position and condition at a time-tick. The various values of states are listed in Table 5.3. A complete route of a tank car can be defined by the set of states 0-1-2-3-4-5-6-7-0. Figure 5.13 displays the states of a specific tank car over the entire route. This specific tank car completed about 14 routes over 200 days, i.e., average 14.3 days per route. The time portion of all tank cars spent on each state is shown in Figure 5.14.

Table 5.3: Tank states

State	Description
0	Empty tank car at warehouse
1	Empty tank car transit from warehouse to plant
2	Tank car at plant
3	Full tank car transit from plant to warehouse
4	Full tank car at warehouse
5	Full tank car transit from warehouse to customer
6	Tank car at customer
7	Empty tank car transit from customer to warehouse

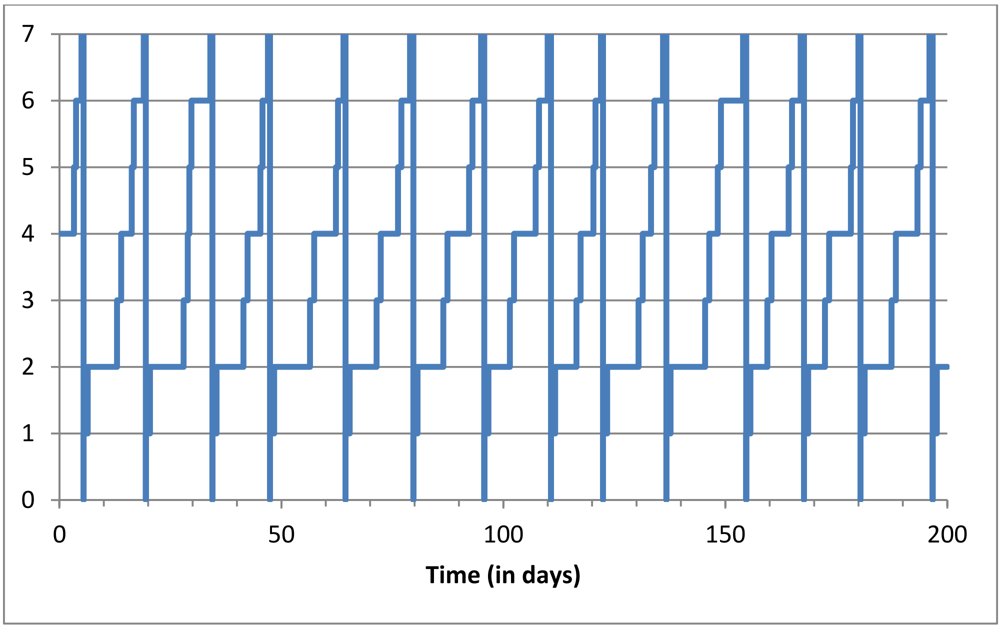


Figure 5.13: Time profile of tank states of a single tank car in a typical run

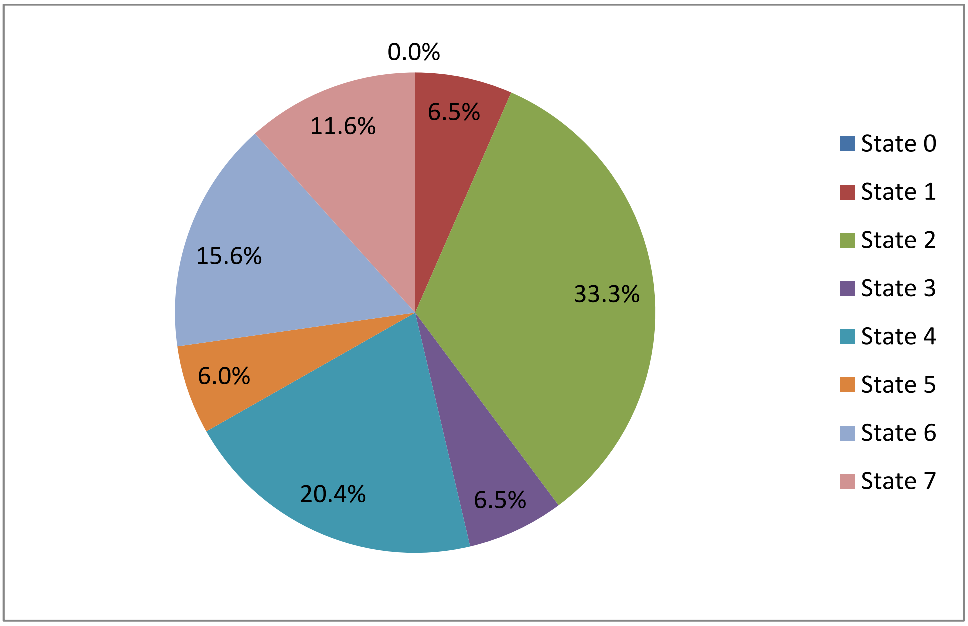


Figure 5.14: Distribution of states of all tank cars in a typical run

The largest time portion that tank cars spent is in the plant site (State 2), which is 33.3%. Despite that shutdowns still occurred in some plants (e.g. Plant 6 shown in Figure 5.8). The tank cars spent 0% of time as empty in warehouses (State 0), so all the empty tank cars were immediately allocated to the plants once they returned from the customers. If we account for all the transit states together (state 1, 3, 5 and 7), on average each tank cars spent 30.7% of the time on transportation, 20.4% of the time at the warehouse before delivering to the customer, and 15.6% of the time at customers' site. The reason why more than one fifth of time was spent at warehouse site is that the (S, s) inventory control policy makes customer place fewer large orders which require warehouse to keep many full tanks cars. For instance, an order size of 5000 units requires warehouse to accumulate as many as 10 tank cars to initiate the product delivery. Such kind of big orders are also easily influenced by the plant shutdowns because they are not allowed to deliver partially. Any tank car gets delayed by the shutdown may led to a delay of the product delivery. In such cases, customers do not receive any product for a long time, but the ordered amount is still accounted into their inventory position. These customers would do nothing except waiting for the product delivery. As a result, the market demand may not be fully satisfied by the customers as they do not have sufficient stock, and thus the total amount of the product ordered from the customers would be less than the actual market demand. This motivates us to develop better policies to manage the tank fleet.

5.6 Tank Fleet Routing and Sizing Problem

In the normal routing policy shown in Section 5.5, the direct cause of the low customer satisfaction and market satisfaction is the tank car shortage in the plant site, which forces plants to shutdown and further delays the warehouse transfer and product delivery. One possible solution is to buy or lease more tank cars. For instance, if the tank fleet size increases to 140, the customer satisfaction can increase from 89.3% to 98.0% and market satisfaction can increase from 95.75% to 98.8%. However, increasing the fleet size is expensive. In this section, we use the detailed supply chain model described in Section 5.4 to explore and derive tank routing policies that can achieve better system performance.

5.6.1 New Tank Routing Policies

As mentioned in the previous section, shutdowns still occurred in some plants although the largest time portion that tanks spend is in the plant site (33.3%). There could be two possible explanations for the shutdowns: (1) is that the plants have tank car shortage during certain time of the replenishment cycles and excessive tank cars for the rest of the time, or (2) empty tank cars are not repositioned optimally, so some plants have excessive tank cars while others have a shortage.

In the nominal policy, every empty tank car released by the customers travels back to the warehouse where the product delivery was initiated. Warehouses receive the empty tank cars and allocate them to different plants according to replenishment plans through logistics department. As a result, the empty tank cars have to travel a very long distance especially when the warehouse is far away from the customer and the plant. Besides, in this policy, each tank car serves only one specific warehouse. If a certain warehouse is busier than others, it needs more tank cars, but the tank cars of the other warehouses would not help, which is quite unproductive from the view point of the whole system.

An optimal routing policy has to solve two problems: (1) shorten the transportation distance of the repositioning of empty tank cars; (2) optimally allocate the empty tank cars to the plants. Considering these requirements, two different types of policies are developed. In these new policies, every empty tank car discharged from customer is returned directly to a specific plant rather than to a warehouse, so the transportation distance of tank car return is shortened and the plants can get empty cars faster. The return location is decided differently in the two types of policies. In the first type, the return location is decided by the warehouse. When the warehouse delivers a tank car to a customer, it would assign the return location of the tank car to be the plant which has previously transferred a full one to it. Once the tank car is discharged from customer, the logistics department would collect the return request from customer and transfer the empty tank car to the plant. Based on the time at which the plant is considered as a tank car return location of the warehouse, two different policies, tank on-arrival policy and tank on-release policy are developed. In the tank on-arrival policy, only when the tank car has arrived at the warehouse site, the warehouse would consider the plant as a tank return location; while in the tank on-release policy, when the plant initiates the warehouse transfer, a notification will be sent to the warehouse and the plant is considered as a return location.

In the second type of policies, the logistics department solves an optimization problem to decide the return location of empty tank cars. The logistics department requests plants for the daily number of empty tank cars they require for a logistics planning horizon, and allocate the empty tank cars based on the plants' demand and locations so as to minimize shutdowns.

In the following description, let $TD_{m,p}$ denote transportation distance between the customer site where tank car m is located to plant p, $TR_{p,d}$ the number of tank cars requested by plant p for day d, and $TA_{p,d}$ the number of tank cars assigned to plant j for day d. We also define a decision variable $DV_{m,p}$ the value of which is 1 if tank car m is assigned to plant p or 0 if tank car is not assigned to plant p. The objective is to minimize the total travelling time of the empty tank cars from customers to plants. If the number of available empty tank cars is more than the total number requested by the plants ($\sum_p TR_p$), the constraints are the empty tank car demand of individual plant, which can be formulized as:

$$\begin{aligned} &\textit{Minimize} \quad \sum_m \sum_p DV_{m,p} TD_{m,p} \\ &\textit{Subject to} \sum_m DV_{m,p} \geq \sum_d TR_{p,d}, \quad \forall p \end{aligned}$$

If the number of empty tank cars available is less than $\sum_p TR_p$, it becomes a two-step optimization problem. In the first step, we define a weight DW_d to represent the importance of tank cars requested by plants for day d. obviously, the smaller d is, and the bigger the value of DW_d is. Then the number of empty tank cars assigned to each plant can be determined by

$$\textit{Minimize} \quad \sum_p \sum_d DW_d (TR_{p,d} - TA_{p,d})^2$$

Followed by assignment of the individual tank cars to specific plants

$$\begin{aligned} &\textit{Minimize} \quad \sum_m \sum_p DV_{m,p} TD_{m,p} \\ &\textit{Subject to} \sum_m DV_{m,p} = \sum_d TA_{p,d}, \quad \forall p \end{aligned}$$

The logistics planning horizon is set as 10 days and the policy is termed optimal allocation-10 policy. We also simplify this policy by shortening the logistics planning horizon to 3 days and setting the DW_d the same through the horizon, formulating a new policy termed optimal allocation-3 policy. In this new policy, two new parameters are used, TR_p the number of tank cars requested by plant p and TA_p the number of tank cars assigned to plant p. The optimization problem is then simplified. The objective is to minimize the total travelling time of the empty tank cars from customers to plants. If the number of available empty tank cars is more than the total number requested by the plants ($\sum_p TR_p$), the constraints are the empty tank car demand of individual plant, which can be formulized as:

$$\begin{aligned}
&\textit{Minimize} \quad \sum_m \sum_p DV_{m,p} TD_{m,p} \\
&\textit{Subject to } TA_p = \sum_i DV_{m,p} \geq TR_p \quad \forall p
\end{aligned}$$

If the number of empty tank cars available is less than $\sum_p TR_p$, it becomes a two-step optimization problem. The number of empty tank cars assigned to each plant TA_p is decided in the first step,

$$\textit{Minimize} \quad \sum_p (TR_p - TA_p)^2$$

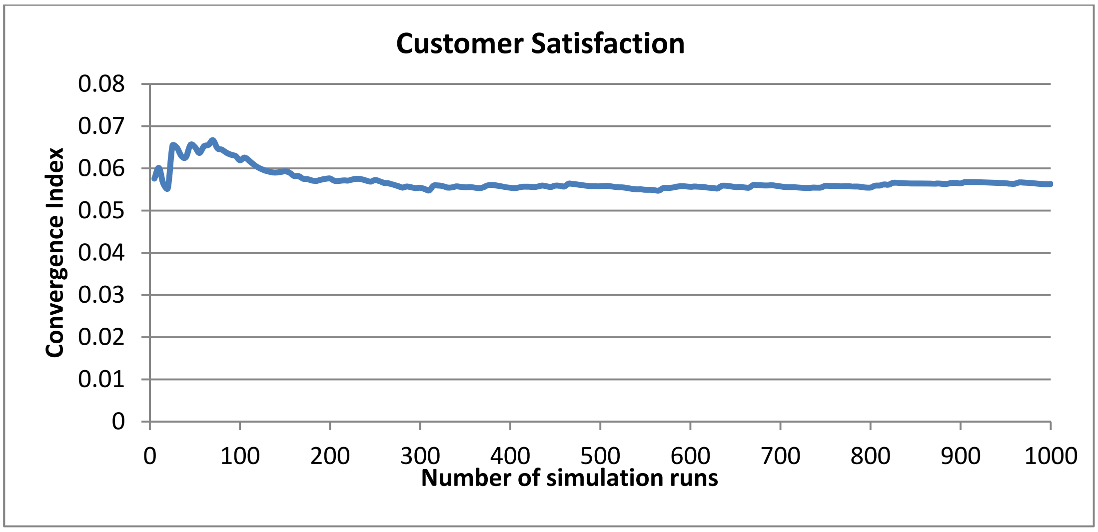
Followed by assignment of the individual tank cars to specific plants

$$\begin{aligned}
&\textit{Minimize} \quad \sum_m \sum_p DV_{m,p} TD_{m,p} \\
&\textit{Subject to } \sum_i DV_{m,p} = TA_p, \quad \forall p
\end{aligned}$$

The comparison of the nominal policy and new policies can be made by evaluating the values of KPI defined in Section 5.4. However, given the stochastic factors in the models, such as market sales, order assignment and replenishment planning, different simulation runs will result in different customer order size distribution, order assignment and product target assignment, i.e., the KPI values will likely be different from run to run, even with the same settings. A true estimate of the KPI values can be calculated by averaging the KPI values from an infinite number of simulation runs. To get representative KPI values within a small number of simulation runs, convergence of the KPI values must be ensured. We define the following convergence index (Law and Kelton, 2000):

$$C.I._{,i} = \frac{S.D._{,i}}{M._{,i}}$$

where $S.D._{,i}$ and $M._{,i}$ are the standard deviation and mean of KPI after i^{th} simulation run respectively. Figure 5.15 shows the convergence index of the customer satisfaction and market satisfaction versus simulation runs following the system settings described in Section 5.5. The convergence index stabilizes around 200 simulation runs. Hence, we conclude that 200 runs of simulation is needed for each policy to compare the performance of various policies.



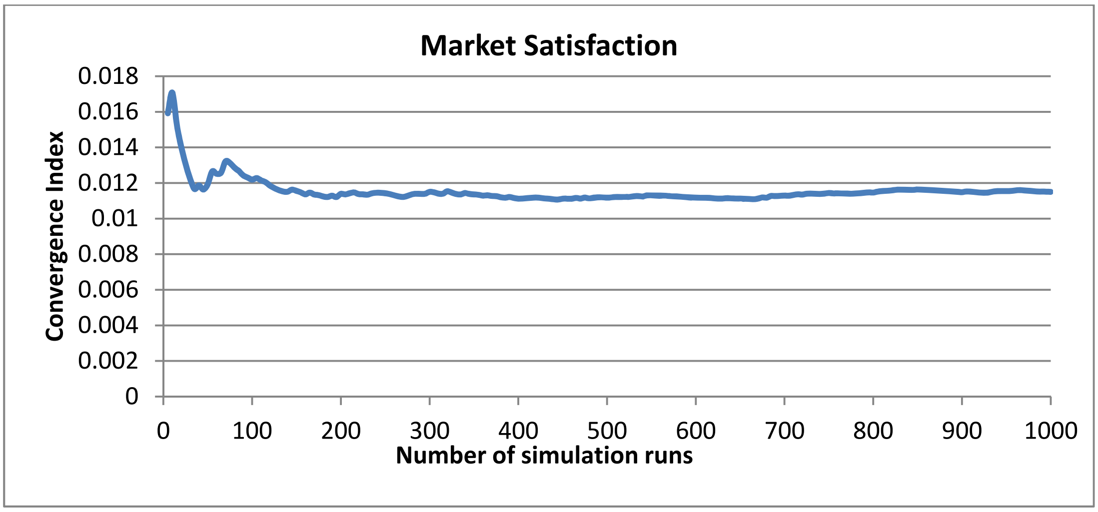


Figure 5.15: Profile of convergence index in customer satisfaction and market satisfaction versus number of simulation runs in the nominal policy

Table 5.4 summarizes the system performance of the five tank routing policies with the settings listed in Table 5.2. Compared with the nominal policy, the tank on-arrival policy improves the customer satisfaction from 87.0% to 97.8% and market satisfaction from 96.0% to 98.3%; the tank on-release policy improves the customer satisfaction to 98.3% and market satisfaction to 98.2%; while the optimal allocation-3 and optimal allocation-10 policy achieve nearly 100% for both customer satisfaction and market satisfaction. Shutdown duration is reduced by over 50% by the tank on-arrival policy and tank on-release policy from 45.6 days to 21.5 days and 21.0 respectively and almost to zero by the optimal allocation-3 and optimal allocation-10 policies. The average number of completed routes increases by 2.3% in the tank on-arrival and tank on-release policies, and 3.3% in the optimal allocation-3 and optimal allocation-10 policy. In conclusion, all the four new tank routing policies significantly improve the over system performance with the same fleet size.

Table 5.4: System performance in five tank routing policies with tank fleet size of 122, market demand of 6000 and system settings listed in Table 5.2

	Customer Satisfaction	Market Satisfaction	Shutdown Duration	No. of Completed Routes
Nominal	87.0%	96.0%	45.6	2306.3
Tank On-Arrival	97.8%	98.3%	21.5	2358.8
Tank On-Release	97.7%	98.2%	21.0	2359.1
Optimal Allocation-3	100.0%	99.3%	0.4	2381.3
Optimal Allocation-10	100.0%	99.2%	0.8	2381.9

Table 5.5 presents the time distribution of the tank cars in the five routing policies. Due to the shorter distance for repositioning the empty tank car, the time spent on transportation (transit states) reduces by about 3% in the tank on-arrival, tank on-release and optimal allocation-3 policy, and over 1% in the optimal allocation-10 policy. The time spent at the plant site also decreases by 3.43% in the optimal allocation-3 policy and 5.64% in the optimal allocation-10 policy with almost zero shutdowns. This implies that both the two optimal allocation policies result in the best repositioning of the empty tank cars.

Table 5.5: Distribution of states of all tank cars under five tank routing policies with tank fleet size of 122, market demand of 6000 and system settings listed in Table 5.2

	Plants' site	Warehouses' Site	Customers' site	Transit States
Nominal	32.33%	20.24%	16.58%	30.85%
Tank On-Arrival	33.37%	20.23%	18.60%	27.79%
Tank On-Release	33.01%	20.25%	18.83%	27.92%
Optimal Allocation-3	28.90%	22.14%	21.23%	27.73%
Optimal Allocation-10	26.69%	22.05%	21.38%	29.89%

Table 5.6: System performance in five tank routing policies with tank fleet size of 98 and system settings listed in Table 5.2

	Customer Satisfaction	Market Satisfaction	Shutdown Duration	No. of Completed Routes
Nominal	62.7%	84.5%	182.8	2025.3
Tank On-Arrival	78.0%	91.4%	102.6	2193.3
Tank On-Release	80.2%	91.8%	97.7	2205.1
Optimal Allocation-3	95.4%	97.6%	28.0	2341.6
Optimal Allocation-10	93.8%	97.2%	33.4	2334.1

Since the four new policies have achieved a high system performance, we investigated if an acceptable system performance can be achieved with a smaller fleet size. The supply chain model was simulated with 98 tank cars. The resulting KPI values are shown in Table 5.6. With the smaller fleet size, the customer satisfaction decreases from 87.0% to 62.7% in the nominal policy and market satisfaction decreases from 96.0% to 84.5%. The market satisfaction can still be maintained above 90% in the tank on-arrival and tan on-release policies, but the customer satisfaction decreases to 78.0% and 80.2%. The optimal allocation policies however still result in a satisfactory performance. The customer satisfaction is 95.4% for the optimal allocation-3 policy and 93.8% for the optimal allocation-10 policy; and the market satisfaction is achieved at 97.6% for the optimal allocation-3 policy and 97.2% for the optimal allocation-10 policy. Compared with the KPI values of the nominal policy with a fleet size of 122 (see Table 5.4), the optimal allocation-3 and optimal allocation-10 policies with 98 tank cars have a better performance. So the chemical enterprise can save on investment and operation costs while achieving comparable performance through fairly simple internal changes.

Table 5.7 shows the time distribution of the five routing policies with a fleet size of 98. The time spent at the plant site in both the optimal allocation-3 and optimal allocation-10 polices is about 12% lower than that in the nominal policy. However, the time spent in the transit states is about 4% higher, which is far different from the results of system with tank fleet size of 122. As seen from Table 5.5, with a tank fleet size of 122, the time spent at the transit states in the optimal allocation policies is lower than that in the nominal policy because of the shorter tank return distance. The main reason for this difference is that with a tank fleet size of 98, taking the optimal allocation-3 policy for instance, 15.6% more completed routes are achieved than that in the nominal policy (see Table 5.6) in contract to 3.3% more in the case of 122 tank cars. The increase in the completed routes contributes to the larger time portion spent on the transportation and the better over performance. In summary, the four new routing policies achieve significantly better performance compared to the nominal policy. The optimal allocation-3 and optimal allocation-10 policy in particular do better even with a smaller size of tank fleet.

Table 5.7: Distribution of states of all tank cars under five tank routing policies with tank fleet size of 98 and system settings listed in Table 5.2

	Plants' site	Warehouses' Site	Customers' site	Transit States
Nominal	28.50%	23.57%	15.23%	32.70%
Tank On-Arrival	26.72%	23.58%	17.69%	32.01%
Tank On-Release	26.26%	23.56%	17.92%	32.27%
Optimal Allocation-3	16.53%	24.93%	21.78%	36.76%
Optimal Allocation-10	17.04%	24.82%	21.52%	36.62%

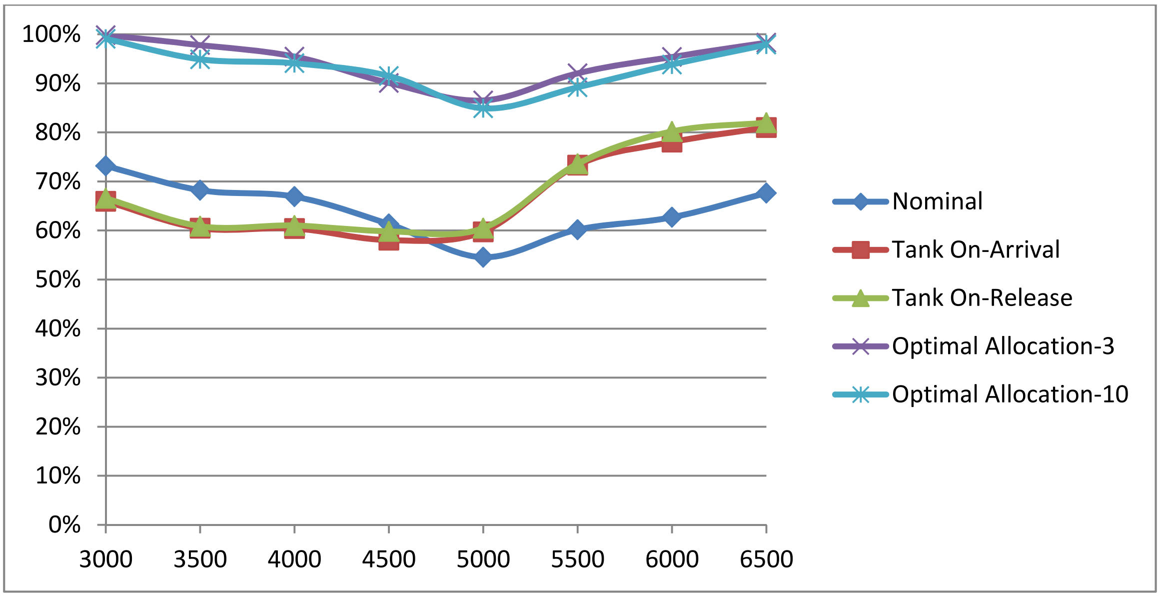
5.6.2 **Market Demand Sensitivity Analysis**

The system performance under various routing policies has been discussed above for the case of constant market demand of 6000 units per day which is equal to the total production capacity of the plants. Here, we evaluate the performance of these policies under market demands varying from 3000 to 6500 units per day.

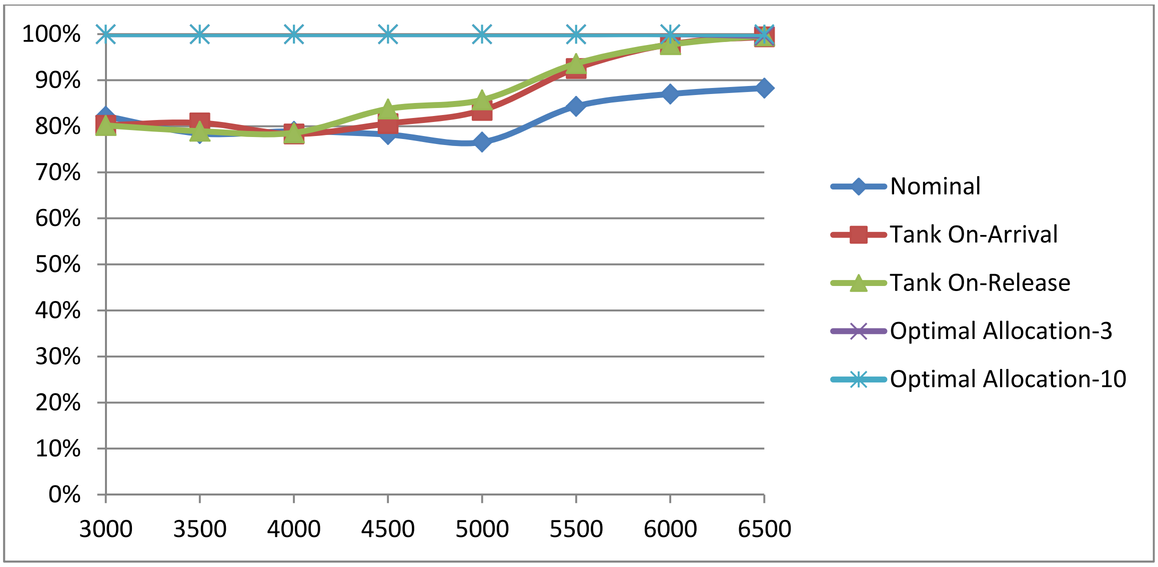
Figure 5.16 (a) shows the customer satisfaction profile of the five routing policies with a fleet size of 98. In the nominal policy, the customer satisfaction is initially 73.2% at a market demand of 3000, and drops dramatically with increasing market demand until it reaches a bottom at 54.5% when the market demand is 5000 units per day. Then it rises up as the market demand increases and reaches 67.6% at the maximum market demand. The customer satisfaction in the optimal allocation-3 policy has the similar same as that in the nominal policy and has a bottom at 86.5% when the market demand is 5000 units per day. The difference between the customer satisfaction in the optimal allocation-3 policy and that in the optimal allocation-10 policy is negligible. In the tank on-arrival policy, the customer satisfaction does not have a clear bottom. Instead it starts at 66.0% at the demand of 3000, stays around 60% and then drastically increases when the market demand goes beyond 5000 units per day. The difference between the customer satisfaction in the tank on-arrival policy and that in the tank on-release policy is also negligible.

Figure 5.16 (b) shows the customer satisfaction profile of the five routing policies with a fleet size of 122. The customer satisfactions in the optimal allocation-3 and optimal application-10 policies maintain at 100% across the market demands. The customer satisfaction in the nominal policy starts at 82.2% at demand of 3000 units per day, and decreases with increasing market demand until it arrives at the bottom (76.6%) when the market demand reaches 5000 units per day. Then it increases as the market demand increases. The customer satisfactions in the tank on-arrival and tank on-release policies stay around 80% when the market demand is lower than 5000 units per day. Afterwards, they dramatically increase and approach 100% when the market demand reaches 6500 units per day.

These behaviors originate from the underlying supply chain dynamics. It can be seen that the customer satisfaction generally reach a minimum when the market demand reaches 5000 units per day (except for the optimal allocation policy with tank fleet size of 122). All the customers offer their products to the market agent, which then selects based on the lowest price. When market demand is low, it is common that a single customer satisfies the entire market demand on a given day. This clears the customer's inventory; hence this is followed by a big order to the enterprise. As the market demand increases, the size of the order that the customer makes gets bigger until the market demand reaches 5000 units per day which is the maximum amount of product that the customer can hold. Since the order is not allowed to be delivered partially, bigger order will retain more tank cars at warehouse site, which reduces the mobility of the tank cars in the system, and hence increases the probability of delayed product delivery. When the market demand goes beyond 5000 units per day, it cannot be satisfied by a single customer. As a result, the order coordinator receives multiple smaller orders which are easier to be fulfilled on time by the warehouses. Therefore, the customer satisfaction increases.



(a)



(b)

Figure 5.16: Customer satisfaction profile of the five routing policies with (a) 98 tank cars, (b) 122 tank cars with system settings listed in Table 5.2

It can also be seen that with the tank on-arrival policy and the tank on-release policy, although the customer satisfaction is satisfactory during the high market demand (≥5000), when the market demand drops below 5000, the customer satisfaction is no better than that in the nominal policy and sometimes even worse (see Figure 16(a)). The plants in the tank on-arrival policy and the tank on-release policy only receive the same amount of empty cars as the full ones they previously transferred to the warehouses. Thus it is strongly dependent on the market demand. In the low market demand scenario, it takes a long time for tank cars to complete a full cycle and return to the plant as products are consumed slowly at the customer site.

The completed routes for tank cars are shown in Table 5.8 for a fleet size of 98 and in Table 5.9 for a fleet size of 122. With 122 tank cars at a market demand of 3000 units per day and the tank on-arrival policy, it takes an average of over 20 days for an empty tank car to return to the plant after the plant has transferred a full tank car to the warehouse. If a busy plant urgently needs an empty tank car, even if one is available in another plant, it cannot be allocated. With the nominal policy, despite the longer transportation time, at low market demand, empty tank cars can be relatively quickly relocated to plants which need them more urgently, based on the replenishment plans. As the market demand increases, the frequency of tank cars released by customers increases and it takes shorter time for them to return to the plants in the tank on-arrival policy (only 10 days at a market demand of 6000 units per day). Thus the operational efficiency increases, leading to better customer satisfaction in the nominal policy.

Table 5.8: Number of completed routes of five routing polices with tank fleet size of 98 and system settings listed in Table 5.2

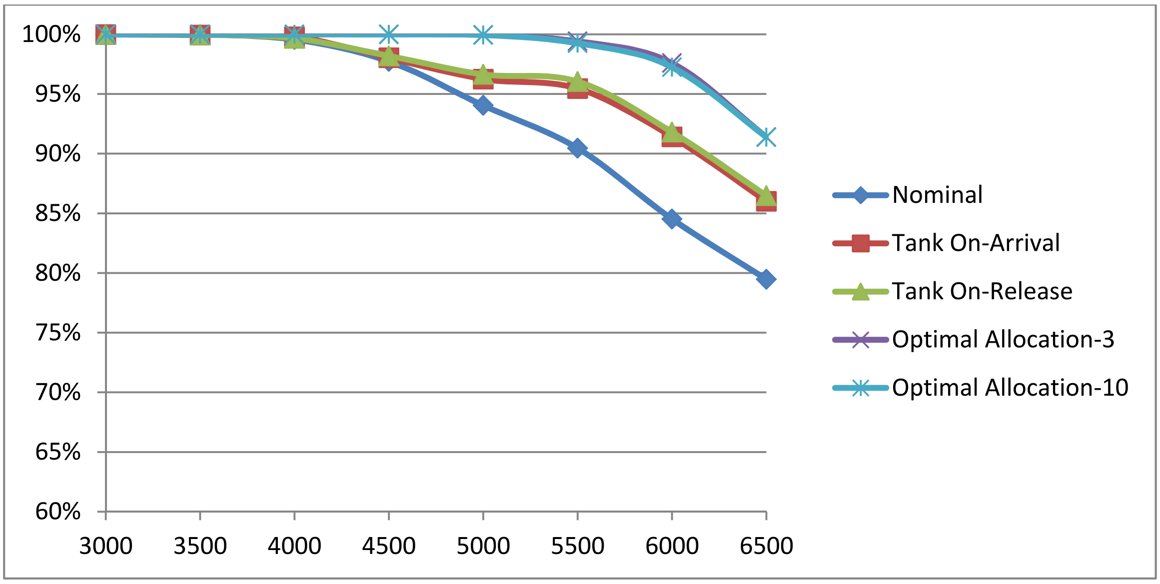
Market demand	Nominal	Tank On-Arrival	Tank On-Release	Optimal Allocation-3	Optimal Allocation-10
3000	1196.98	1198.56	1199.76	1201.02	1200.00
3500	1395.53	1397.86	1399.04	1400.49	1400.31
4000	1598.36	1597.35	1596.24	1600.87	1600.63
4500	1762.75	1764.03	1769.72	1800.52	1800.95
5000	1879.50	1927.20	1931.90	1999.80	2000.10
5500	1989.46	2098.87	2115.58	2187.85	2184.41
6000	2025.32	2193.28	2205.11	2341.61	2334.13
6500	2066.95	2236.44	2247.55	2375.91	2377.04

Table 5.9: Number of completed routes of five routing policies with tank fleet size of 122 and system settings listed in Table 5.2

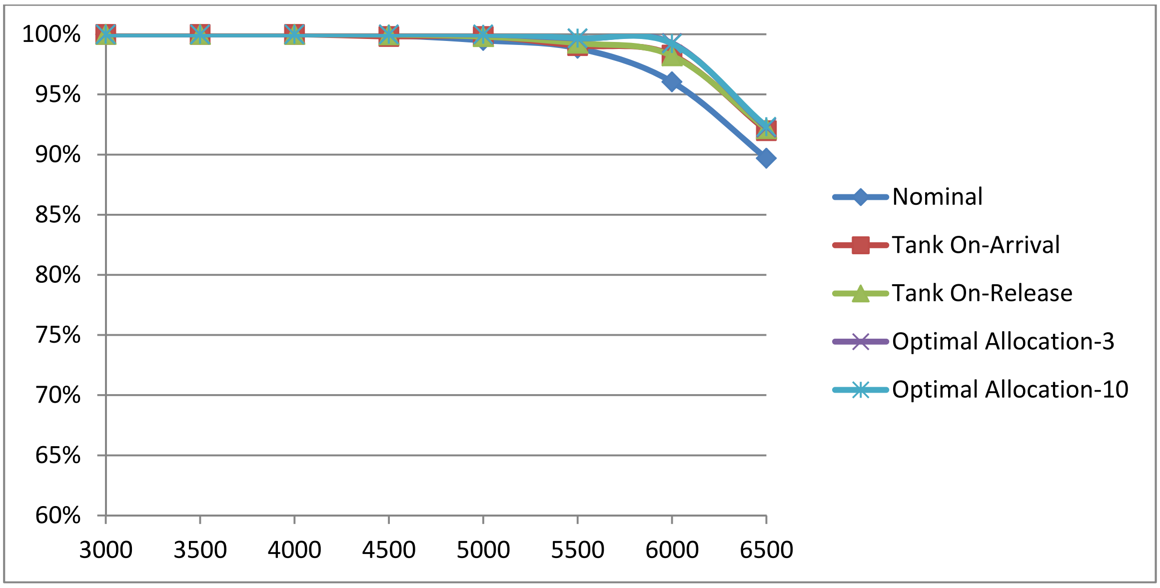
Market demand	Nominal	Tank On-Arrival	Tank On-Release	Optimal Allocation-3	Optimal Allocation-10
3000	1198.74	1197.62	1196.91	1201.13	1200.93
3500	1399.75	1400.77	1399.72	1400.77	1400.70
4000	1598.43	1599.50	1599.22	1599.80	1600.51
4500	1798.75	1797.17	1801.81	1800.13	1799.77
5000	1990.45	2001.25	1998.65	2001.10	1999.85
5500	2175.31	2180.16	2183.83	2193.30	2194.40
6000	2306.34	2358.76	2359.06	2381.27	2381.94
6500	2331.74	2396.23	2393.89	2397.48	2400.20

Figure 5.17 shows that all the five routing policies can reach nearly 100% market satisfaction during low market demand; if the market demand goes higher, market satisfaction starts to drop first with the nominal policy, followed by the tank

on-arrival policy and the tank on-release policy. The optimal allocation-3 policy and the optimal allocation-10 policy can achieve almost 100% market satisfaction when the market demand is less than 6000 units per day. At higher market demands, the plant production capacities become the bottleneck in the system and market satisfaction drops significantly for all routing policies.



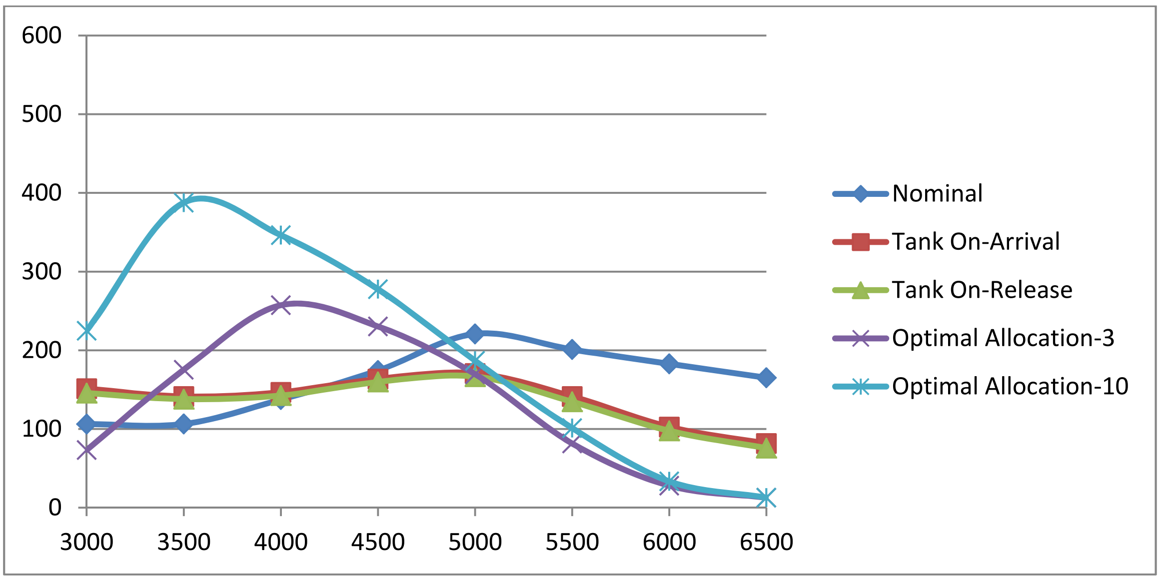
(a)



(b)

Figure 5.17: Market satisfaction profile of the five routing policies with (a) 98 tank cars, (b) 122 tank cars with system settings listed in Table 5.2

The shutdown duration of the different routing policies is shown in Figure 5.18. In the optimal allocation-3 policy, there is almost no shutdown across the market demands with tank fleet size of 122, but the shutdown duration with fleet size of 98 dramatically increases from market demand of 3000 to 4000, and then drops and approaches zero as the demand increases. In the optimal allocation-10 policy, the shutdown duration with fleet size of 98 radically increases from market demand of 3000 to 3500 and falls and approaches zero with demand increasing; while with tank fleet size of 122, the shutdown duration has a peak at the market demand of 5000, and is almost zero under other market demands. The shutdown durations in the other three policies also share a common peak at the market demand of 5000. As defined in the system, warehouses have to hold and accumulate full tank cars until they have enough stock to deliver. As the order size from customer increases, it would take more time for warehouses to hold full tank cars, which restricts the mobility of the tank cars and results in tank car shortage at plant site, and further force plants to shut down. Hence, overall, the optimal allocation-3 policy achieves the best performance followed by the optimal allocation-10 policy. The difference between the performance in the tank on-arrival and tank on-release policy is negligible.



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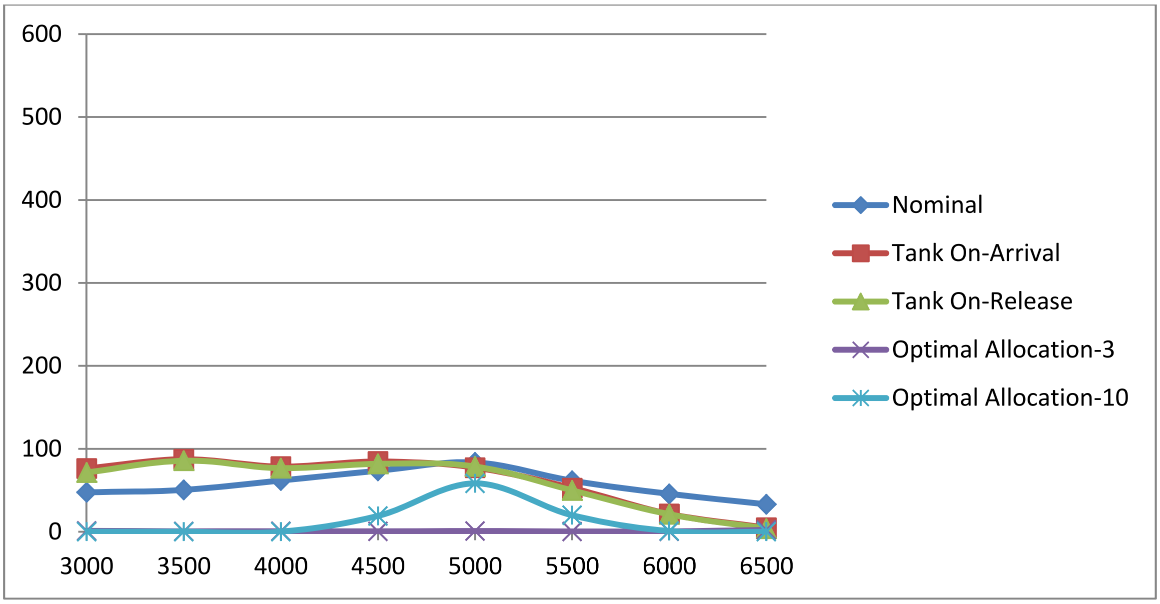


(b)

Figure 5.18: Shutdown duration profile of the five routing policies with (a) 98 tank cars, (b) 122 tank cars with system settings listed in Table 5.2

5.6.3 Inventory Control Policy

The customer inventory policy also significantly impacts the system performance as it determines their order sizes. So, we evaluate the effect of a different (S, s) setting – specifically (2000, 1000) for all customers. Unlike the case with (5000, 2500) which requires as many as 80 tank cars for customers to hold their full inventory, in the new case, only 32 tank cars are required. Further, the maximum customer order size is 2000 units, which in turn means that warehouses take lesser time to accumulate the necessary tank cars to initiate product delivery. Thus the mobility of tank car becomes higher and there are plenty of empty tank cars in the system. As a result, the customer satisfaction is almost 100 percent across all situations (see Table 5.10). However, as seen from Figure 5.19, with the new values of customer inventory control policy parameters, the market demand cannot be fully satisfied by any of the five routing policies even at low demand. It is most probably caused by the low inventory holding at the customer site. The customer inventories resulting from the low parameter value of (S, s) inventory control become the bottleneck of the supply chain. On the contrary, when all the customers running (S, s) inventory control at (5000, 2500), the market demand can be fully satisfied with enough tank cars. This is because all customers are holding excessive inventory due to the high value of order point S. Nevertheless, when the daily market demand increases to 6500 units per day which exceeds the total production capacity of the plants, the market satisfaction dramatically drops as the production capacity starts to limit the system performance. In short, high inventory in the system necessitates a large number of expensive tank cars but results in high market satisfaction. This trade-off between tank car fleet size and performance has to be balanced based on the enterprise's long term financial plans, market expectations, contract types, and negotiation with customers.

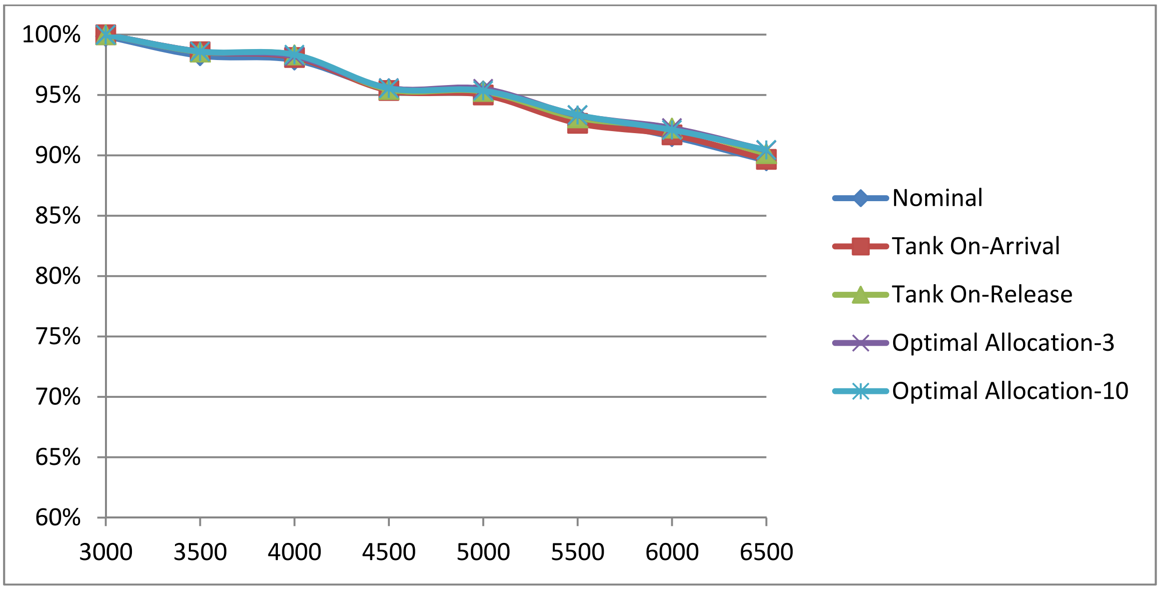
Table 5.10: Customer satisfaction of five routing policies when all customers running inventory control at (2000, 1000) with (a) 98 tank cars, (b) 122 tank cars

(a)

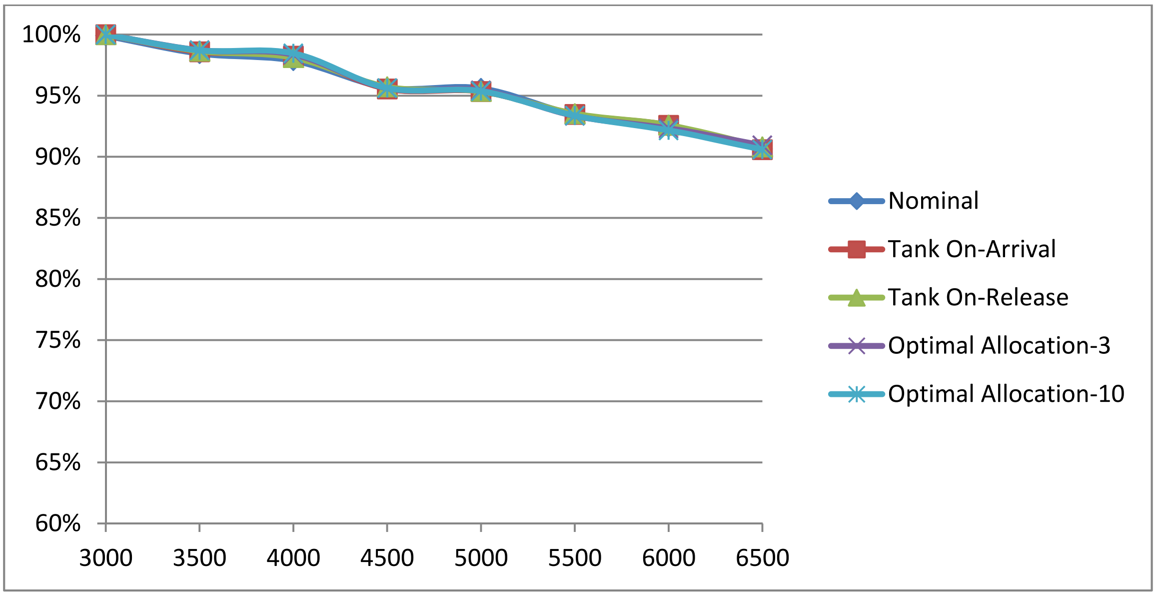
Market demand	Nominal	Tank On-Arrival	Tank On-Release	Optimal Allocation-3	Optimal Allocation-10
3000	99.9%	100.0%	100.0%	100.0%	100.0%
3500	100.0%	100.0%	100.0%	100.0%	100.0%
4000	100.0%	100.0%	100.0%	100.0%	100.0%
4500	100.0%	100.0%	100.0%	100.0%	100.0%
5000	100.0%	100.0%	100.0%	100.0%	100.0%
5500	100.0%	100.0%	100.0%	100.0%	100.0%
6000	100.0%	100.0%	100.0%	100.0%	100.0%
6500	100.0%	100.0%	100.0%	100.0%	100.0%

(b)

Market demand	Nominal	Tank On-Arrival	Tank On-Release	Optimal Allocation-3	Optimal Allocation-10
3000	100.0%	100.0%	100.0%	100.0%	100.0%
3500	100.0%	100.0%	100.0%	100.0%	100.0%
4000	100.0%	100.0%	100.0%	100.0%	100.0%
4500	100.0%	100.0%	100.0%	100.0%	100.0%
5000	100.0%	100.0%	100.0%	100.0%	100.0%
5500	100.0%	100.0%	100.0%	100.0%	100.0%
6000	100.0%	100.0%	100.0%	100.0%	100.0%
6500	100.0%	100.0%	100.0%	100.0%	100.0%



(a)



(b)

Figure 5.19: Market satisfaction profile when all customers running inventory control at (2000, 1000) with (a) 98 tank cars, (b) 122 tank cars

5.7 Conclusions and Future Work

In this chapter, we developed an agent-based simulation model which mimicked the various supply chain operations in the real industries, including inventory management, order assignment, replenishment planning and tank fleet management. The entities in the supply chain model are locally controlled and can negotiate with each other using pre-defined conversation protocols. Based on current system, we proposed five different tank fleet management policies, and simulated the supply chain model under these tank fleet management policies with different market demands, tank fleet sizes and inventory control policies. The simulation results captured the emergent phenomenon of the system and demonstrated how simulation model can be used to select a proper tank fleet management policy with optimum tank fleet size.

The market demand is defined as constant in the system and there is no outside disturbance and disruptions. The complex behavior of the system is majorly caused by the shortage of the tank cars internally. In the next step, we would like to introduce fluctuated market demand, transportation disruption, production disturbance or disruption into the system, and study how the system would behavior with different management policies under these circumstances.

5.8 Nomenclature

Indexes

c	customer
p	plant
t	time
w	warehouse

Constants

C	number of customers
$D_{k,j}$	distance between location i and location j, k, j ϵ (c, p, w)
DSP	order delivery scheduling policy
P	number of plants
s	reorder point of (S, s) inventory control policy
S	order point of (S, s) inventory control policy
SH	simulation horizon
W	number of warehouses

Variables

Objects

CPO	customer purchase order
CPO^{id}	id of the corresponding *RFQ*
CPO^{c}	customer id
CPO^{Amt}	ordered amount
CPO^{CmfDD}	confirmed due date
CPO^{Cmplt}	completion status that is set to 1 when the order has been delivered
MPO	market purchase order
MPO^{SPID}	id of the corresponding sale proposal to which the purchase order is replied to
MPO^{BuyAmt}	confirmed amount market agent purchases for the proposal
PD	product delivery
PD^{Amt}	product amount delivered
$PD^{OrderID}$	id of the order based on which the product delivery is initiated
PD^{TCList}	list of tank cars in the product delivery
RFQ	request for quotation

RFQ^{id}	unique id to identify a particular request for quotation
RFQ^{c}	customer id number
RFQ^{Amt}	ordered amount
RFQ^{DD}	due date
RFQ^{Tol}	tolerance days defined as the maximum number of days after the due date by which the order must be delivered
RRFQ	reply to RFQ
$RRFQ^{id}$	id which matches the corresponding RFQ^{id}
$RRFQ^{Cmf}$	acceptance (1) or rejection (0) of the order
$RRFQ^{CmfDD}$	confirmed due date on acceptance.
RT	replenishment transfers
RT^{Amt}	amount of product is transferred through warehouse transfer
RT^{DD}	due date of the warehouse transfer
RT^{id}	ID to identify a particular replenishment transfer
RT^{w}	destination of the warehouse transfer
RT^{p}	plant where the warehouse transfer is initiated
SP	sale proposal
SP^{MaxAmt}	maximum amount customer is willing to sell
SP^{c}	customer id
SP^{id}	id to identify a particular sale proposal
SP^{Price}	offer price of the compound
TC	tank car
TC^{Amt}	current inventory of product in the tank car
TC^{Cap}	capacity of the tank car
TC^{id}	unique id to identify a particular tank car
TCList	list of tank car used as inventory holding facilities
WT	warehouse transfer
WT^{amt}	product amount transferred
WT^{RPID}	index number of the replenishment plan based on which the warehouse transfer is initiated
WT^{TCList}	list of tank cars in the warehouse transfer.

Agents

<u>Market Agent</u>

CMS	cumulative market satisfaction
MD	market demand

MS	market satisfaction
SM	amount of sales
SPList	sale proposals collected from customers

Customer Agents

BP_c	base price for compound price calculation
CDD_c	number of orders delivered delayed
CDO_c	number of orders delivered on time
CCS	cumulative customer satisfaction
$CPOList_c$	list of confirmed customer orders
CS_c	customer satisfaction
FP_c	pricing factor for compound price calculation
IL_c	inventory level
IP_c	inventory position

Order Coordinator

OM	number of missed orders

Warehouse Agents

CPO^{ShipDT}	latest time by which the warehouse should initiate product delivery for the order to be delivered
DSP	scheduling policy
IL_w	inventory level
IP_w	inventory position
ODS_w	order delivery schedule
$ProjSch_w$	projected order delivery schedule
$SchOrder_w^{cmplt}$	projected order completion date by warehouse w
TL_w	inventory target level of warehouse inventory
TT	transportation time
WD_w	warehouse demand

Replenishment Coordinator

RC	replenishment cycle

RC^{ET}	end time of replenishment cycle
RC^{ST}	start time of replenishment cycle
T	production sub-target

Plant Agents

AP_p	actual production in replenishment cycle
BL_p	backlog from previous replenishment cycle
CSR_p	cumulative shutdown rate CSR
PR_p	production rate
PSR_p	plant shutdown rate
PT_p	production throughput
SD_p	production status

Policies

DV	decision variable the value of which is 1 if tank car is assigned to plant or 0 if tank car is not assigned to plant p
DW	weight used to evaluate the urgency of daily tank car request
TA	number of tank cars assigned to plant
TR	number of tank cars requested by plant

Chapter 6

Study in the Ease of Extensions

The scenario studies in Chapter 4 demonstrated the advantages of the proposed ABMS framework for supply chains. In this chapter, we will discuss it by studying two detailed extensions of the model developed in Chapter 5, and show how different supply chain problems can be studied in an easy fashion through ABMS of supply chains using BPMN.

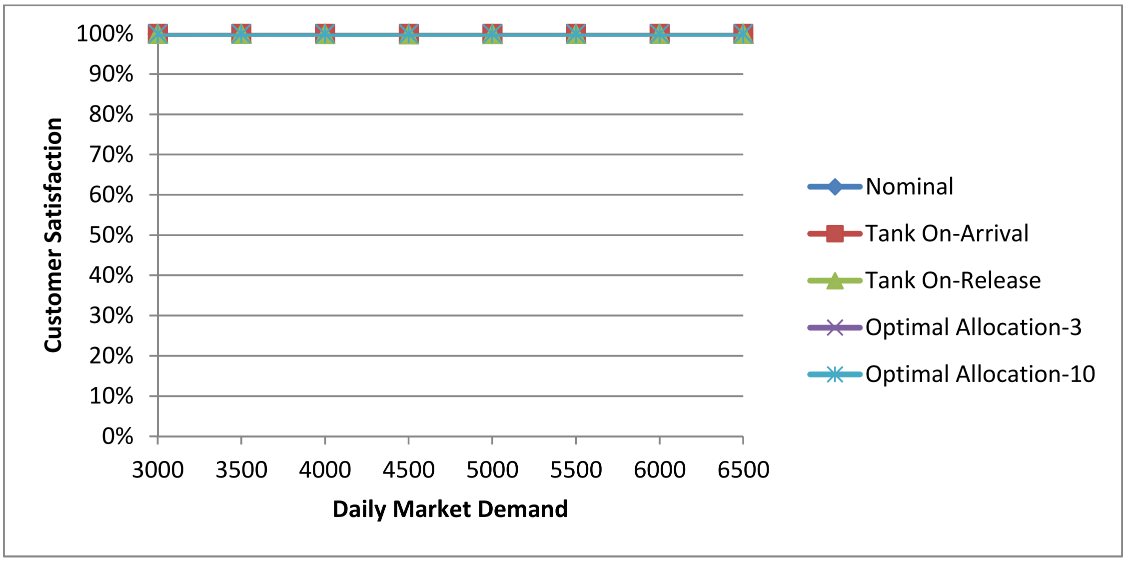
6.1 Transportation Disturbance

In the previous chapter, emphasis has been placed on the development of optimal tank fleet management policy to achieve a high customer service level and market satisfaction with minimum number of tank cars. The transportation time for material flow and empty tank car return is determined based on the geographical locations of the departure location and destination. In reality, logistics network is exposed to a dynamic environment. Therefore, transportation delay, termed transportation disturbance, would occur because of the traffic flow dynamics, communication delays, extreme weather, machine fouling, and even natural disaster. Transportation disturbance would lead to serious consequences if it is not taken into account when managing the supply chains. Take the complex chemical supply chain model in the previous chapter as an example. Transportation delay in empty tank car return might cause a temporary tank car shortage at plant site, which will force the plant to shut down and further postpone the warehouse transfer. Transportation delay in warehouse transfer will make warehouse fail to initiate product delivery on time. Transportation delay in product delivery might directly ship the products after the order due date, resulting in a decrease in customer service level.

In this section, we will study the impact of transportation disturbance on the chemical supply chain model developed in Chapter 5, and develop strategies to overcome the drawbacks of the transportation delay.

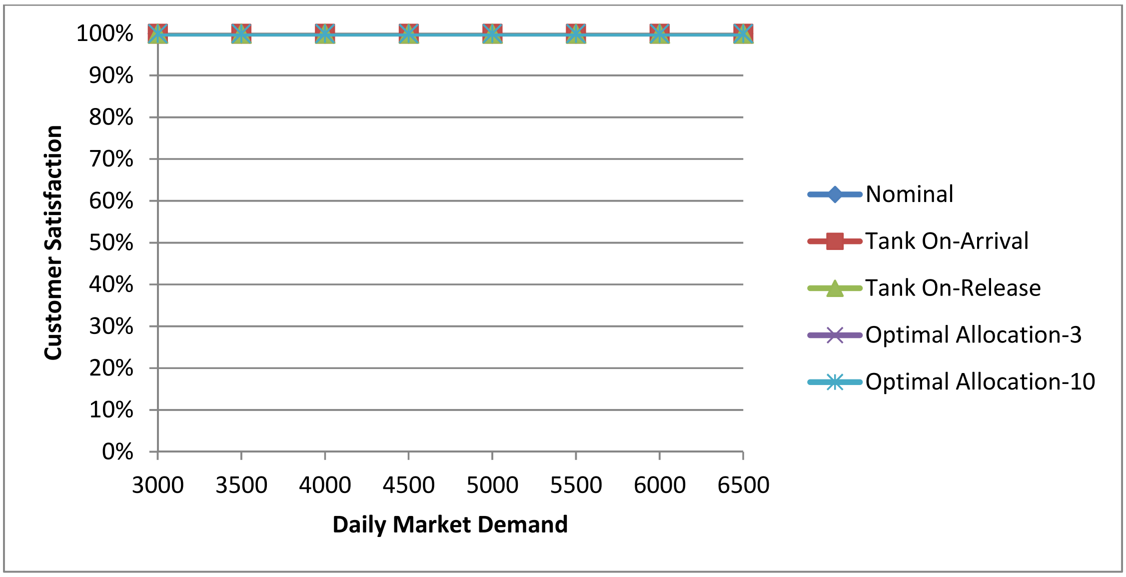
6.1.1 Impact of Transportation Disturbance

All the system parameters in the chemical supply chain model in chapter 5 remain the same, except that the (S, s) inventory policy of customers changes from (5000, 2500) to (2000, 1000). Figure 6.1 shows the customer satisfaction and market satisfaction for tank fleet size of 98 and 122. The simulation results were obtained following the procedures as described in the previous chapter. As seen from the figure, the customer satisfaction can be maintained at 100% whereas the market satisfaction cannot achieve 100% even at the low demand. For instance, when the daily market demand is only 3500 units per day, the market satisfaction is around 98% for all the five policies. When more tanks cars are added into the system, from 98 cars to 122 cars, there is hardly any improvement on the market satisfaction (see Figure 6.1(d)). Only the difference between the performance of the nominal policy and those of other polices become negligible.



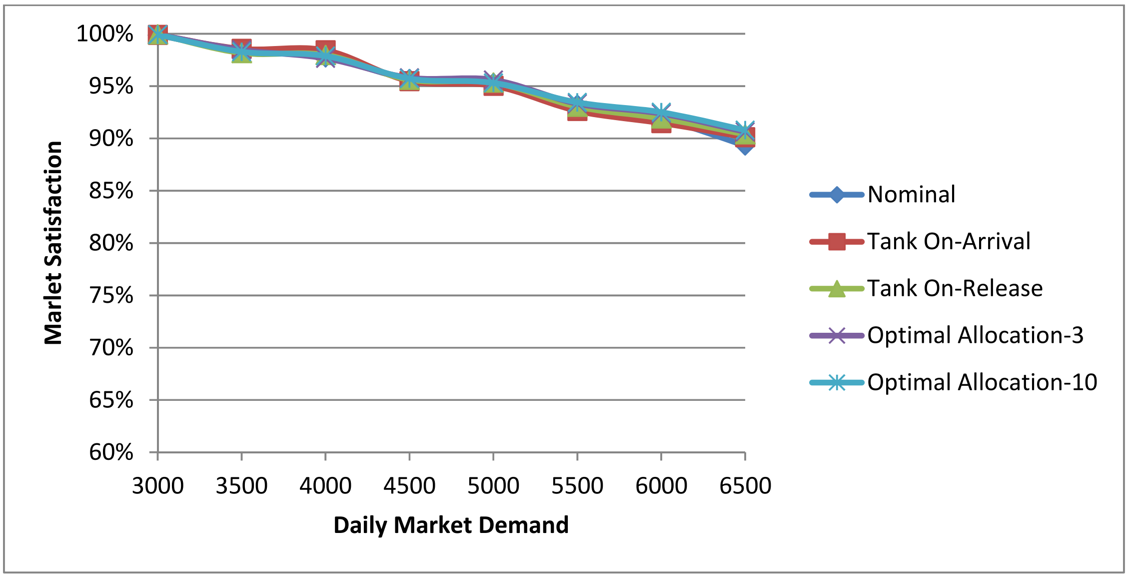
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
Customer Satisfaction
3000
3500
4000
4500
5000
5500
6000
6500
Daily Market Demand
Nominal
Tank On-Arrival
Tank On-Release
Optimal Allocation-3
Optimal Allocation-10

(a)

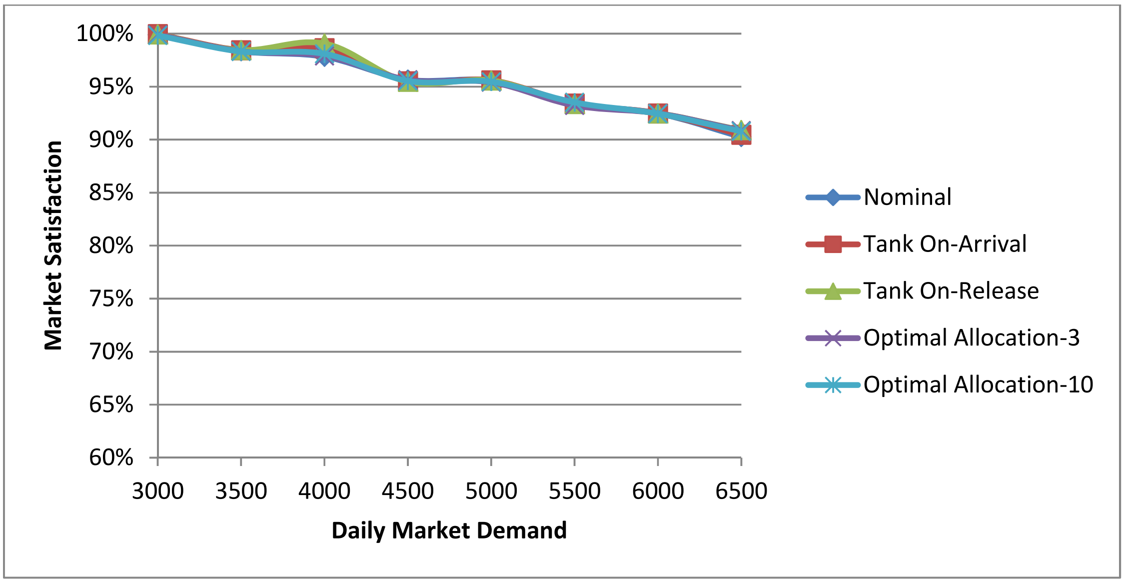


100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
Customer Satisfaction
3000
3500
4000
4500
5000
5500
6000
6500
Daily Market Demand
Nominal
Tank On-Arrival
Tank On-Release
Optimal Allocation-3
Optimal Allocation-10

(b)



(c)



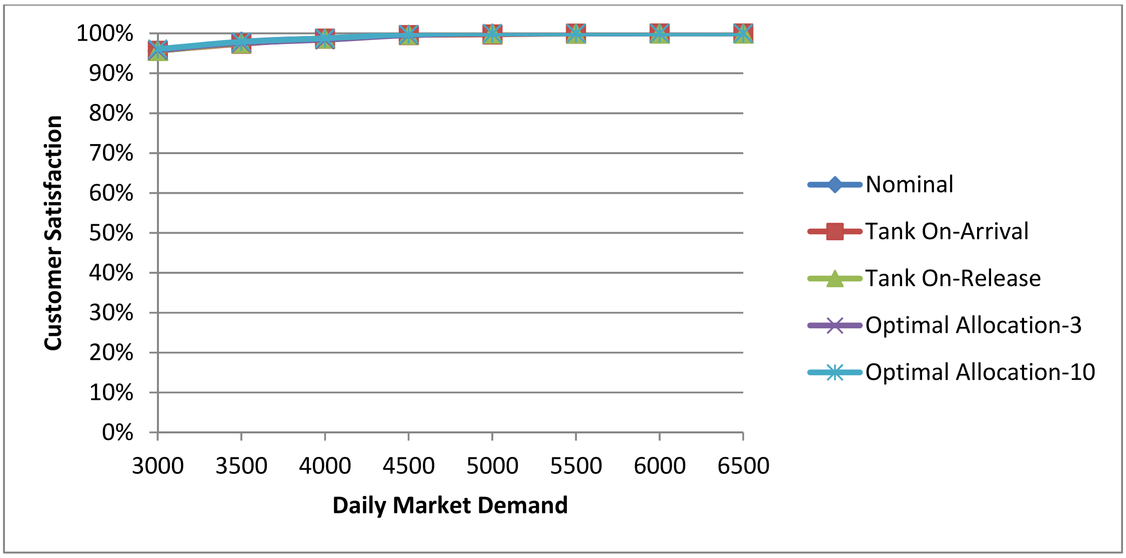
(d)

Figure 6.1 Simulation results for supply chain model without transportation time delay: (a) customer satisfaction with 98 tank cars; (b) customer satisfaction with 122 tank cars; (c) market satisfaction with 98 tank cars; (d) market satisfaction with 122 tank cars

We deployed a transportation delay in the logistics agent which takes charge of all the transportation between different supply chain entities. The transportation delay was set as an additional percentage time delay added to the original transportation time, which follows a uniform distribution ranging from 0 % to a maximum percentage of time delay value. The maximum percentage of time delay value was set as 50%, 100% and 200%. The resulting customer satisfaction and market satisfaction are shown in Figure 6.2, Figure 6.3 and Figure 6.4 respectively. The followings can be observed from these figures:

1) With transportation disturbance, the overall market satisfaction decreases. Taking the market demand of 4000 unit per day in the five policies for example, the market satisfaction is around 96% with maximum 50% transportation delay, 95% with maximum 100% transportation delay, and 93% with maximum 200% transportation delay.
2) For the customer satisfaction, the supply chain system can still maintain 100% during the high demand while there is a sharp decrease at the low demand. Taking the market demand of 3000 units per day for example, the customer satisfaction decreased to 95% with maximum 50% of transportation delay, 88% with maximum 100% transportation delay, and 77% percentage with maximum 200% transportation delay. This can be explained by the production policy. As the plants manufacture products at an average rate, it takes longer time for an order to be completed at the plant side during low market demand, resulting in higher risk of delayed product delivery of the customer order.
3) The performance of optimal allocation-3 is getting worse at high transportation disturbance. With maximum 200% delay with 122 tank cars, optimal allocation-3 performs the worst among these policies in terms of the customer satisfaction and market satisfaction. It is possible due to the short length of the logistics planning horizon as 200% transportation delay may already approach or even exceed the planning horizon, i.e. three days.
4) Adding more tank cars into the system does not make a significant improvement to the customer satisfaction and market satisfaction.

These findings indicate that we have to modify other operational policies to overcome the drawbacks of the transportation disturbance rather than simply increasing the number of tank cars in the system.



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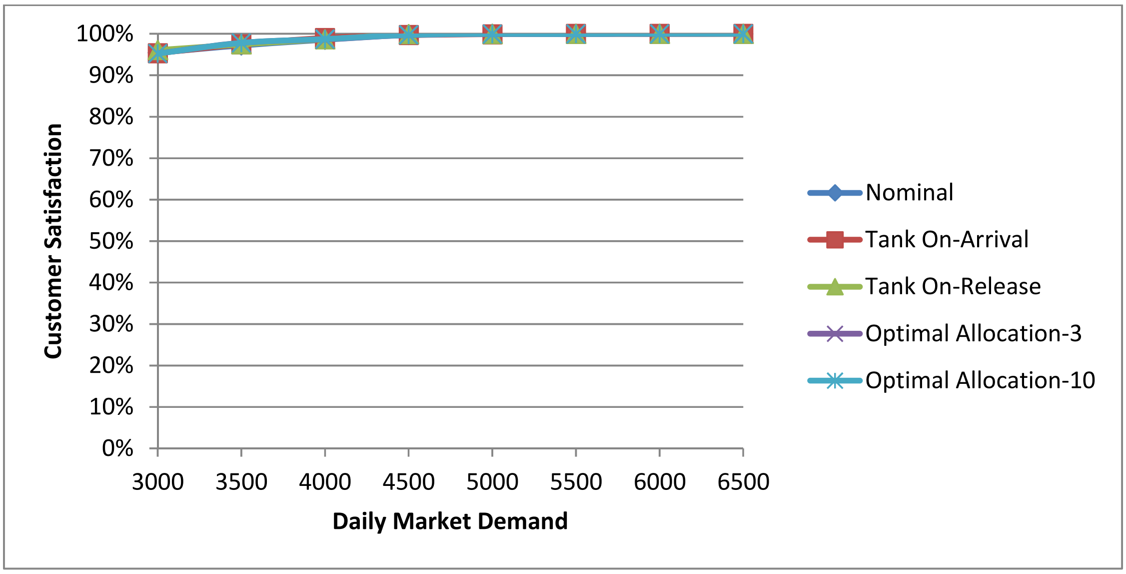

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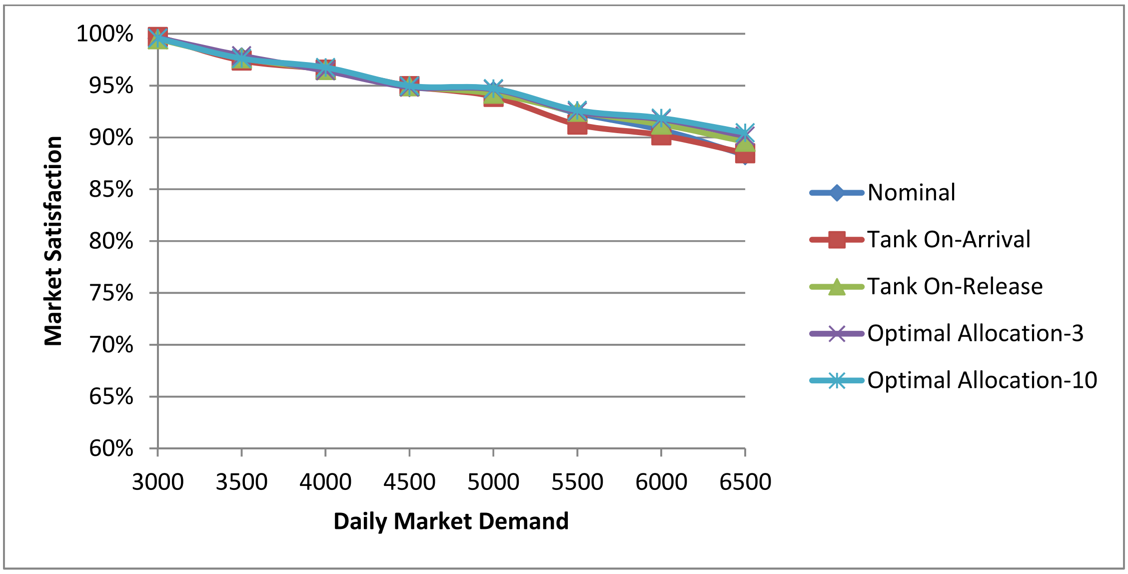

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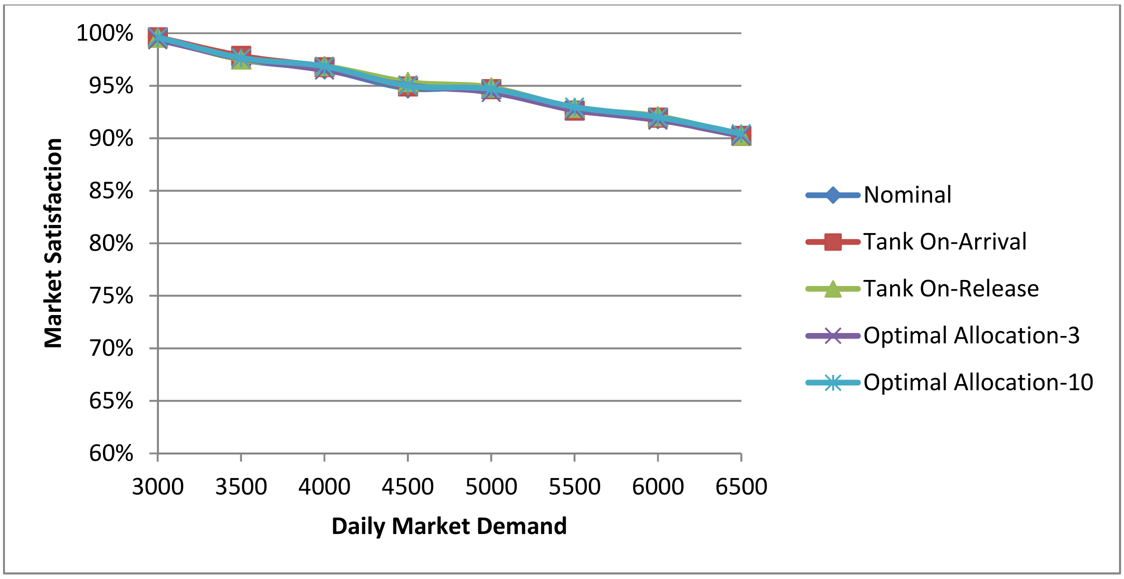

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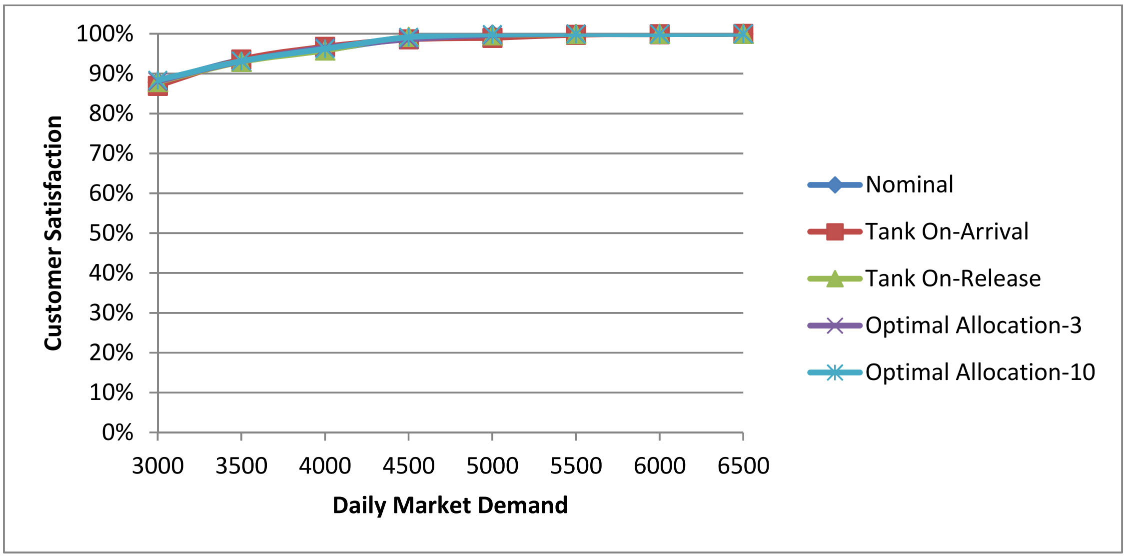
Figure 6.2 Simulation results for supply chain model with maximum 50% transportation time delay: (a) customer satisfaction with 122 tank cars; (b) customer satisfaction with 98 tank cars; (c) market satisfaction with 98 tank cars; (d) market satisfaction with 122 tank cars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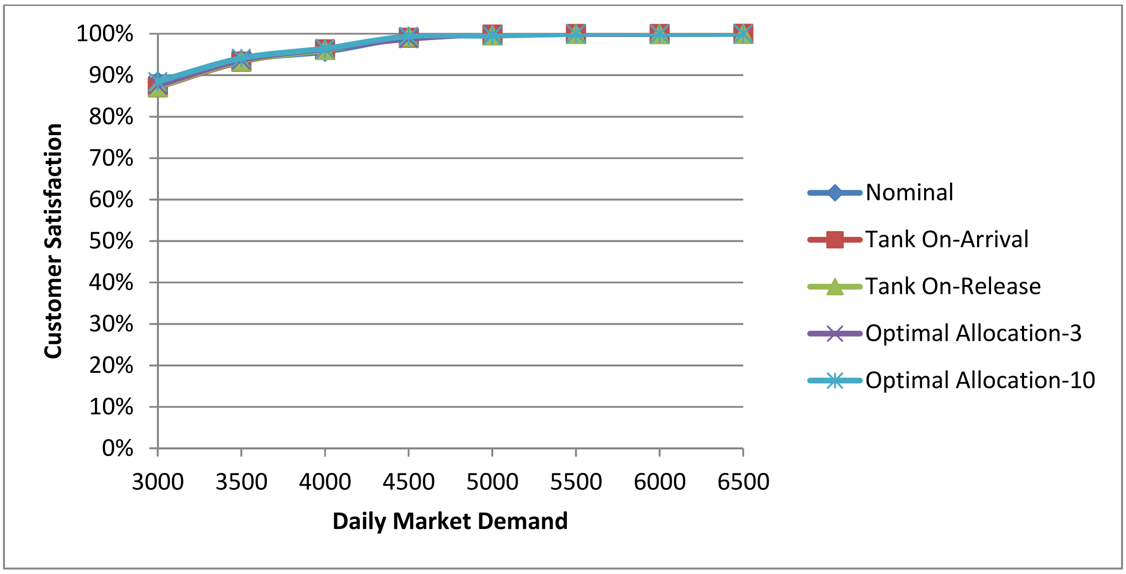
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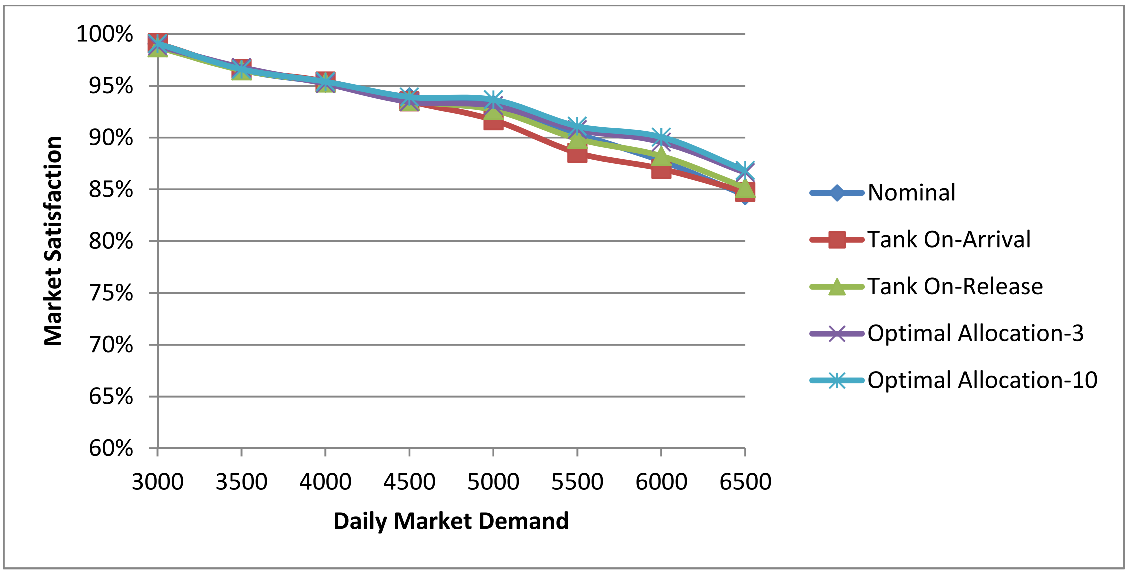

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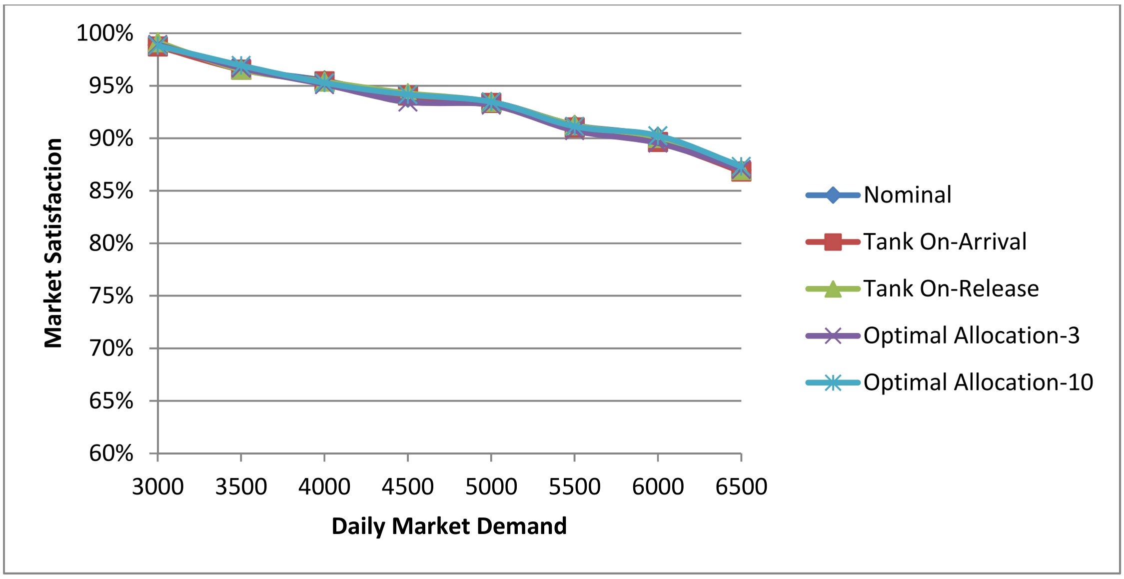

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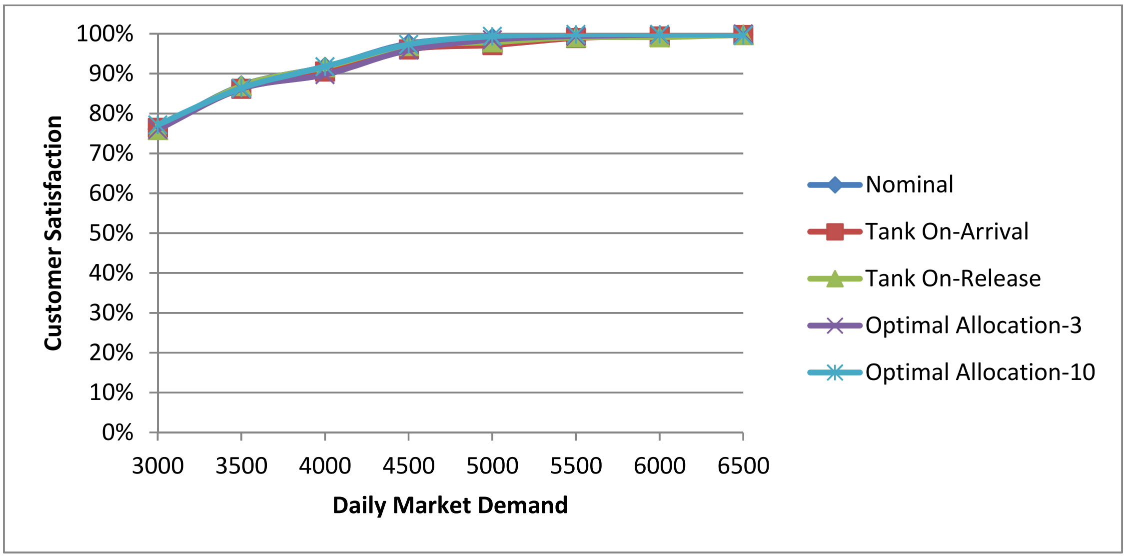
Figure 6.3 Simulation results for supply chain model with maximum 100% transportation time delay: (a) customer satisfaction with 98 tank cars; (b) customer satisfaction with 122 tank cars; (c) market satisfaction with 98 tank cars; (d) market satisfaction with 122 tank cars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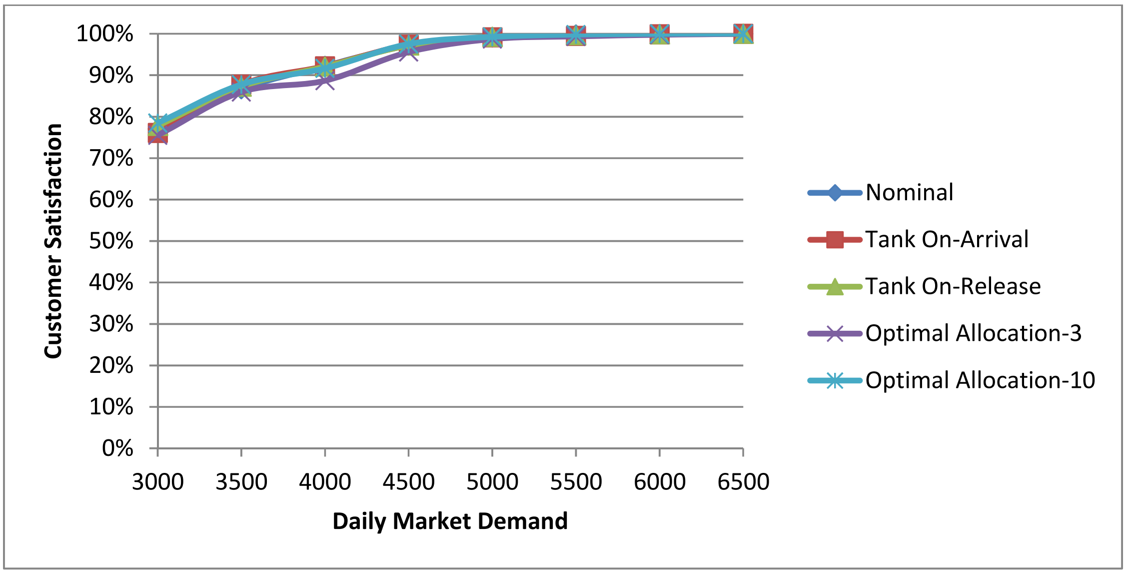
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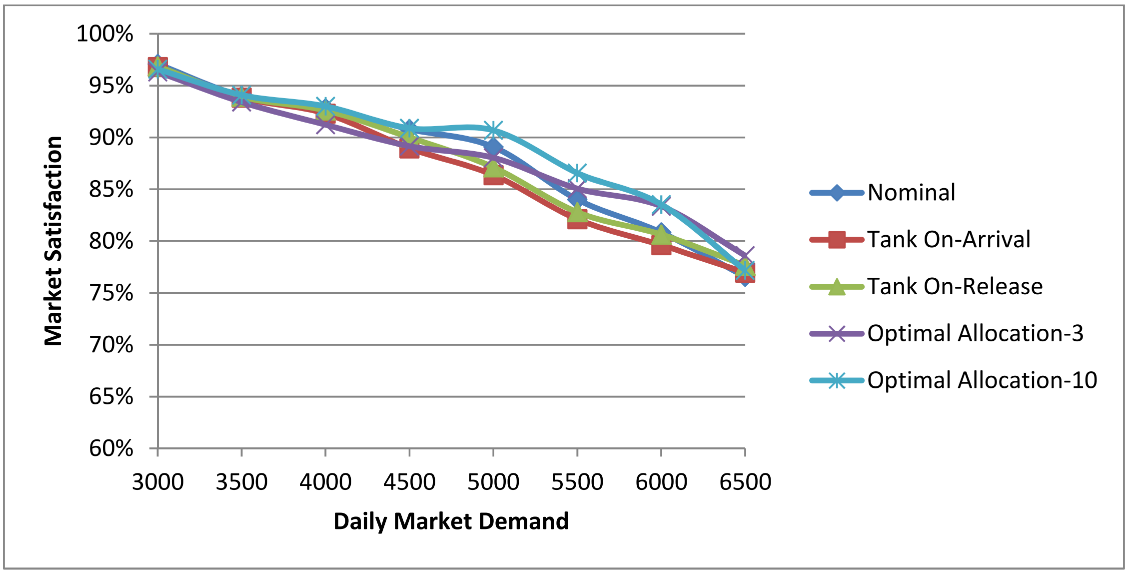

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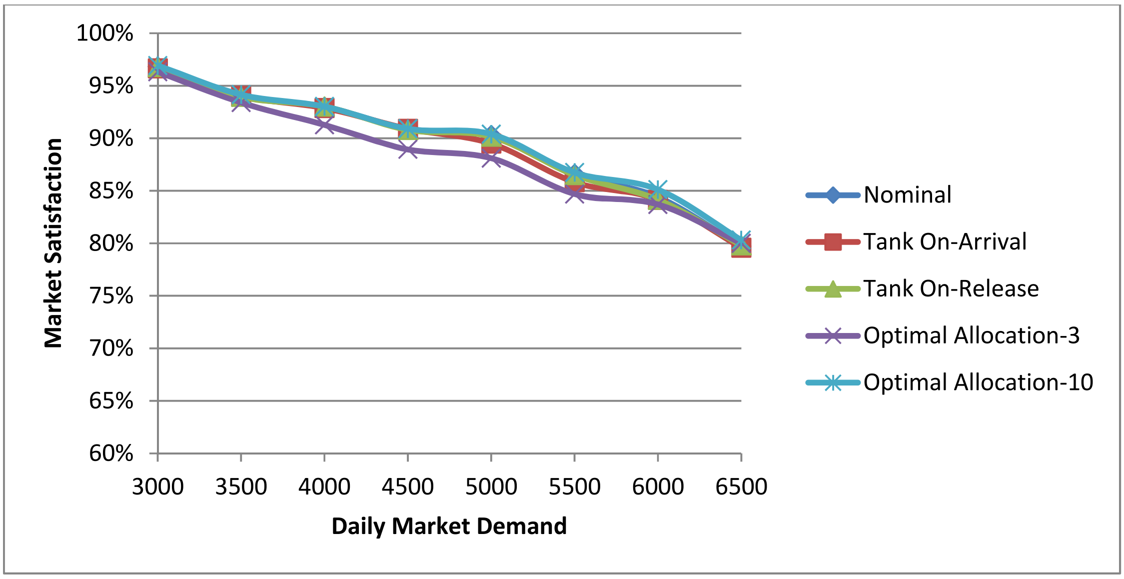


(d)

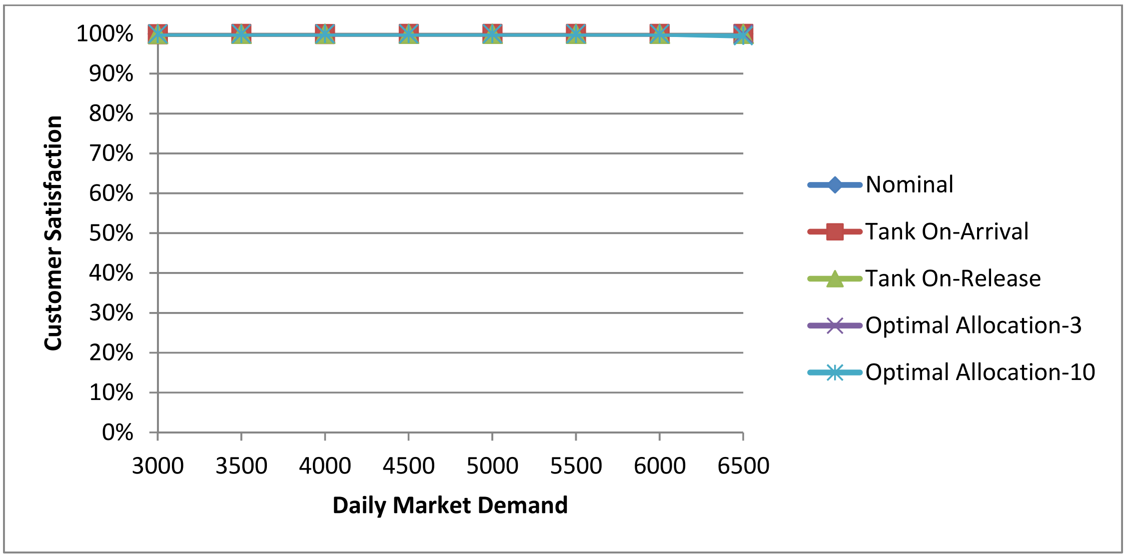
Figure 6.4 Simulation results for supply chain model with maximum 200% transportation time delay: (a) customer satisfaction with 98 tank cars; (b) customer satisfaction with 122 tank cars; (c) market satisfaction with 98 tank cars; (d) market satisfaction with 122 tank cars

6.1.2 Safety Stock

Safety stock is a level of extra stock held to absorb the uncertainties in supply and demand, which serves as an insurance against product or material shortage. It is mainly used when there is a variation in customer demand or long lead time of manufacturing (Tersine, 1994). Holding certain amount of safety stock is one way to hedge the transportation disturbance. As described in Chapter 5, the sum of the top-up levels of all warehouses in the chemical supply chain model is exactly equal to the total market demand of the planning period, so there is no safety stock at warehouses. Here, we added a safety stock at warehouses by modifying the warehouse top-up level as follows

$$\text{Modified warehouse top-up level} = \frac{\text{Market Demand} \times \text{Replenishment Planning Horizon} \times 2.5}{\text{Number of warehouses}}$$

The simulation results of the chemical supply chain model with safety stock and no transportation delay are shown in Figure 6.5. Comparing with the results shown in Figure 6.1, we can find that the safety stock greatly improves the market satisfaction when the market demand is not beyond the total production capacity of the chemical enterprise. For example, the market satisfaction maintains at 100% when the market demand is below 6000 unit per day with 98 tank cars in the supply chain, and it can reach 100% at market demand of 6000 units per day if the fleet size increases to 122. It is because the safety stock creates a buffer between plants and customers. Thus the time required for customers to receive product delivery after order placement is reduced, which overcomes the drawback of the small values of inventory control parameters of the customers.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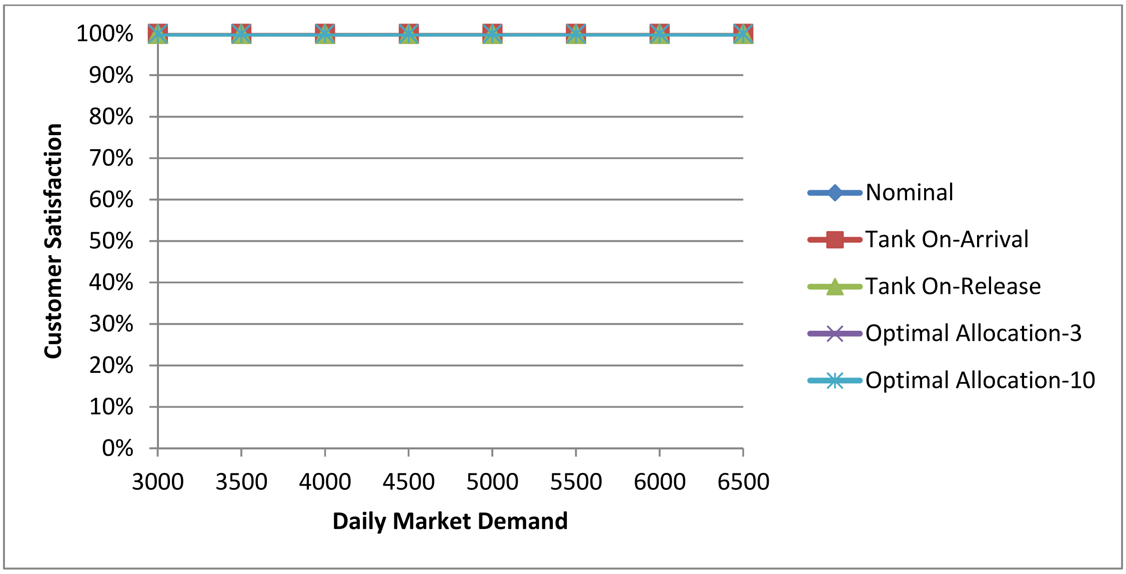
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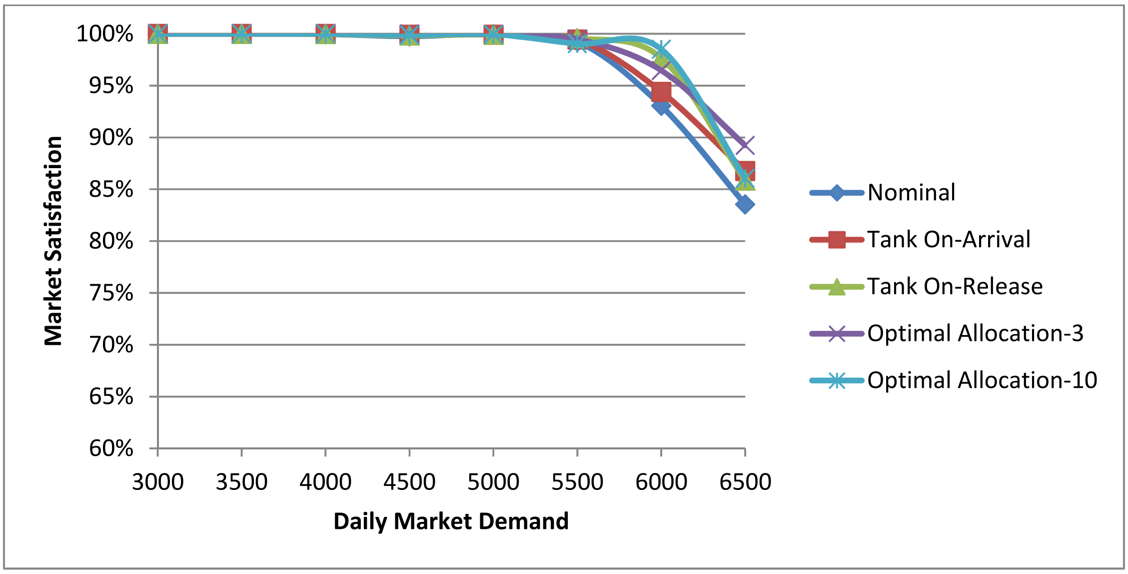

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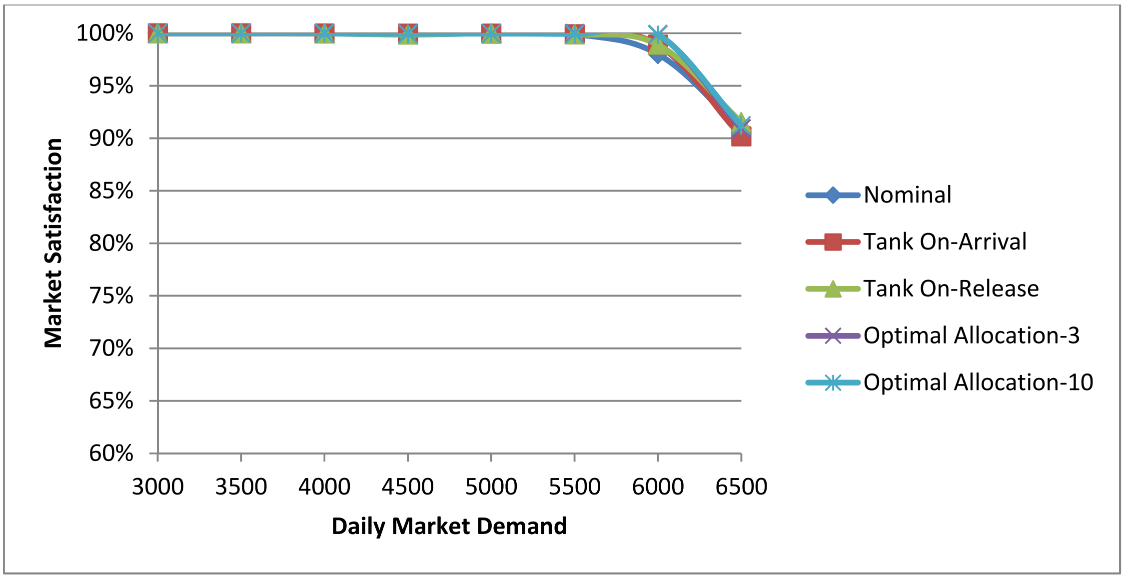

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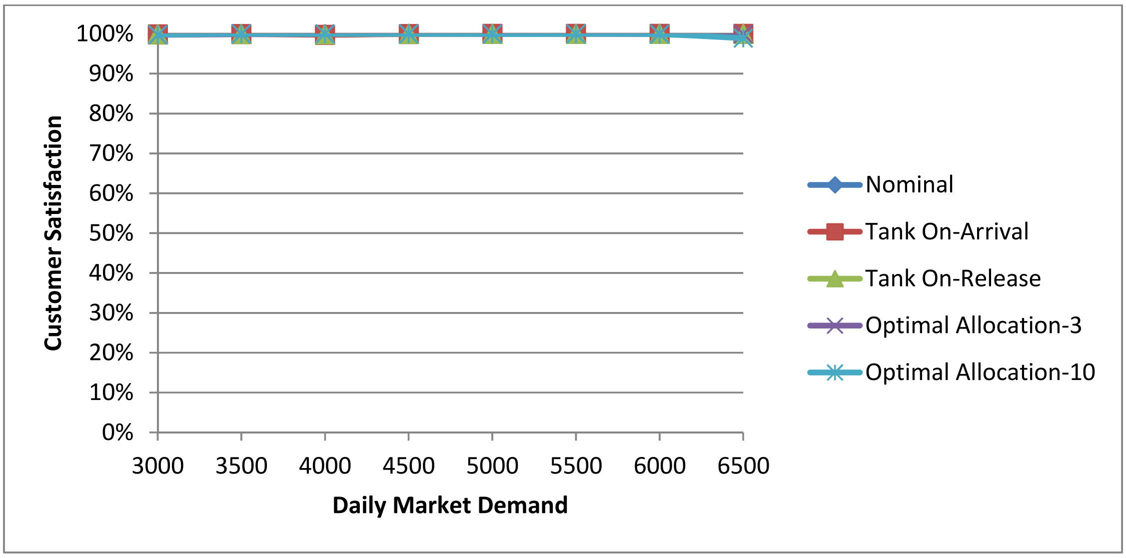
Figure 6.5 Simulation results for supply chain model with safety stock at warehouses and no transportation time delay: (a) customer satisfaction with 98 tank cars; (b) customer satisfaction with 122 tank cars; (c) market satisfaction with 98 tank cars; (d) market satisfaction with 122 tank cars

We introduced the transportation delay to the new system. The maximum percentage time delay value was set as 50%, 100% and 200%. The resulting customer satisfaction and market satisfaction are shown in Figure 6.6, Figure 6.7 and Figure 6.8 respectively. The comparison between these results and those shown in previous section indicates that:

1) Safety stock at warehouses greatly improves the overall market satisfaction whenever there is a transportation disturbance in the system if the demand is not beyond the total production capacity of the chemical enterprise.
2) Safety stock at warehouses also improves the customer satisfaction under low market demand when the transportation disturbance is introduced into the system. It is because the safety stock creates a buffer between plants and customers and further reduces the time required for customers to receive product delivery after order placement.
3) As the tank cars are the only space to store and transport products in the supply chain model, warehouses retain tank cars for the safety stock, resulting in lower customer satisfaction and market satisfaction under high market demand (beyond production capacity) with transportation delays. However, an increase in tank fleet size can improve the system performance in such situation.

The size of safety stock in this section was determined through simulation experiments and it is evenly distributed among the warehouses. In the reality, the size of safety stock is determined and optimized by considering demand variance, lead time variance and other factors. The safety stock of each warehouse is also varied according the geographical location of the warehouse and the historical order and warehouse information.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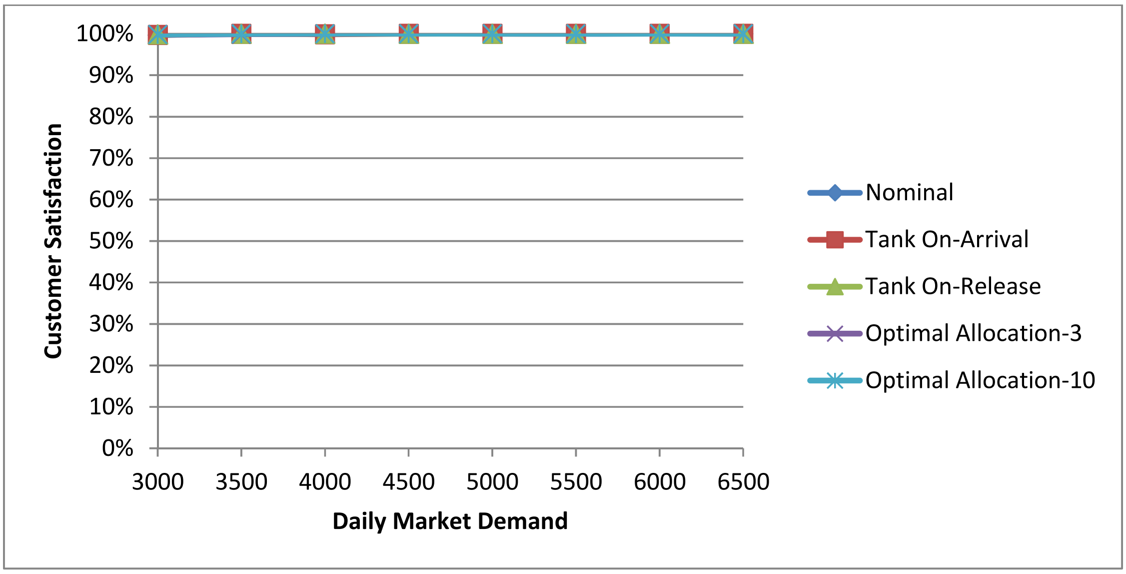
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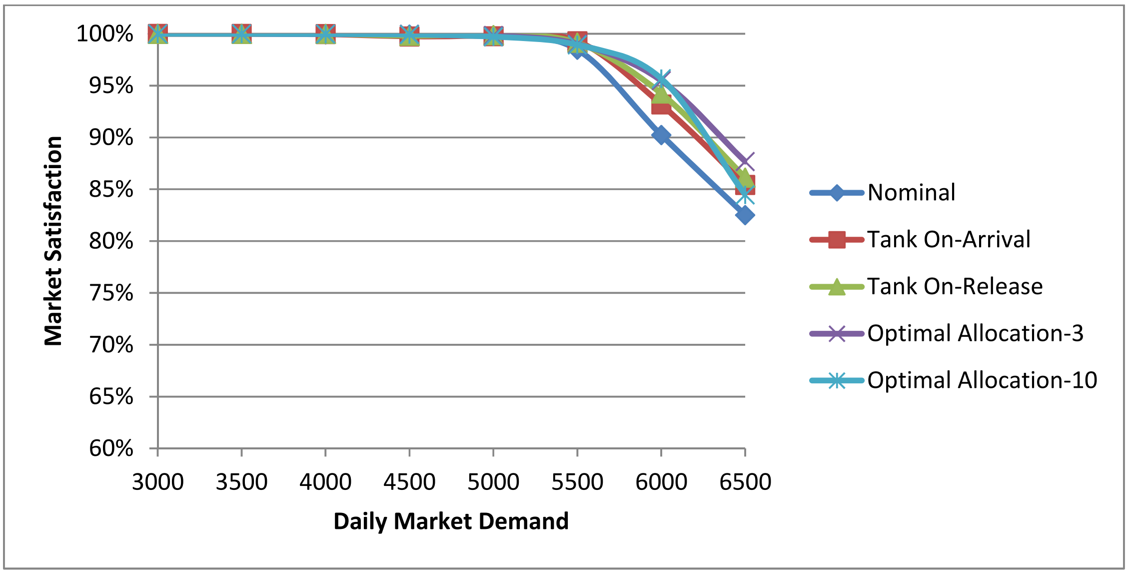

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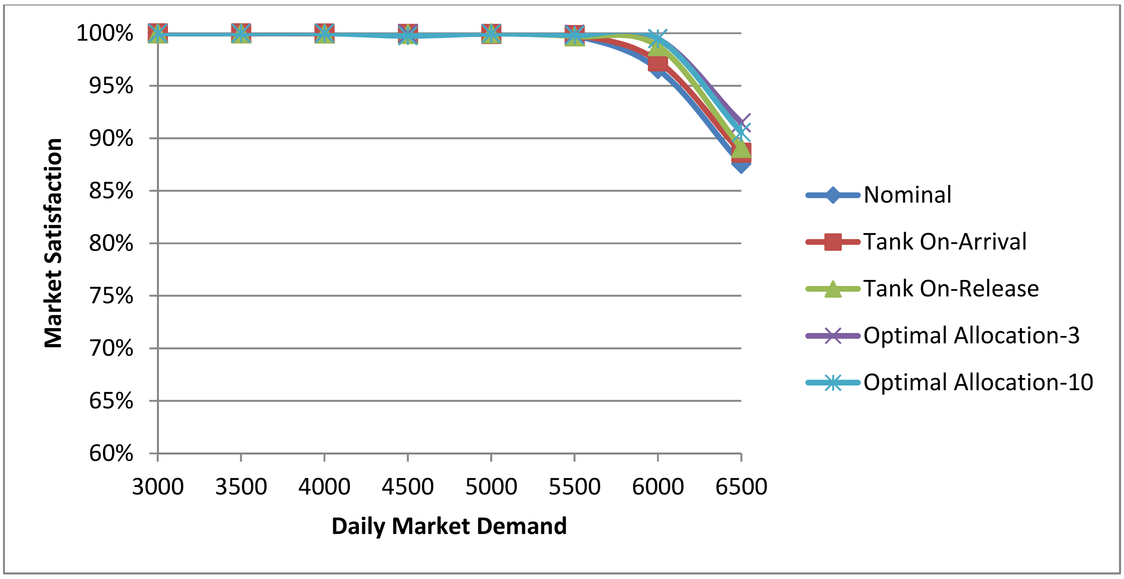

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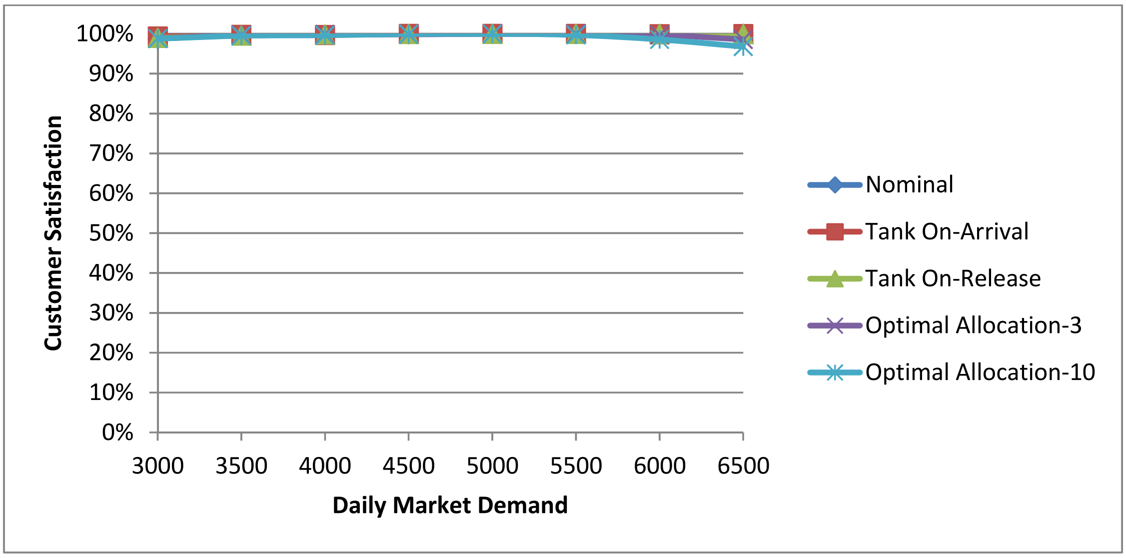
Figure 6.6 Simulation results for supply chain model with safety stock at warehouses and maximum 50% transportation time delay: (a) customer satisfaction with 98 tank cars; (b) customer satisfaction with 122 tank cars; (c) market satisfaction with 98 tank cars; (d) market satisfaction with 122 tank cars



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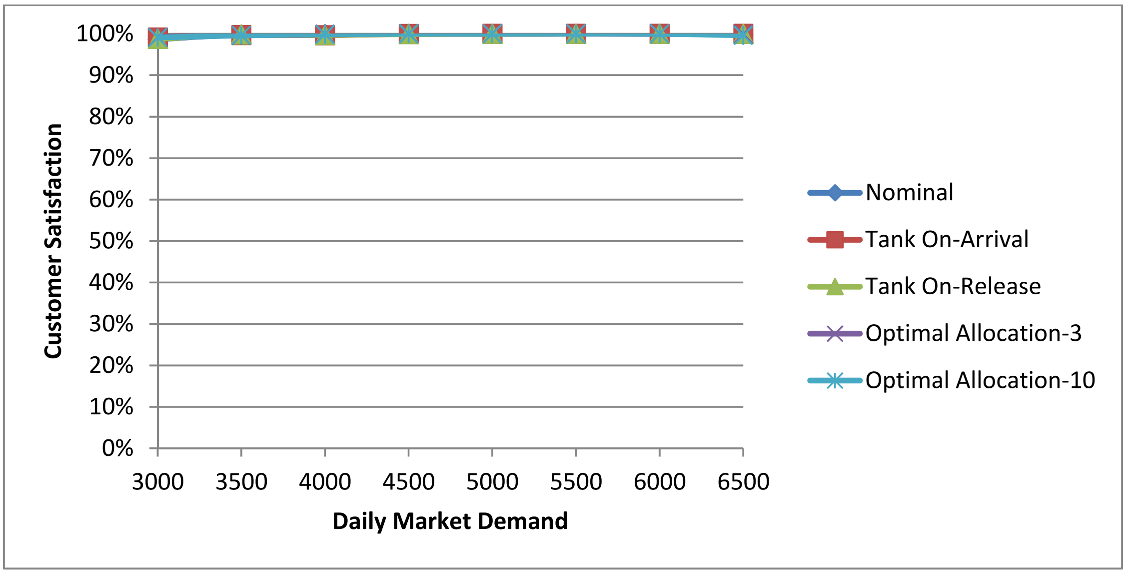

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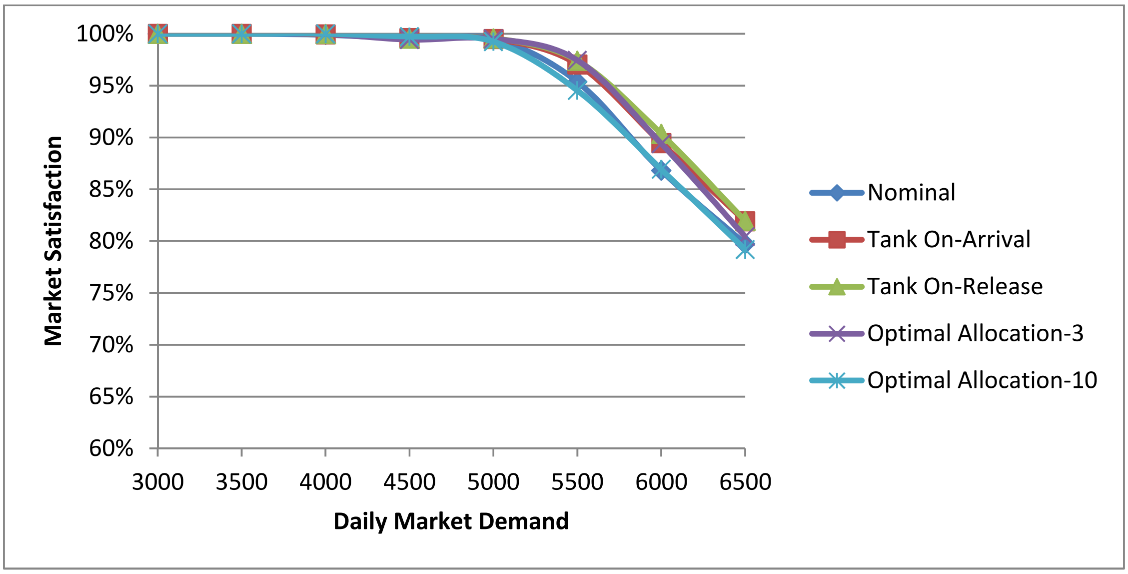

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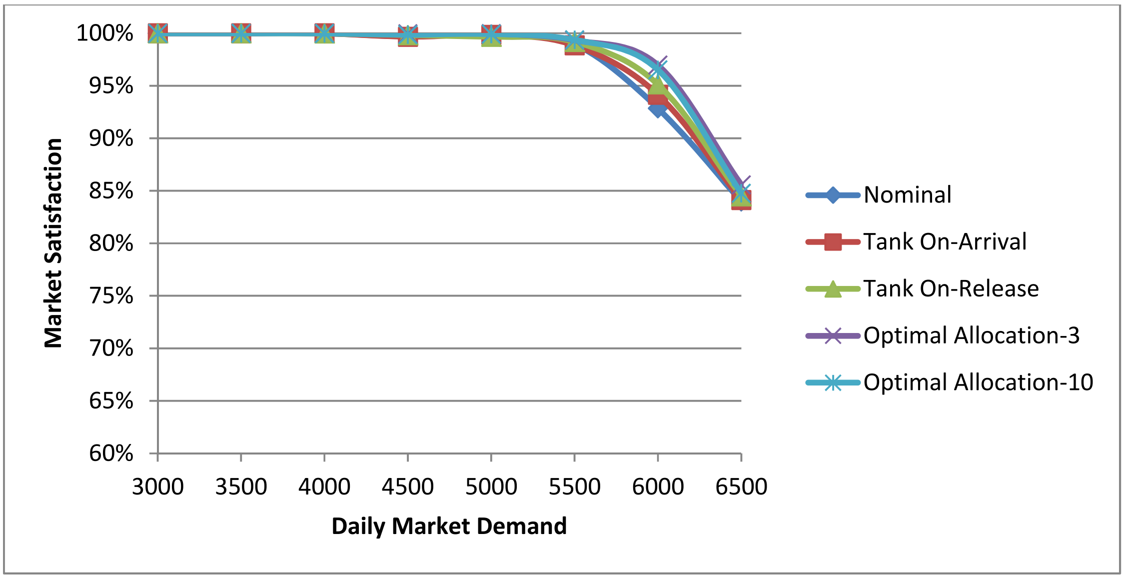

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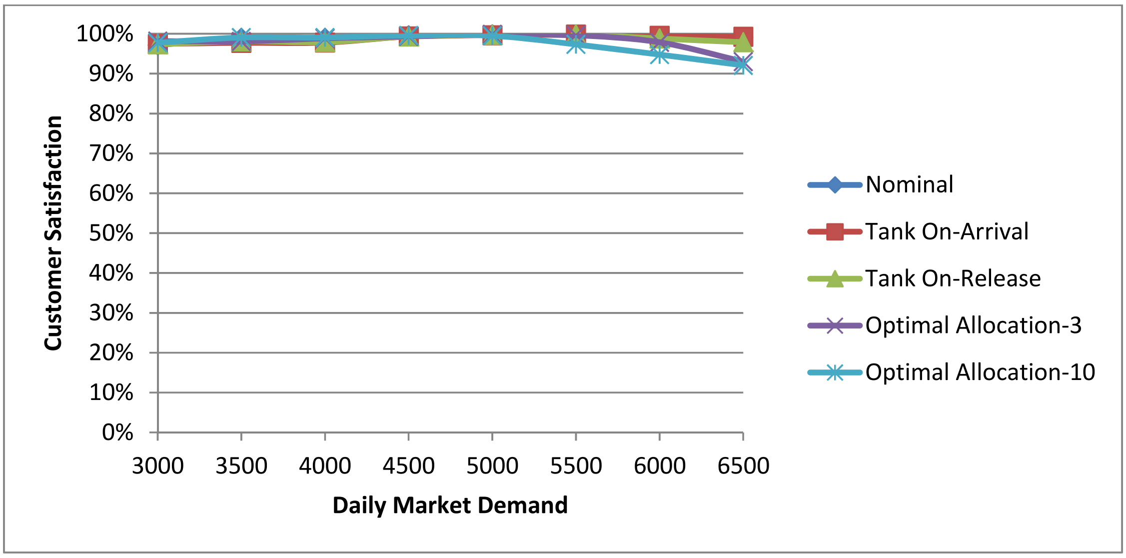
Figure 6.7 Simulation results for supply chain model with safety stock at warehouses and maximum 100% transportation time delay: (a) customer satisfaction with 98 tank cars; (b) customer satisfaction with 122 tank cars; (c) market satisfaction with 98 tank cars; (d) market satisfaction with 122 tank cars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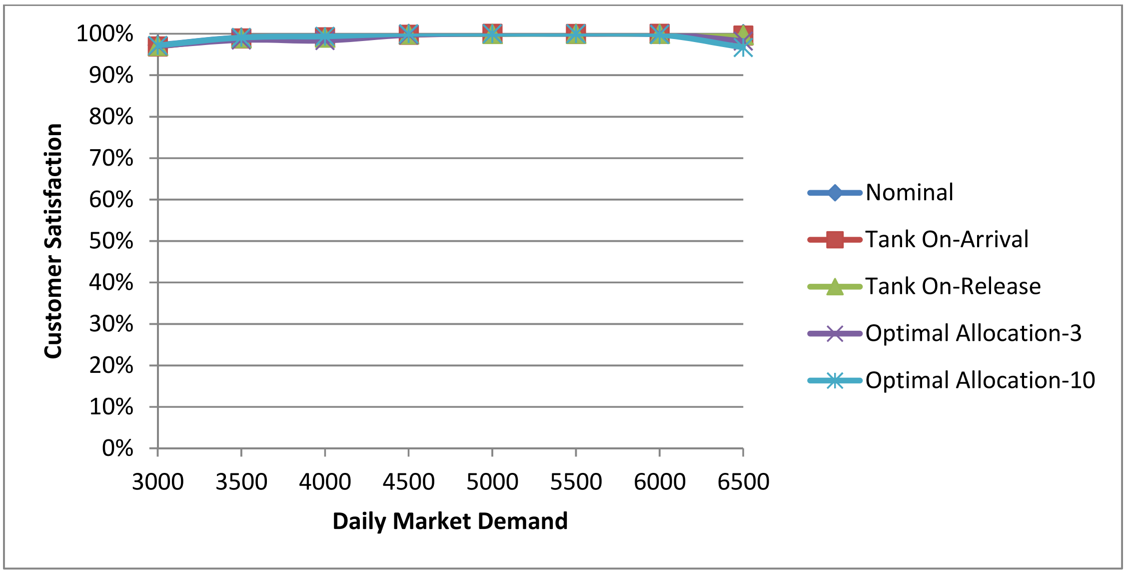
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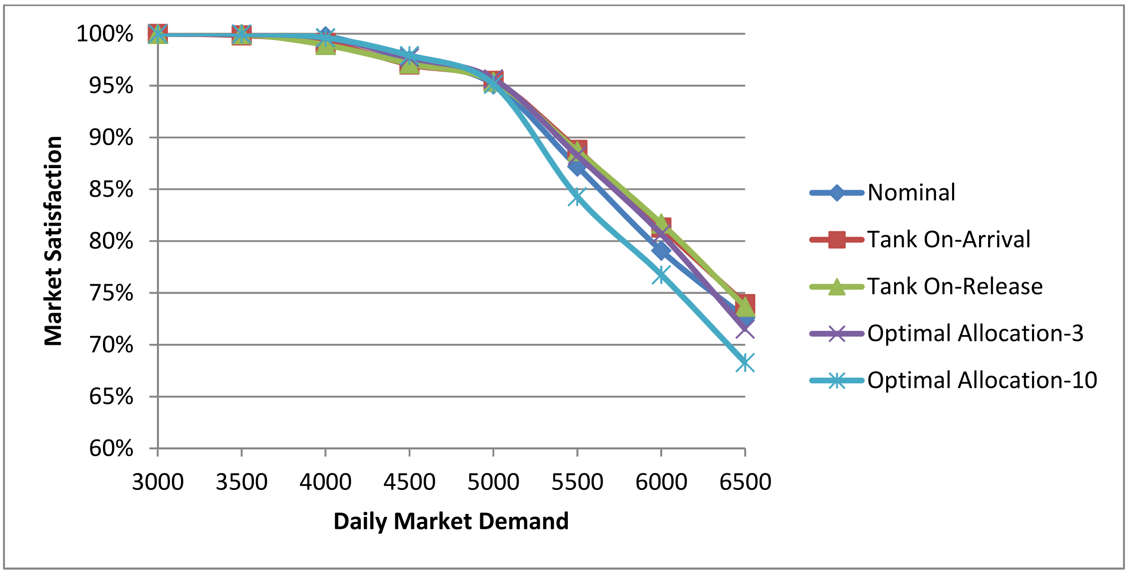

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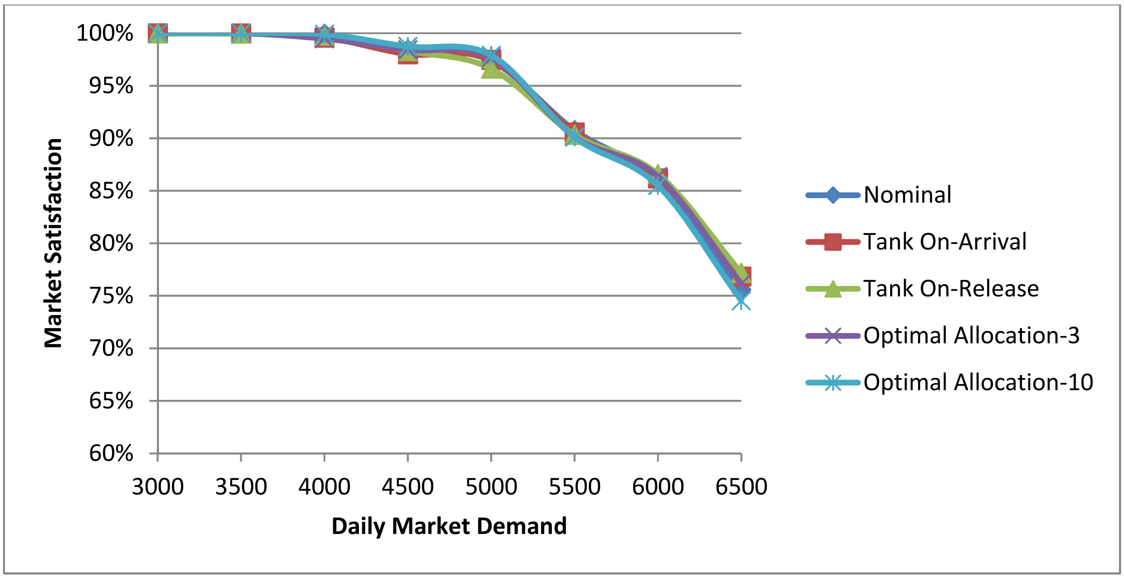

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Figure 6.8 Simulation results for supply chain model with safety stock at warehouses and maximum 200% transportation time delay: (a) customer satisfaction with 98 tank cars; (b) customer satisfaction with 122 tank cars; (c) market satisfaction with 98 tank cars; (d) market satisfaction with 122 tank cars

6.1.3 Paranoid Production

As discussed above, the plants' production policy is an important factor for the low performance of the supply chain in Section 6.2. The plants follow an 'optimistic production policy', and they make replenishment schedule and production schedule by maintaining the same throughput throughout the planning horizon. If the plant undergoes a shutdown during production due to unavailability of empty tank cars, the production rate of the plant would increase to the maximum until it catches up with the original plan. The production rate of this policy at time t, $PR_p(t)$, is determined as:

IF size of $TCList_p$ >0 THEN

    INIT AmountToProduce as 0

    Set TC to the first tank car in $TCList_p$

    Set RT_1 to the last replenishment transfer in production schedule

    Compute AmountToProduce as $RT_1^{Amt} - TC^{Amt}$

    Compute AverageProduction as $(RT_1^{DD} - t)\times PR_p^{Ave}$

    IF AmountToProduce – AverageProduction ≥ PR_p^{Max} THEN

        Set $PR_p(t)$ to PR_p^{Max}

    ELSEIF AmountToProduce – AverageProduction > PR_p^{Ave} THEN

        Set $PR_p(t)$ to AmountToProduce – AverageProduction

    ELSE

        Set $PR_p(t)$ to PR_p^{Ave}

    ENDIF

ELSE

    Set $PR_p(t)$ to 0

ENDIF

This production policy may cause two problems:

1) Longer manufacturing time under low market demand. Low market demand would cause a smaller average production rate. For the same size of order, it requires longer manufacturing time at the plants.

2) Delayed warehouse transfer under frequent shutdown. The production rate is only adjusted after shutdown. If the plant undergoes frequent or long-time shutdown, there is high possibility that the plant cannot accomplish warehouse transfer as scheduled.

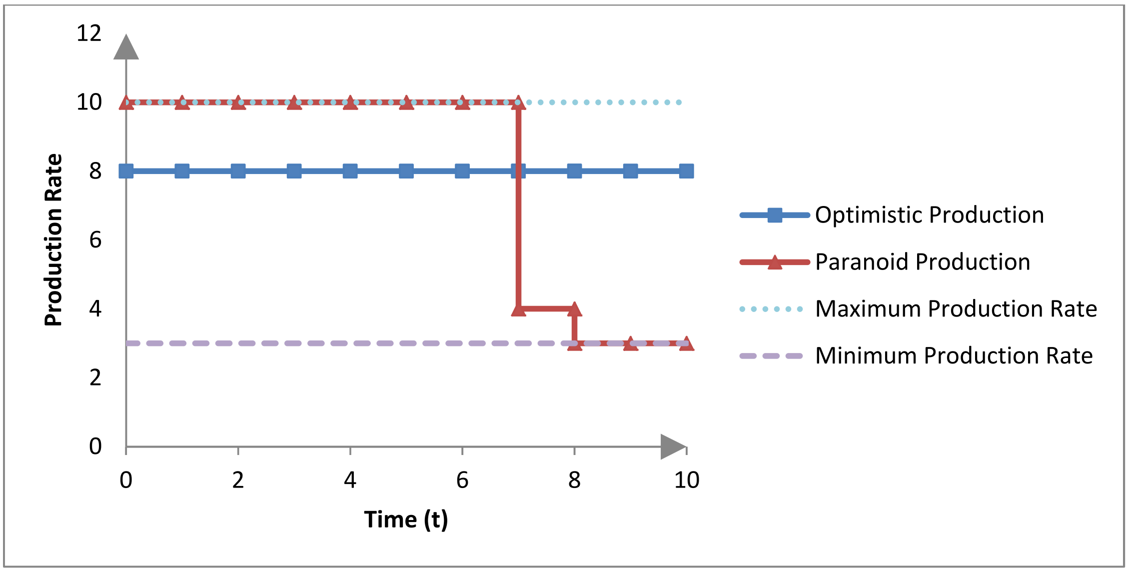
These two problems put chemical enterprise in the risk of low customer satisfaction and market satisfaction. Thus, we developed a new production policy, termed 'paranoid production policy'. Under this policy, plants still make replenishment plans using average production rate during replenishment planning; however, during production, the plants would maximize the production rate at the beginning of each planning horizon first and then adjust it back to the minimum rate at certain time point providing that the production target can be achieved. The real-time production rate of plant at time t, $PR_p(t)$, can be determined by:

IF size of $TCList_p$ >0 THEN
    INIT AmountToProduce as 0
    FOR each replenishment transfer RT in production schedule
        Update AmountToProduce as AmountToProduce + RT^{Amt}
    ENDFOR
    Set TC to the first tank car in $TCList_p$
    Compute AmountToProduce as AmountToProduce - TC^{Amt}
    Set RT_f to the last replenishment transfer in production schedule
    Compute MinimumToProduce as $(RT_f^{DD} - t) \times PR_p^{Min}$
    IF AmountToProduce – MinimumToProduce ≥ PR_p^{Max} THEN
        Set $PR_p(t)$ to PR_p^{Max}
    ELSEIF AmountToProduce – MinimumToProduce > PR_p^{Min} THEN
        Set $PR_p(t)$ to AmountToProduce – MinimumToProduce
    ELSE
        Set $PR_p(t)$ to PR_p^{Min}
    ENDIF
ELSE
    Set $PR_p(t)$ to 0

ENDIF

Figure 6.9 demonstrates a simple case study of optimistic production policy and paranoid production policy. Figure 6.9 (a) shows the production rate profile of the two production policies that produce 80 units of products under normal operation from t = 0 to t = 10. Optimistic production maintained an average production rate of 8 throughout the time; while paranoid production policy had a maximum production rate from t = 0 to t = 7, and adjusted it back to minimum production rate.

Figure 6.9 (b) shows the production rate profile of the two production policies under an incidence of shut down from t = 5 to t = 7. Before the shutdown occurred, optimistic production policies maintained at a production rate of 8, while paranoid production maximized the production rate. When the production operation resumed from the shutdown, both the two policies manufactured at the maximum rate. At t = 10, optimistic production policy only made 70 units while paranoid production policy was able to complete the production target.



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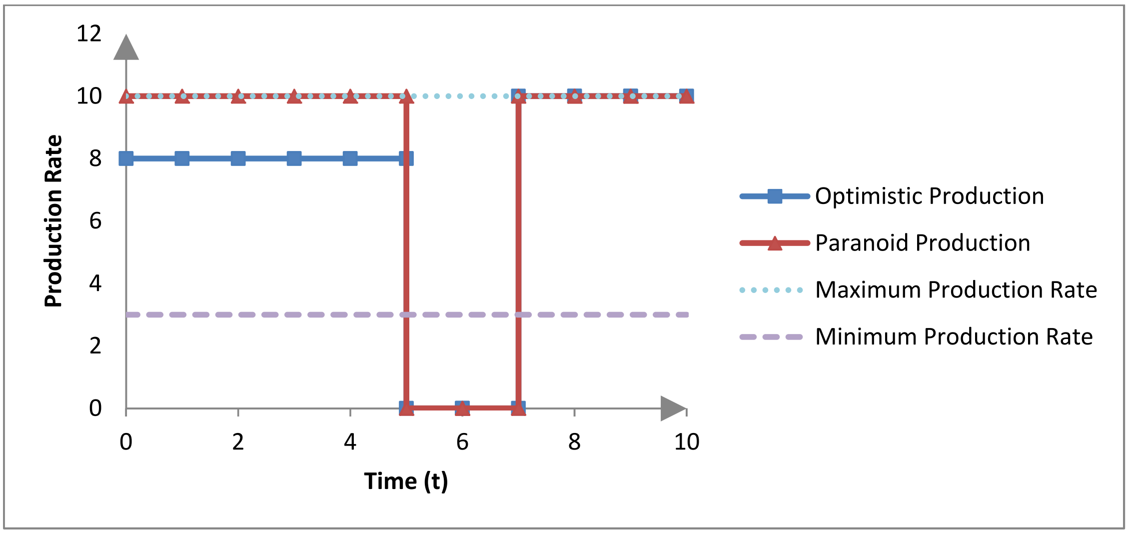

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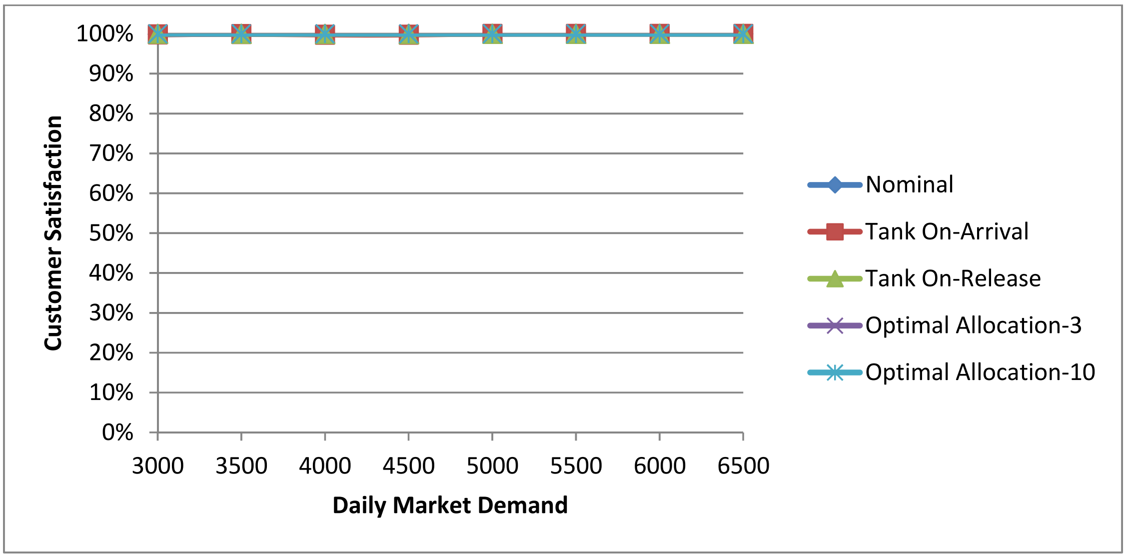
Figure 6.9 Optimistic Production versus Paranoid Production (a) under normal operation, (b) under an incidence of shutdown

Paranoid production policy was employed into the chemical supply chain model with no safety stock at warehouses. The simulation results for the modified model under no transportation disturbance are shown in Figure 6.10. Comparing the new results with previous results, we can find that

1) Paranoid production policy pushes the plants to maximize the production rate at the beginning of each planning horizon, resulting in a reduced time required for the order to be completed at plants side.
2) The time required for customers to receive product delivery is reduced, which overcomes the disadvantages of the small value of customer inventory control parameters. As a result, the market satisfaction is greatly improved.
3) Paranoid production policy performs better than safety stock approach if there is no transportation disruption. The market satisfaction with take fleet size of 98 can be achieved as good as that with tank fleet size of 122 in the safety stock approach.



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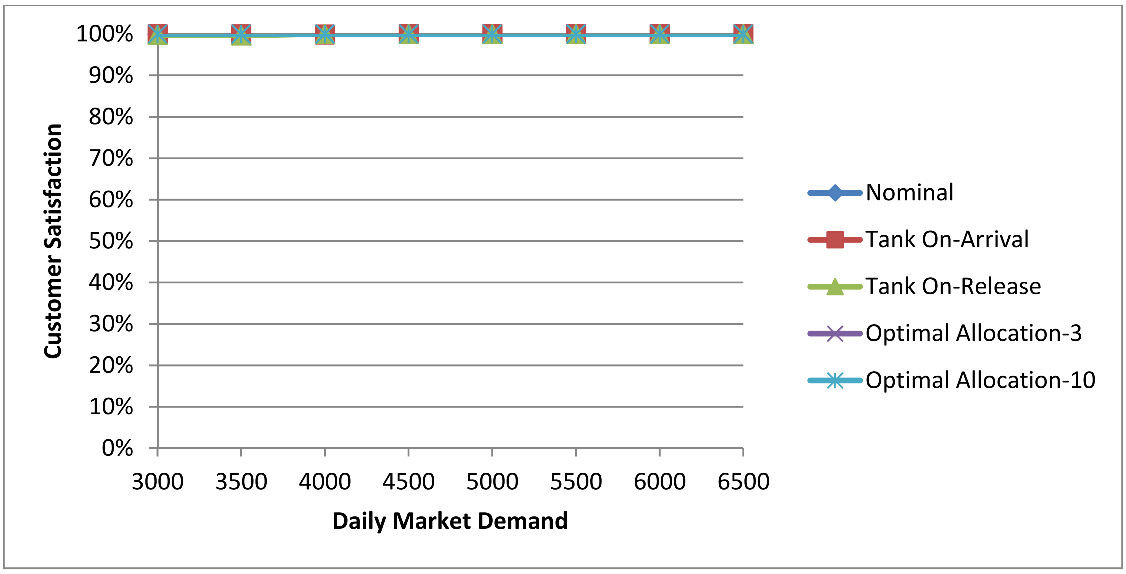

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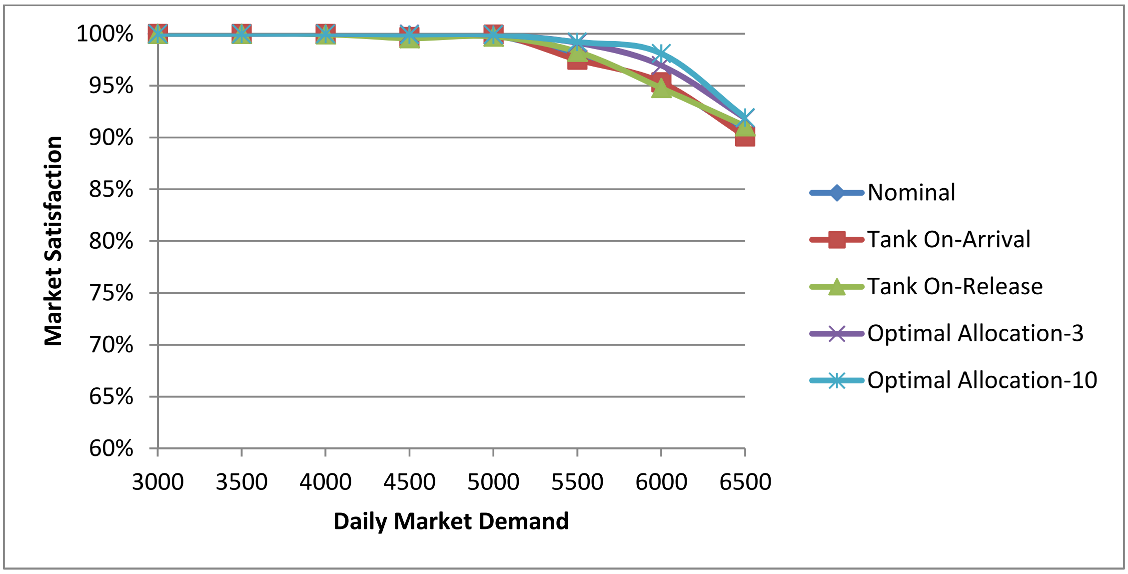

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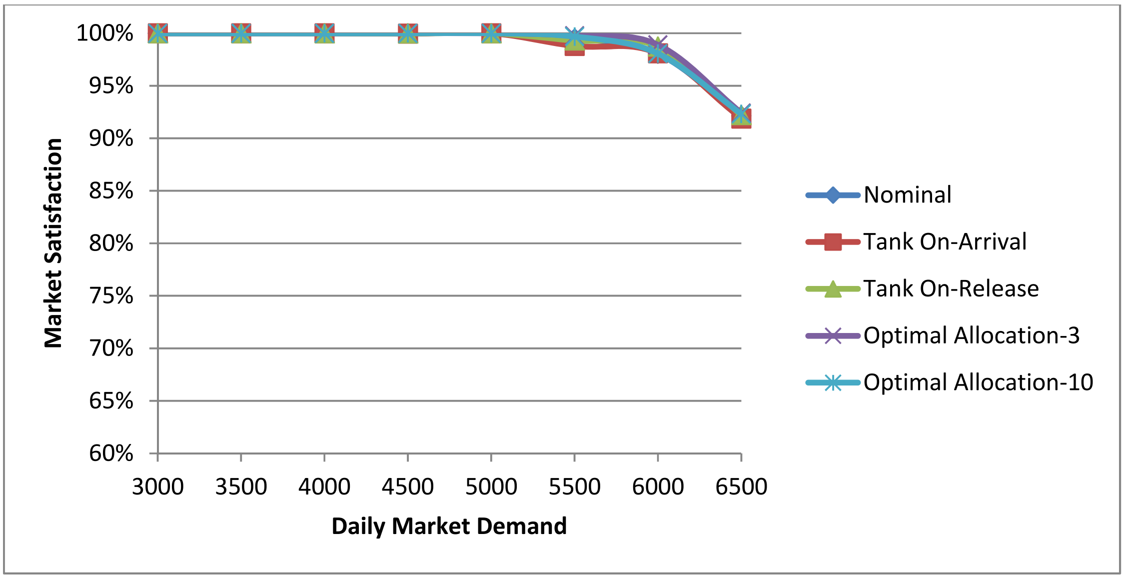

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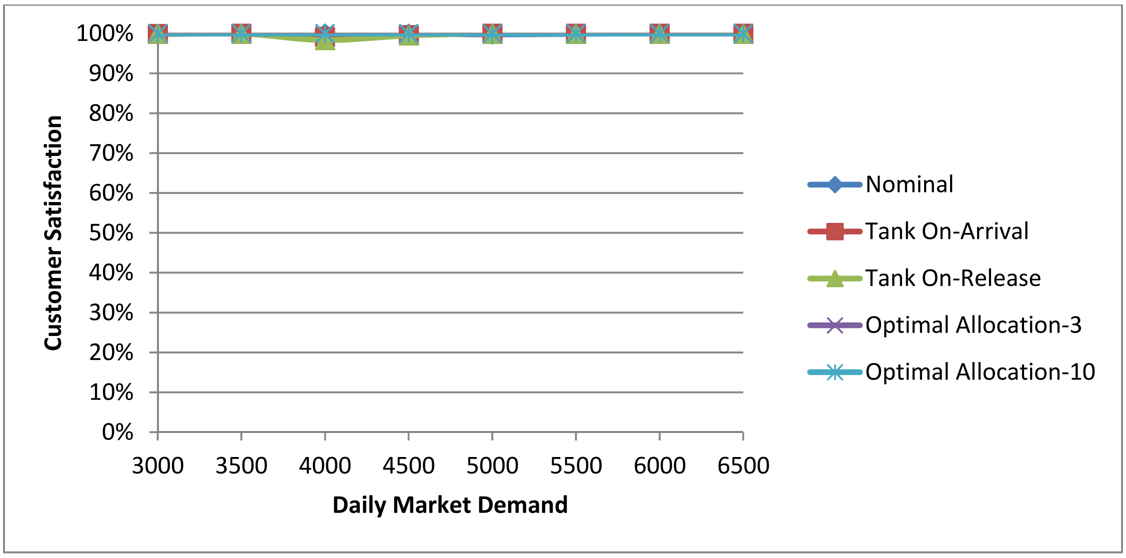
Figure 6.10 Simulation results for supply chain model with Paranoid production policy and no transportation time delay: (a) customer satisfaction with 98 tank cars; (b) customer satisfaction with 122 tank cars; (c) market satisfaction with 98 tank cars; (d) market satisfaction with 122 tank cars

The modified model was then simulated under transportation delay with maximum percentage time delay of 50%, 100% and 200%. The resulting customer satisfaction and market satisfaction are shown in Figure 6.11, Figure 6.12 and Figure 6.13 respectively. The followings can be observed from these figures and the comparison between the new set of results and the previous results in last two sections:

1) Compared with the optimistic production policy, paranoid production approach greatly improves the customer satisfaction and market satisfaction.
2) The performance of optimal allocation-3 is getting worse under high transportation disturbance. At maximum 200% delay with 122 tank cars, optimal allocation-3 performs the worst among these policies in terms of customer satisfaction and market satisfaction.
3) Except for optimal allocation-3, paranoid production approach achieves better customer satisfaction under transportation disruptions.
4) Compared with safety stock approach, paranoid production approach achieves better market satisfaction under transportation disruptions when the market demand is beyond the production capacity of the chemical enterprise.
5) Under transportation disturbances, market satisfaction in paranoid production approach is not as high as that in safety stock in safety stock approach when the daily market demand between is 4000 and 6000 units per day.

From the discussion above, both safety stock approach and paranoid approach have shortcomings. Warehouses in the safety stock approach tend to retain tank cars to build safety stock; while plants in the paranoid approach have a big demand of empty tank cars at the beginning of each replenishment planning horizon. The negative impact of these factors varies with the magnitude of daily market demand. For example, when the market demand is beyond the production capacity, safety stock would make some products transferred to certain warehouses where the products are not urgently needed. However, when the market demand is below the production target, this negative impact would be eliminated by the benefits of creating the buffer between plants and customers. Besides, optimal allocation-3 performs worse than other policies with higher the transportation disturbance in both original supply chain model and supply chain model in paranoid production approach. This can be explained by the short length of the empty tank return planning horizon compared with the transportation delay. However, this phenomenon does not exist in the supply chain model in safety stock approach.



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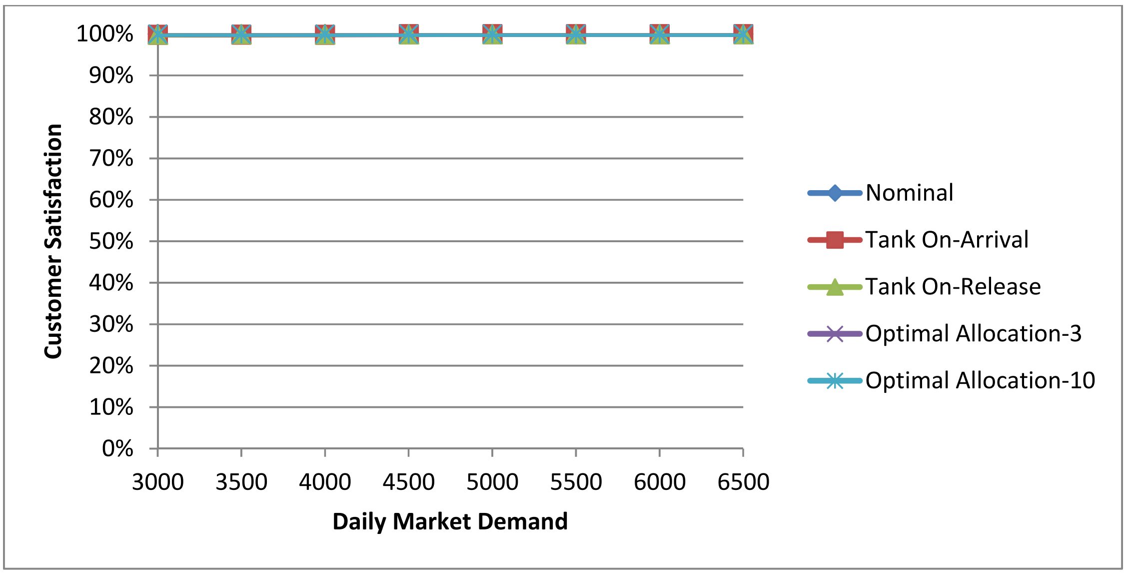

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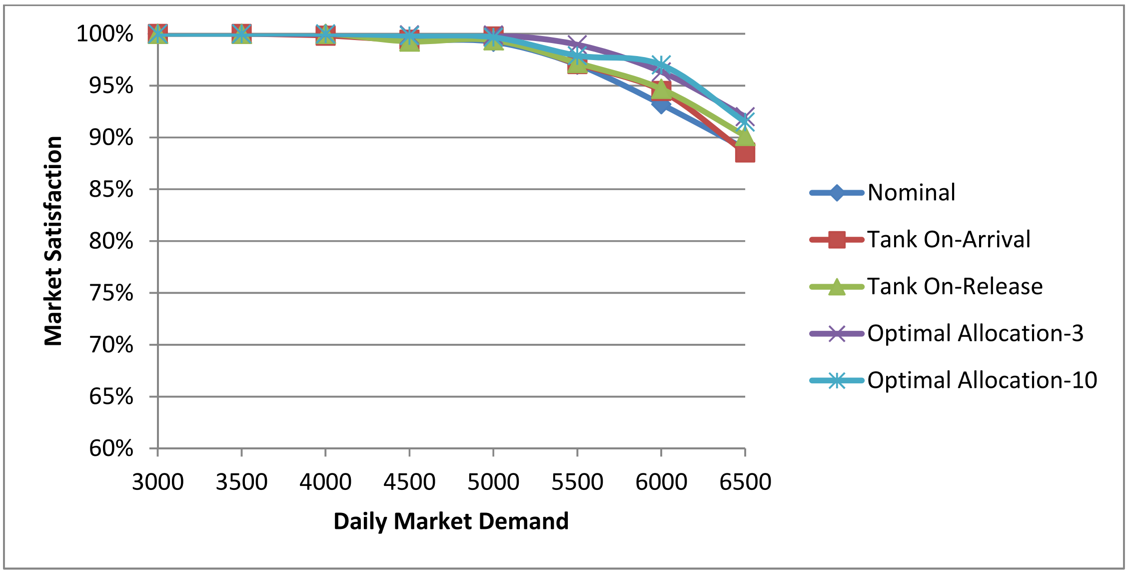

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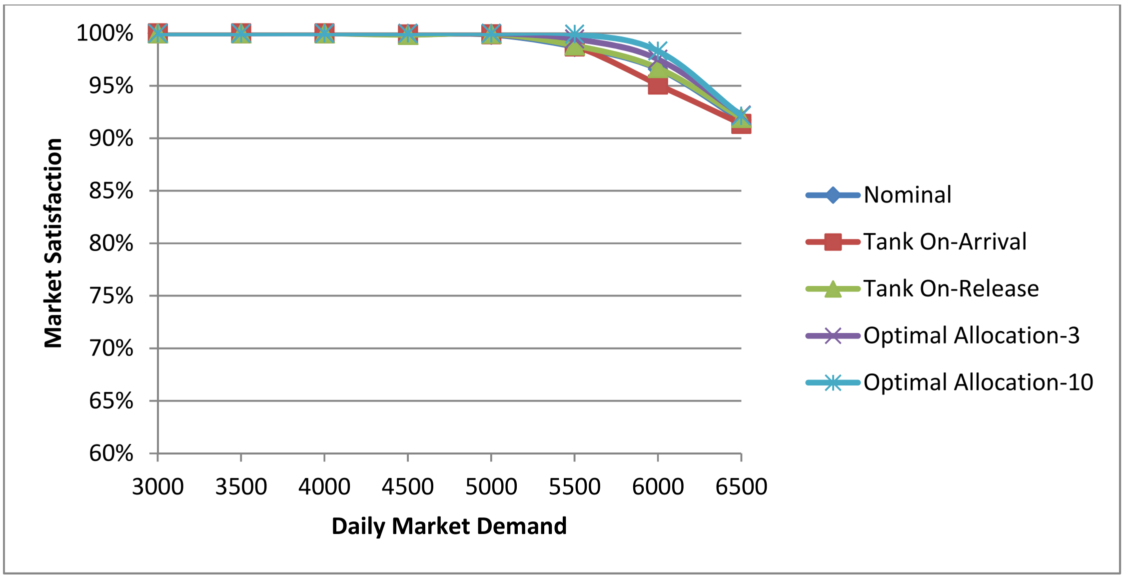

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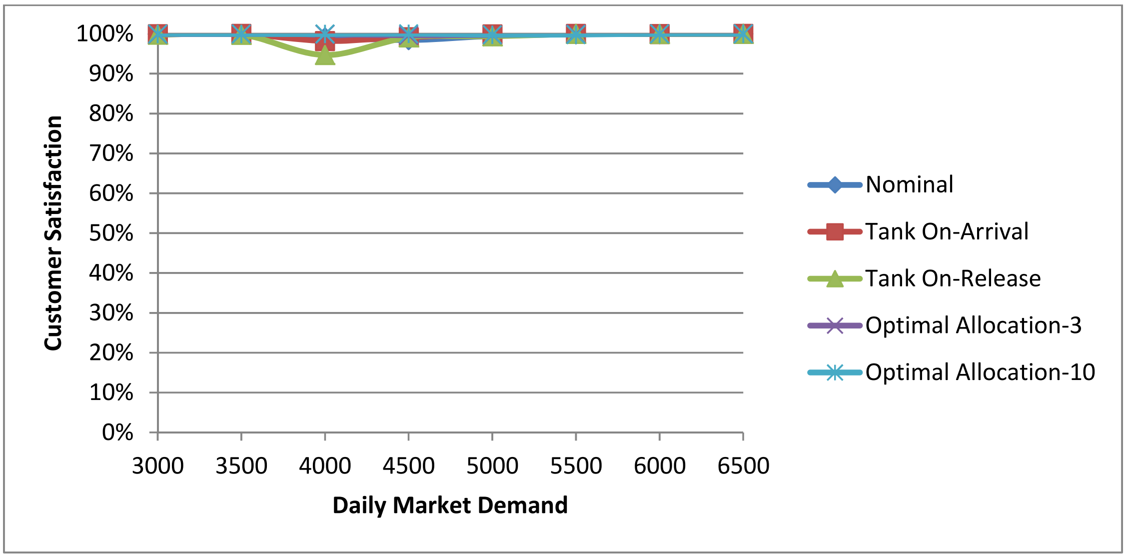
Figure 6.11 Simulation results for supply chain model with Paranoid production policy and maximum 50% transportation time delay: (a) customer satisfaction with 98 tank cars; (b) customer satisfaction with 122 tank cars; (c) market satisfaction with 98 tank cars; (d) market satisfaction with 122 tank cars



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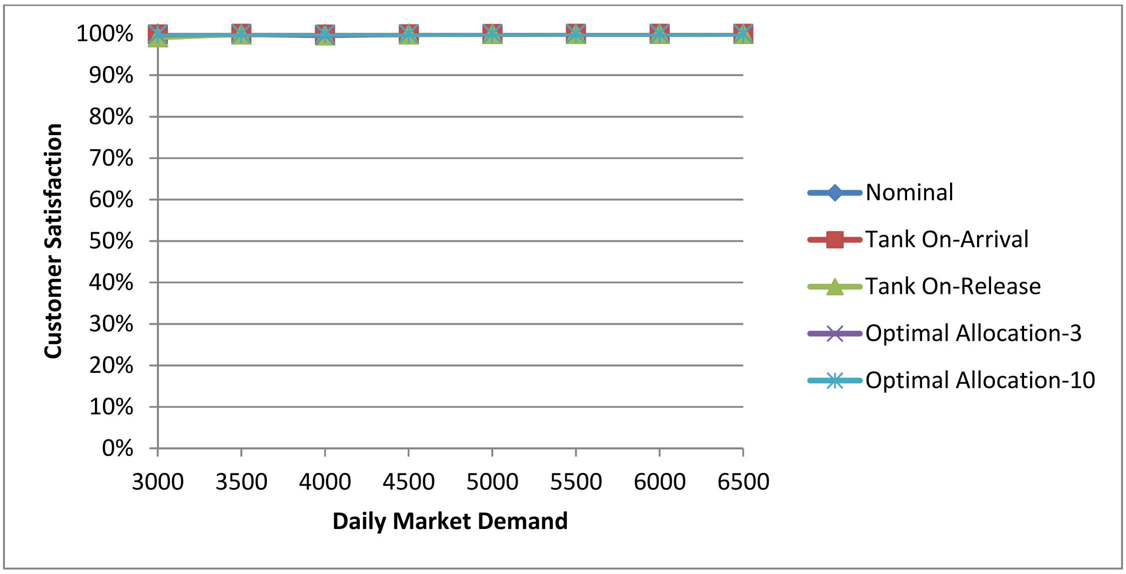

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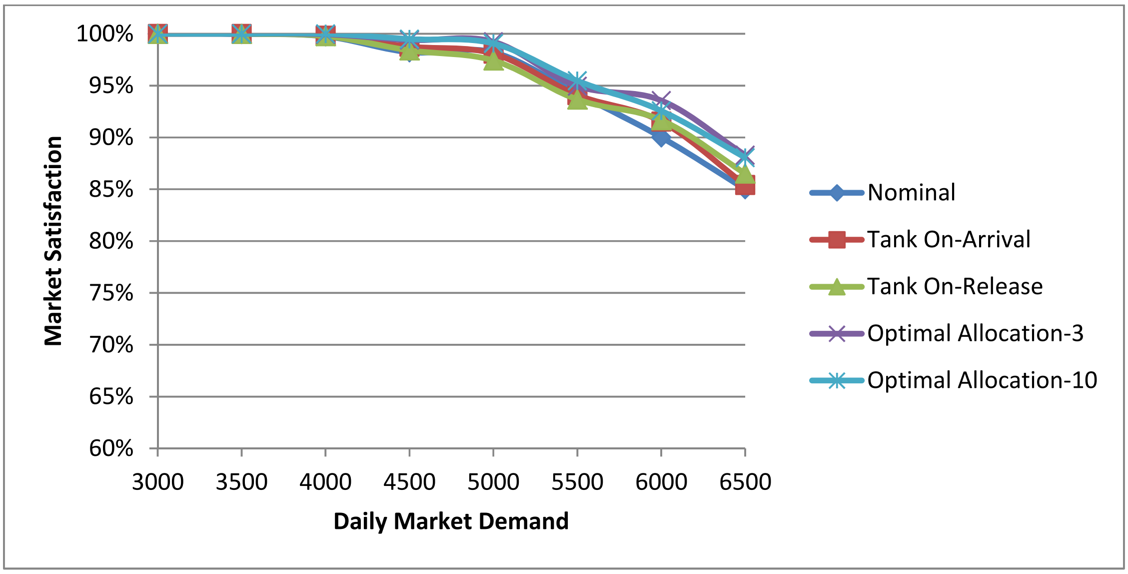

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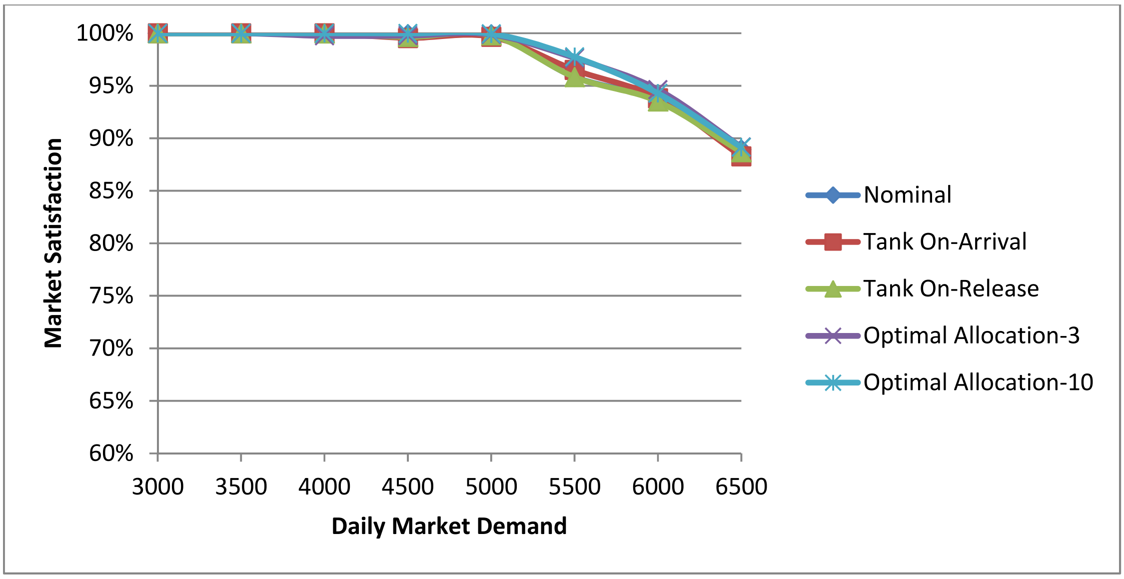

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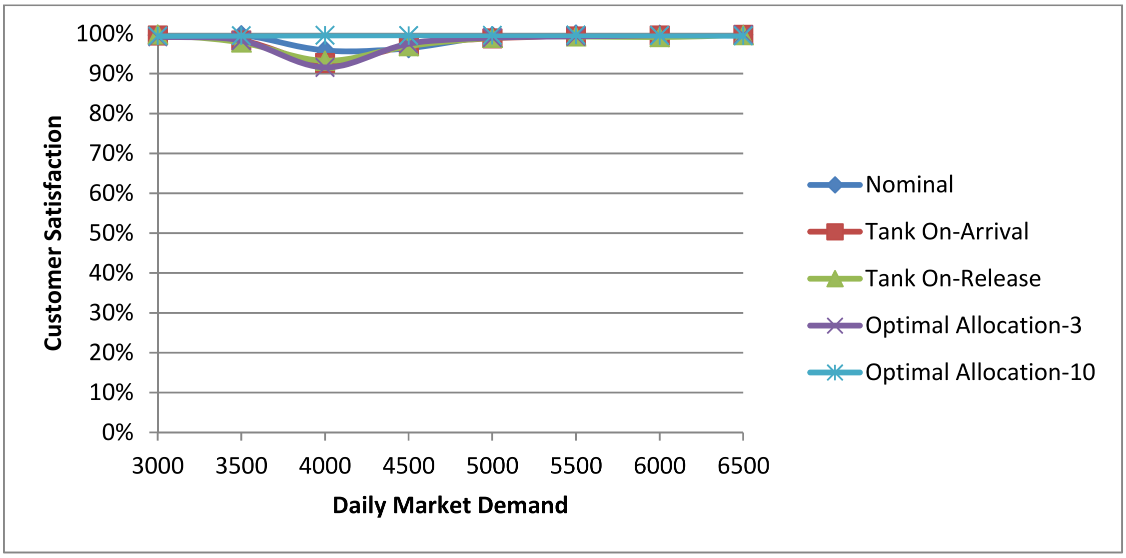
Figure 6.12 Simulation results for supply chain model with Paranoid production policy and maximum 100% transportation time delay: (a) customer satisfaction with 98 tank cars; (b) customer satisfaction with 122 tank cars; (c) market satisfaction with 98 tank cars; (d) market satisfaction with 122 tank cars



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Optimal Allocation-10

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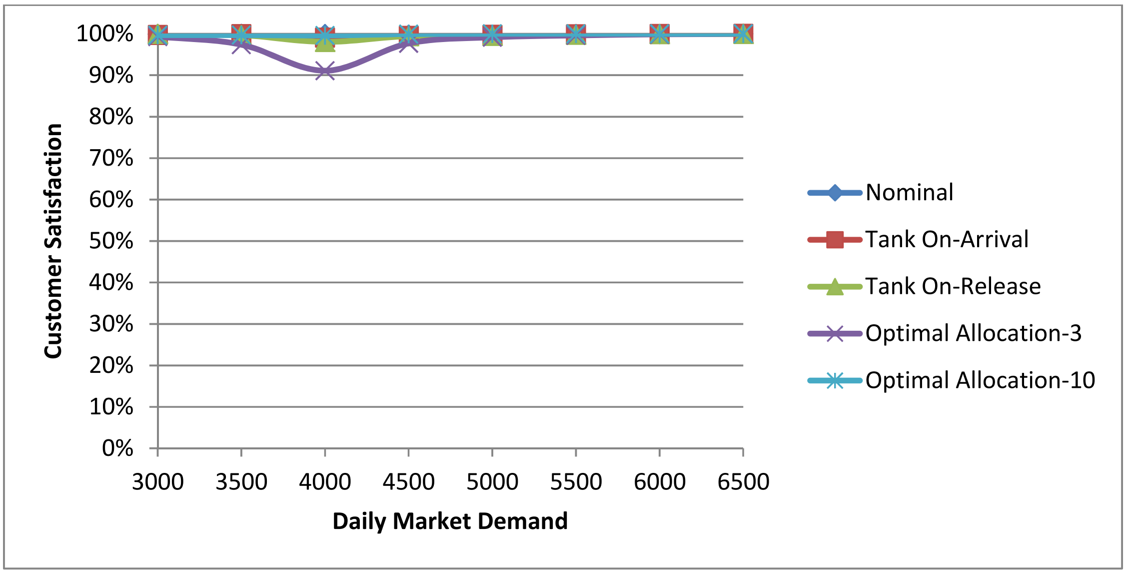

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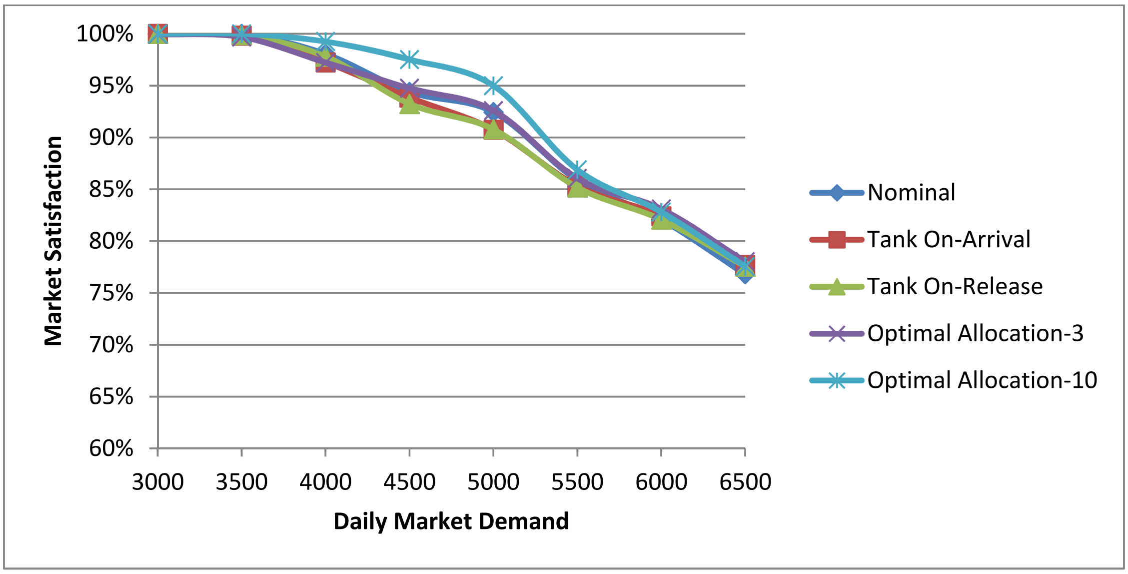

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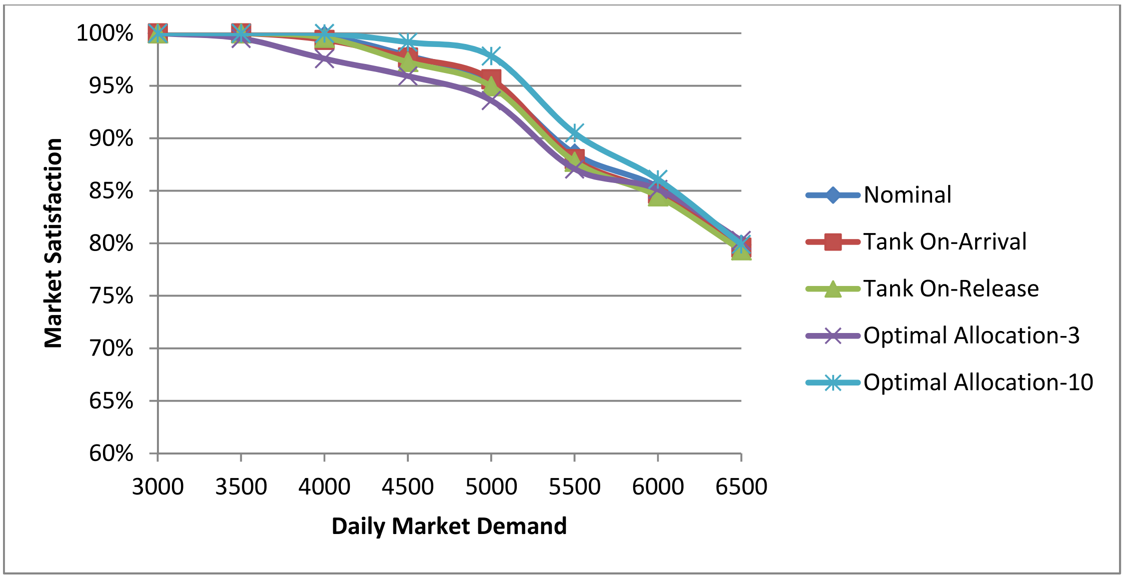

(d)

Figure 6.13 Simulation results for supply chain model with Paranoid production policy and maximum 200% transportation time delay: (a) customer satisfaction with 98 tank cars; (b) customer satisfaction with 122 tank cars; (c) market satisfaction with 98 tank cars; (d) market satisfaction with 122 tank cars

6.1.4 Concluding Remarks for Transportation Disturbances Study

The transportation disturbance was introduced into the model as an additional percentage of time delay added to the original transportation time, which follows a uniform distribution ranging from 0 % to a maximum percentage time delay value. The simulation results showed the major impacts of transportation delays: 1) with transportation disturbance, the overall market satisfaction decreases; 2) customer satisfaction can still maintain 100% during the high demand while there is a sharp decrease at the low demand; 3) adding more tank cars into the system does not make a significant improvement to the customer satisfaction and market satisfaction.

As a result, two different policies were then developed to overcome the drawbacks of the transportation delay. One is to add a safety stock at warehouses, and the other one is to change the plant production policy from 'optimistic production policy' to 'paranoid production policy'. With safety stock, the customer satisfaction and market satisfaction can be improved when the market demand is not beyond the production capacity of the enterprise. When transportation delay was introduced, the market satisfaction and customer satisfaction can be greatly improved in the low demand compared with that without safety stock under transportation delay. However, since safety stock uses extra tank cars, the customer and market satisfaction were lower than that without safety stock when the market demand is beyond total production capacity. As a result, when the market demand is low, some tank cars can be used as safety stock to improve the system performance, while during the high demand, safety stock should be reduced to increase the mobility of tank cars, and hence make a more effective usage of the tank fleet.

With 'paranoid production policy', the system performance has been greatly improved, which is even better than the safety stock approach when the market demand is beyond the total production capacity, which can be also observed when transportation disturbance was introduced into the system. However, the system performance of the paranoid production policy is not as good as that of the safety stock approach when the market demand is not high.

Comparing Figure 6.2-6.13, we can observe that

1) With two new approaches, the system performance of tank fleet size of 122 can achieve a significant improvement over that of tank fleet size of 98 only when the daily market demand is higher than 5500 units.
2) With two new approaches, there is no significant difference on the performance the five different tank fleet routing policies when the market demand is no higher than 5500 units, except for the paranoid production approach with maximum 200% transportation time delay where optimal allocation -10 is better than other policies.
3) With tank fleet size of 98, the safety stock approach can achieve a better performance than the paranoid production approach when the daily market demand is no higher than 5500 units. An increase of the tank fleet size from 98 to 122 can make the safety stock approach still perform better when the daily market demand reaches 6000 units except for situation under high transportation disturbances.

.A optimum set of management policies can be selected for the supply chain under different scenarios through these comparisons and discussions. When the daily market demand is no higher than 5500 units, tank fleet size of 98 with the safety stock approach is recommended for the system. When the daily market demand is 6000 units, tank fleet size of 122 with safety stock approach and optimal allocation -3 tank fleeting policy is the best for low and middle transportation disturbances (maximum 50% and 100%), while tank fleet size of 122 with paranoid production is the best for high transportation disturbance (maximum 100%). When the daily market demand is beyond the total production capacity, e.g. 6500 units, tank fleet size of 122 with paranoid production is the optimum choice for the system.

6.2 Multi-Product Chemical Supply Chains

Chemical industry comprises the companies that convert oil, natural gas, air and other natural resources into tens of thousands of different products such as gases, fuels, and other industrial chemicals. A typical chemical plant produces more than one chemical product: one main product with side products or multiple main products. The sourcing, manufacturing, storage, transportation and marketing of the products may share facilities and resources. Chemical enterprises thus cannot investigate the supply chain activities of each product in an isolated way. They have to consider the complex interactions of multiple products in the production and distribution activities. As a result, , the supply chain simulation models that serves as qualitative decision support tools should have the competence to handle multi-products problems.

The BPMN-based ILAS model developed in Chapter 4 considered different types and grades of lubes. The production of these lubes shares the same raw materials and facilities. Customer orders of each product type are generated based on a predetermined demand curve by a single agent. The difference between the products only lies on the receipt and processing time. There is no special consideration on the storage and transportation of products. In this chapter, we will demonstrate the multi-product capability of the proposed agent-based modeling framework by taking the tank fleet into account.

6.2.1 Case Study

As described in the previous chapters, chemical products are commonly toxic, explosive or otherwise hazardous, in case of spills and spoilage, extraordinary care must be taken to ensure that these substances are transported smoothly and safely across the whole supply chain. As a result, the tank cars that transport chemical products are strictly controlled and maintained under safety and environmental regulations. Besides, in order to avoid cross contamination, different tank cars are dedicated for different products. As a result, chemical enterprises have to spend a large amount of money on the maintenance, purchasing and leasing of tank cars. On the other hand, product demand of chemical products varies across the time because of demand seasonality, marketing strategy and other factors. Thus, transferring some tank cars of the products during the low demand period to other product on the peak demand might be a useful strategy to reduce the size of tank fleet and further reduce the operating cost.

The transfer of tank cars dedicated for one product to another product requires that the two products have the same safety regulations and specifications for storage and transportation. Tank car cleaning is required for this process (shown in Figure 6.14).

Figure 6.14 Example of tank car cleaning (http://www.kmtinternational.com)

Generally speaking, tank car cleaning involves three steps. Firstly, residue and vapors have to be removed before washing. Residues are collected for approved disposal or recycle. Petroleum and chemical vapors are collected through pump and sent to the flare (Charles Wilson, 2012). The condition of the tank is then inspected and the main wash and rinse process starts. The detailed cleaning procedure is customized for each tank based on the material safety data sheet. For example, heavy lube oils requires diesel presolve to clean out (Charles Wilson, 2012). Sometimes, tank cars may also need caustic wash or steam process after rinse. Finally, tank car is cooled and dried, and ready to be send out for usage.

The ontology of chemical supply chain model developed in Chapter 5 is capable of dealing with multi-product problem as Array List is used to represent the operational information of chemical products. As a result, only a tank car cleaning agent is required to clean and transfer tank cars from one product to another.

Figure 6.15 presents the BPMN diagram of tank cleaning agent. The whole process is activated by receiving tank car which is required to be cleaned up. The cleaning agent checks the current tank car cleaning schedule. If there is a no job under processing, the tank cleaning process starts, or else it would be scheduled to clean at a later time. The cleaning process is represented as a Task which calculates the cleaning time and an Intermediate Timer Event representing the time required for cleaning. The tank car is sent back once it is cleaned and dried. Then the cleaning agent reviews the cleaning schedule. If there is a tank car waiting onsite, the cleaning process would continue to the next tank car; otherwise, the whole process suspends until new tank car comes.

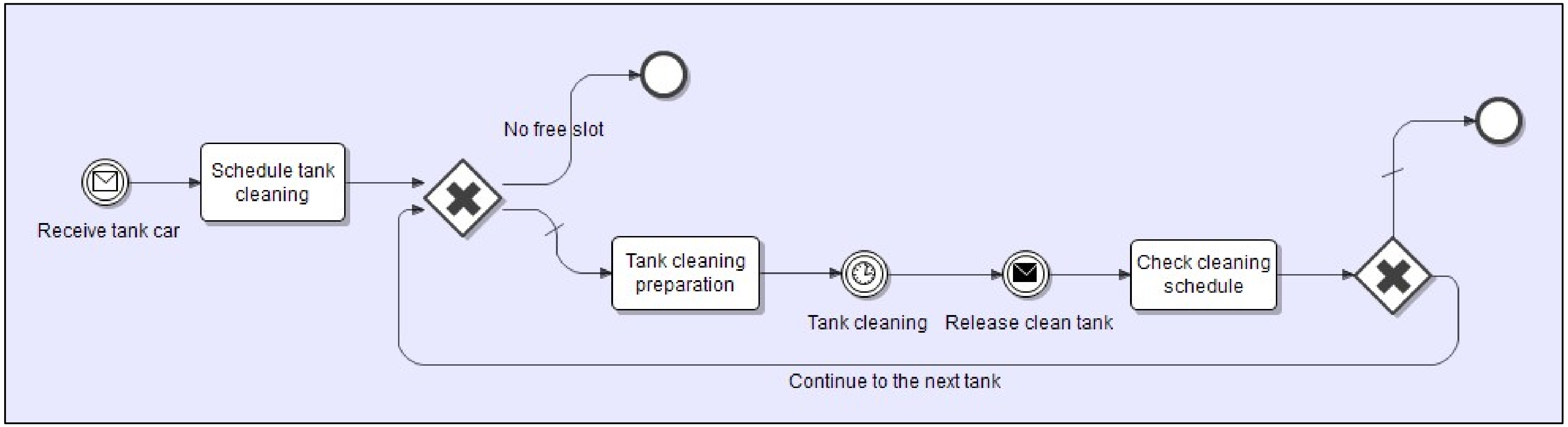

Figure 6.15 BPMN diagram of tank cleaning agent

In this case study, two products, product A and product B, were produced and sold to the market. There assumed to be no correlations between the products in their production and distribution except for sharing of some tank cars, and there was no constrains on the raw materials in the system. The inventory control policy of customers was set as (S, s) with value of (5000, 2500), and optimal allocation-3 policy was determined as the tank management policy. Figure 6.16 shows the demand of the two products over the simulation horizon, i.e. 360 days. During the first half of simulation horizon, the daily market demand of product A is 6500 units per day and that of product B is 4500 units per day; while in the second half of the simulation horizon, the daily market demand of product A decreases to 4500 units per day and that of product B increases to 6500 units per day.

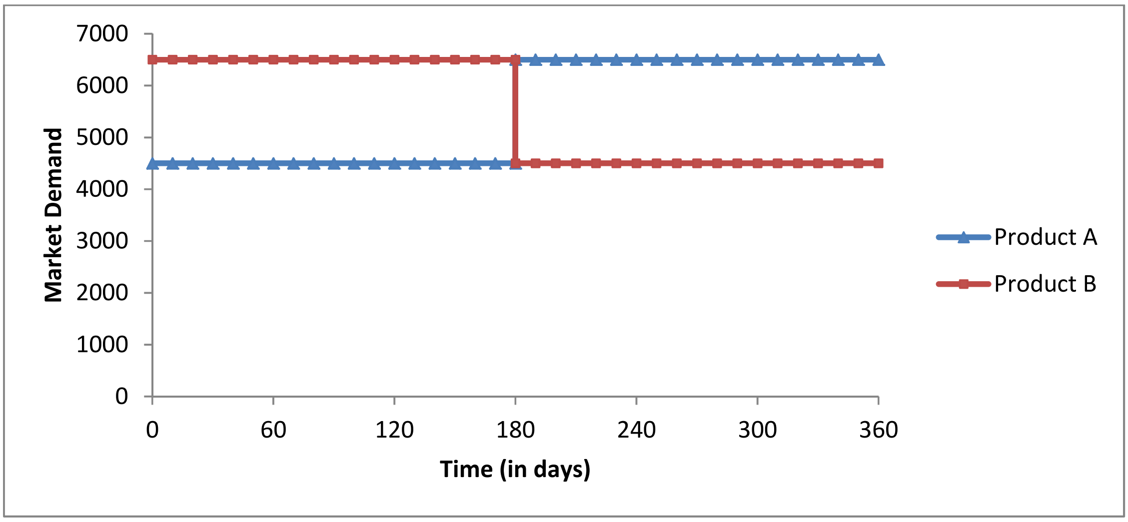

Figure 6.16 Market demand profile of Product A and B

Two scenarios were studied here. In the first scenario, each product was assigned with 86 tank cars, and there was no tank car cleaning and transfer between the two products. In the second scenarios, 80 tank cars were initially assigned to product A and 92 tank cars were assigned to product B. Starting from Day 181, every day an empty tank car assigned to product B was sent to tank cleaning agent and transfer to product A until the number of tank cars assigned to product A reached 92. The total time required for tank car cleaning process was assumed to be one day, and the capacity of tank car cleaning agent was assumed to be one empty car per day. The simulation results of the two scenarios were obtained following the procedures as described in Chapter 5.

Table 6.1 Average customer satisfaction for two scenarios

	Scenario 1	**Scenario 2**
Product A	70.8%	75.6%
Product B	70.1%	78.1%

Table 6.2 Average market satisfaction for Scenario 1

	First 180 days	**Second 180 days**	**Total 360 days**
Product A	99.6%	84.9%	90.9%
Product B	84.5%	99.4%	90.6%

Table 6.3 Average market satisfaction for Scenario 2

	First 180 days	**Second 180 days**	**Total 360 days**
Product A	99.4%	88.3%	92.9%
Product B	89.2%	99.2%	93.3%

As shown in Table 6.1, with implementation of tank car cleaning and transferring between the two products, the customer satisfaction of product A improves from 70.8% to 75.6% and that of product B is improves from 70.1% to 78.1%. Table 6.2 and 6.3 displays the market satisfaction of the products in the two scenarios. Comparing the two tables, a decrease of 6 tank cars for product A in the first 180 days make the market satisfaction drop by 0.2%, but the these tank cars improve the market satisfaction of product B by 4.7%. Similarly, in the second 180 days, the market satisfaction of Product A improves by 4.4% in Scenario 2 compared with Scenario 1 with a cost of only 0.2% decrease in the market satisfaction of Product B.

Figure 6.17 and 6.18 demonstrate the customer satisfaction and market satisfaction profile under different constant market daily demand, which were generated following the same procedure described in Section 5.6. As seen from Figure 6.17, the benefit of employing 92 tank cars other than 86 cars at the demand of 6500 (15.9%) is larger than the detriment of using 80 tank cars other than 92 tank cars at the demand of 4500 units per day (12.1%), which explains why the customer satisfactions of the two products in Scenario 2 is higher than those in Scenario 1. Similarly in Figure 6.18, fleet sizes of 80, 86 and 92 can achieve approximately 100% market satisfaction at the market demand of 4500 units per day, while at the market demand of 6500 units per day, an increase of tank cars can improve the market satisfaction if the tank fleet size is below 98. As a result, employing fewer tank cars at demand of 4500 units per day and more tank cars at demand of 6500 units per day would improve the system performance.

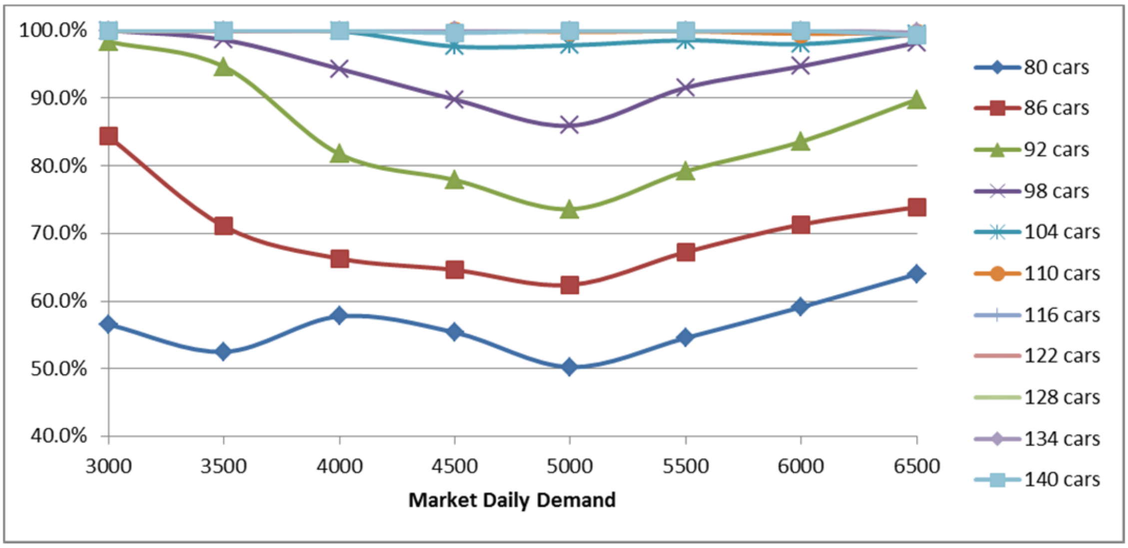

Figure 6.17 Customer satisfactions under constant market daily demand

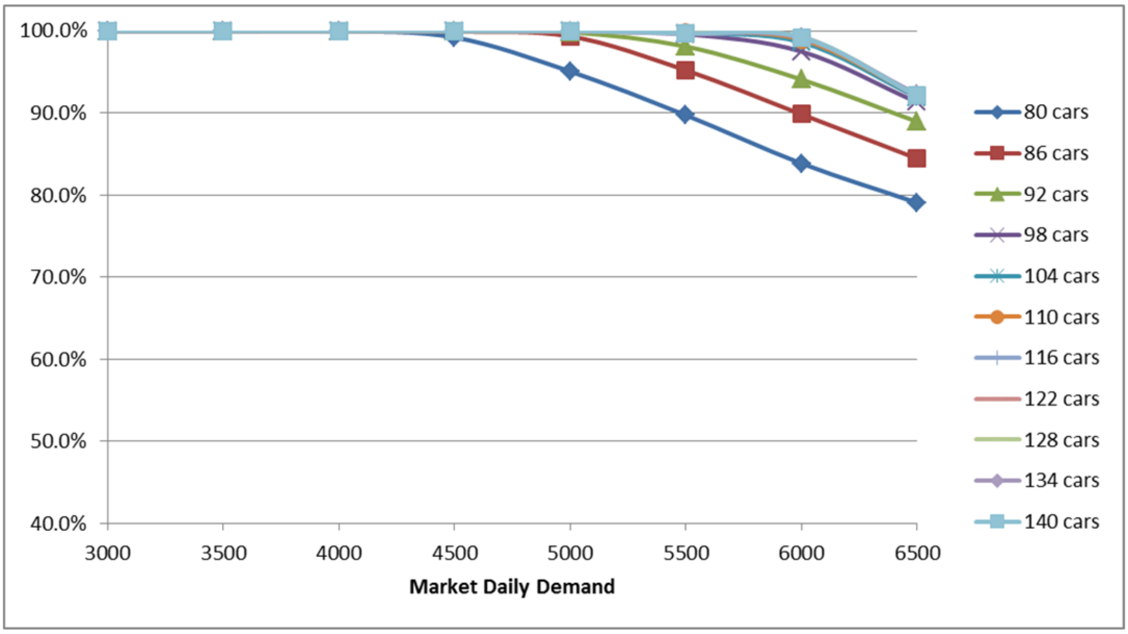

Figure 6.18 Market satisfactions under constant market daily demand

6.3 Chapter Summary

In this chapter, the transportation disturbance and multi-product capability have been studied. The transportation disturbance was introduced into the model as an additional percentage of time delay added to the original transportation time, which follows a uniform distribution ranging from 0 % to a maximum percentage time delay value. The impact of transportation delays was studies through simulation results. Two different policies were then developed to overcome the drawbacks of the transportation delay. One is to add a safety stock at warehouses, and the other one is to change the plant production policy from 'optimistic production policy' to 'paranoid production policy'. The two approaches were employed into the model separately. The respective improvements of the two approaches were investigated through the comparison of simulation result under different market demands, tank fleet sizes and transportation delays. This study demonstrates the capability of the new modeling framework on the stochastic study of complex supply chains.

In multi-product supply chain study, since the ontology of chemical supply chain model is capable of dealing with multi-product problem as Array List is used to represent the operational information of chemical products, only a tank car cleaning agent was create to clean and transfer tank cars from one product to another. The case study showed that the agent-based chemical supply chain model can serve as a quantitative decision support tool for supply chain management as it can help the users to understand the dynamics of the supply chain in a detailed level.

These two model extension studies have demonstrated the benefits of our novel supply chain simulation modeling approach using BPMN. It has great flexibility and capabilities. With a built model built in BPMN, users can study various supply chain problems in an easy fashion.

Chapter 7

Conclusions and Future Work

7.1 Conclusions

Today's global supply chains have been expanding rapidly over the decades. They are delivering products and services to the emerging markets cheaper and faster than ever before at the price of increasing complexities and uncertainties. To cope with the increasing complexities and uncertainties, as noted in Chapter 1 of the thesis, development of simulation models are motivated to support supply chain management for achieving better profitability, efficiency and sustainability. Based on these, two main questions have been raised for this research: "How to develop appropriate models that are rich enough to capture the complex dynamics of supply chains" and "How to employ developed models to support decision making in supply chain management". To answering these two questions, a novel agent-based modeling framework for supply chains has been proposed and implemented in the tank fleet management problem in chemical supply chains. The whole thesis was divided into two major parts:

1) **An agent-based supply chain modeling approach through BPMN**

   Chapter 2 did a comprehensive literature review on the supply chain modeling approaches, and concluded that agent-based modeling is the suitable tool to study complex supply chain dynamics. A survey of agent-based supply chain models showed that current research on agent-based modeling has limitations on real implementation.

Chapter 3 introduced BPMN with the key elements, discussed the advantages of BPMN and demonstrated how it can be employed to model supply chain operations. A simple supply chain operation was modeled and simulated to show the excitability of BPMN. The new framework to model a complex supply chain was also described.

Chapter 4 validated the proposed modeling framework by replicating an existing multisite specialty chemicals supply chain model. The new supply chain model is more friendly to the business users and the simulation time is much less than the previous one. Various scenarios demonstrated that a BPMN-based supply chain model is easier to understand, manipulate, and has high level of scalability and flexibility.

2) **Decision support on tank fleet management in chemical supply chains through agent-based modeling**

Chapter 5 presented an agent-based simulation model of a multisite chemical supply chain to address the tank fleet sizing problem. The simulation model explicitly took into account the independence of supply chain entities and their interactions across various supply chain operations such as replenishment planning and order assignment. Each tank car was modeled as an object that travels across the supply chain. We proposed five different tank fleet routing policies and integrated them into the model. It thus allows users to manipulate polices easily. We simulated the supply chain model with the new tank fleet routing policies and sizes under various conditions, and analyzed their impact on the overall performance of the supply chain, such as customer satisfaction, market satisfaction and plant shutdown duration. Optimal tank fleet routing policy and size were determined based on the comparison of the simulation results.

Chapter 6 studied the impact of uncertain transportation disturbance on the chemical supply chain model developed in Chapter 5. The transportation disturbance was introduced into the model as an additional percentage time delay added to the original transportation time. Two different policies were then developed to overcome the drawbacks of the transportation delay. Chapter 6 also exploited the supply chain model on multi-product problem. A tank car cleaning agent was created to realize the tank car cleaning and transferring process between two products. These two studies demonstrated the capability of this new modeling framework in handing various supply chain problems.

7.2 Future Work

In this section, some suggestions for future research are recommended.

7.2.1 Analysis of Agent-Based Supply Chain Models through Equation Free Approach

Agent-based modeling provides us a powerful tool to study the dynamics of the supply chain networks. However, in reality, we are more interested in their system level behavior, such as the efficiency of a particular complicated supply chain network. To perform system level analysis of a complex supply chain model, we need to set up many initial conditions, for each initial condition we need to do a large number of simulation runs. Even for a change of simple rule, it is required to run the detailed model for a long time to investigate how dynamics changes with time.

Equation-free approach is a recently developed computational technique that allows user to perform macroscopic tasks acting on the microscopic models directly (Kevrekidis et al., 2009). It is designed for a class of complex problems in which one observes evolution at a macroscopic, system level of interest, while accurate models are only given at a more detailed level of description. It is called equation-free because this approach bypasses the derivation of explicit macroscopic evolution equations when these equations conceptually exist but are not available in closed form.

Figure 7.1 shows the schematic of the equation-free approach. The main tool of the equation-free approach is the coarse time stepper which is approximate time integrator for unavailable macroscopic model. It consists of three steps:

1) Lifting: initialize micro-simulator according to given macro-fields by creating fine-scale initial conditions (fine-scale state) which is consistent with given macroscopic initial conditions (coarse state);
2) Micro-simulation: use microscopic simulator to update the fine-scale state;
3) Restriction: update coarse state from the fine-scale state.

In this way, system level tasks such as time-integration and control could be performed with continuum numerical analysis (Kevrekidis et al., 2009), and thus simulations can be accelerated. Very little work has been done to employ this framework into agent-based models. Tsoumains et al. (2010) exploited equation-free approach to extract emergent dynamical information agent-based model of social interactions on networks with “macroscopic, systems-level, continuum numerical analysis tools”. Siettos et al. (2012) continued to use equation-free approach to do stability study of this agent-based social model under uncertainty through bifurcation analysis. Unlike the agent-based model in their study which is homogenous system, supply chain models are heterogeneous system. As a result, identifying suitable coarse states and bridging coarse states to fine-scale states would be a critical challenge.

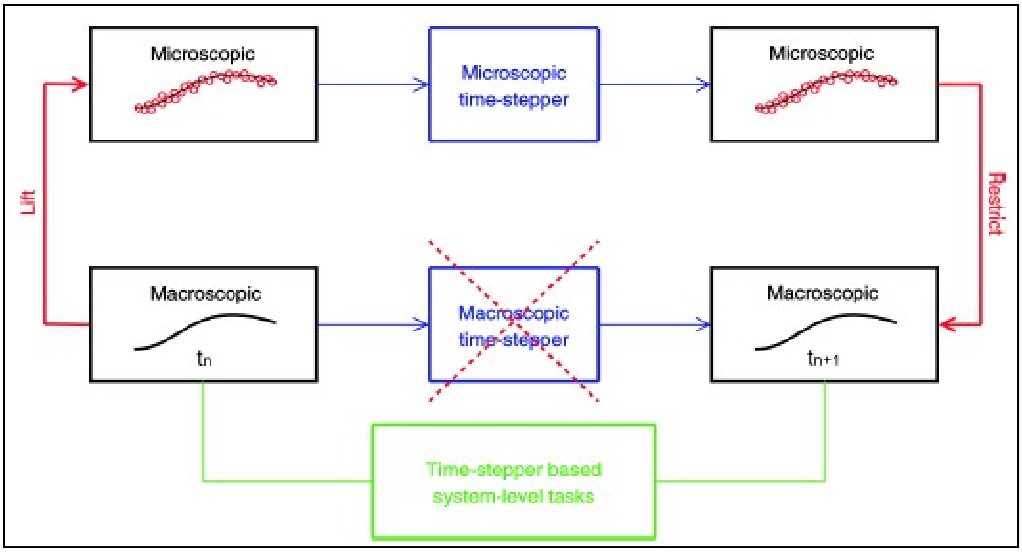

Figure 7.1: A schematic of the equation-free approach (Kevrekidis et al., 2009)

7.2.2 Supply Chain Disturbance and Disruption Management

Chapter 6 studied the impact of uncertain transportation disturbance on the chemical supply chain model. The transportation disturbance was introduced into the model as an additional percentage time delay added to the original transportation time, which follows a uniform distribution ranging from 0 % to a maximum percentage of time delay value. The impact of transportation delays was studied through simulation results. Two different policies were then developed to overcome the drawbacks of the transportation disturbance. One is to add a safety stock at warehouses, and the other one is to change the plant production policy from ‘optimistic production policy’ to ‘paranoid production policy’. The respective improvements of the two approaches were investigated through the comparison of simulation result under different market demands, tank fleet sizes and transportation delays. Similar study can be done to investigate the system performance under uncertain market demand and explore strategies to manage it.

Supply chain disruptions are different from supply chain disturbances. Disturbances involve the variations in the material flows (e.g. transportation time) and market demand, while disruptions involves temporary or permanent removal of supply chain node(s) or link(s), such as maintenance of a plant, permanent closure of a plant and transportation failure between two facilities. In such cases, the agent that represents the unavailable supply chain entity can suspended or be skilled during the supply chain disruption, and resume function or be recreated after disruption to carry out the study.

7.2.3 Development of Better Management Policies

Chapter 5 presented five tank fleet management policies and investigated them through the comparison of simulation results under different market demand, tank fleet sizes and inventory management policies. These management policies are straightforward and only two among them involve some optimization. Thus design of better tank management policies in recommended as a future work. One possible approach is to develop heuristic approach similar to those present in Section 5.2. Another approach is to take the advantage of agent-based models. Machine learning can be employed into the agents to enhance the reactivity and proactivity of agents in dealing with tank fleet management. These new approaches can be evaluated through massive simulations of current chemical supply chain model. Moreover, design of better replenishment policies and inventory management policies can also be exploited.

7.2.4 Realistic Model Extension

The supply chain model built in Chapter 5 can be extended for further studies. For instance, multi-product capability of the model has been presented in Chapter 7.

However, there are no correlations between the products in their production and distribution except for sharing of some tank cars. Future study can add the correlations of the products as constrains into the model, such as raw material sharing and production facilities sharing. The model can also be extended by adding more classes of agents, creating more conversations between agents, and scaling up or down to study various supply chain problems. Because of the business friendly BPMN and the advantages of agents, the BPMN-based supply chain model is an appropriate tool for the supply chain projects cooperated with real industries.

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