The Hong Kong Polytechnic University

Institute of Textiles and Clothing

Optimization of Replenishment Strategy for a VMI-Based Apparel Supply Chain

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CERTIFICATE OF ORIGINALITY

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___________Dong Aihua___________ (Name of student)

Abstract

Vendor Managed Inventory (VMI) is a collaborative strategy between the retailers and manufacturers to optimize the availability of products through a continuous replenishment approach. It has received considerable attention in the apparel industry. Apparel manufacturers adopting VMI strategies make decisions in their management systems with information shared with the retailers. With the responsibility for managing replenishment given to the manufacturers, one challenge facing the apparel supply chain is to balance the benefits of different parties in the supply chain by minimizing the stock out level of the retailers while maximizing the production capacity of the manufacturers.

For this purpose, a simulation-based optimization model for VMI replenishment strategy in the apparel supply chain was proposed. It considers both the Customer Service Level (CSL) of the retailers and the constraints of the manufacturers' production capacity. This simulation based-optimization model consists of two main parts, namely, the simulation model for simulating the supply chain and the optimization algorithms for searching the optimal VMI-based replenishment strategy.

The simulation model was developed to study the relationship between the replenishment strategy (replenishment cycle, lead time and replenishment quantity) and the performance of the supply chain (CSL and Inventory Turnover) in a

VMI-based apparel supply chain. Fuzzy set theory was integrated into the simulation model so as to represent the forecasting error due to the dynamic customers' demands. The influence of dynamic and uncertain customers' demands on the performance of apparel supply chain was identified and examined using the proposed simulation model. Based on the data collected from the industry, the simulation model could generate the replenishment strategy in terms of replenishment quantity in each replenishment cycle. The simulation procedure was validated using the industrial data.

For the simulation-based optimization model developed for the VMI-based apparel supply chain, the replenishment strategy generated by the simulation model was further optimized by using genetic algorithm (GA). Experimental results indicated that the proposed optimization of the VMI strategy could maintain the retailers' targeted CSL while improving the Production Capacity Balance of the manufacturers significantly. Validation of the optimization model was undertaken by comparing the performance of the optimized model with that of the industrial practice.

To understand thoroughly about the current practice of the apparel supply chain adopting VMI-based strategy, in-depth experiments were conducted using the proposed simulation-based optimization model. Full factorial experiments were conducted based on the industrial practice. In the discussion of experimental results, the implications on the VMI-based replenishment strategy were described. Suggestions on how to improve the performance of the whole supply chain (CSL, Inventory Turnover and Production Capacity Balance) were given to the manufacturers and retailers in the VMI-based apparel supply chain based on the implications.

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CHAPTER 1

INTRODUCTION

1.1 An Overview of Apparel Supply Chain Using Vendor Managed Inventory (VMI) Replenishment Strategy

Supply Chain Management (SCM) is an integrated management idea and method, which executes the responsibility of logistics planning and controlling from the suppliers to the final customers along the chain. Basically, SCM involves four fields: supply, schedule plan, logistics, and demand. SCM is realized through centering on supply, production and logistics to meet the demand, with the guide of simultaneous and integrated schedule plan and the support of various technologies, especially Internet/Intranet. It includes planning, cooperation, and controlling of materials (parts and finished products) and information from suppliers to users.

In the earliest stage, people lay the emphasis of SCM on repertory management and consider it as a buffering means to balance the limited production capacity and the need to deal with the change of customers' demand. It seeks the balanced point between the expense of quick and reliable delivery of products and the expense of production and storage so that it can determine the best repertory management. Therefore, its major task is the management of storage and transportation.

Today, SCM considers the enterprises along the chain as an inseparable integration so that the enterprises can accomplish their responsibilities of purchase, manufacture, distribution and sales coordinately and behave as a harmonious organism. With the forthcoming economic globalization and knowledge-based economy, market competition becomes more and more obviously internationalized and integrated. Recently, the apparel enterprises are facing an environment featured with increasingly fierce market competition, uncertainty, individualization of customer demand, speedy development of hi-tech, short product life cycle, complicated product structure, high pressure of information explosion, short production lead time and frequent style change. Thus, the development of an efficient supply chain becomes the focus of many researchers.

In the apparel industry, previous research has been conducted on SCM, especially with the development of Quick response (QR), a revolutionary strategy in the supply chain initiated in the apparel industry since 1980s. Most of the past studies were from the view of apparel retailers, and the recommendations to the apparel industry were about applying QR instead of the traditional replenishment strategy. The apparel manufacturers are therefore under pressure to synchronize their supply and demand activities effectively to ensure that product development, marketing/sales, and supply chains are in close coordination.

Along with the economical availability of necessary information and communication technology, the Vendor Management Inventory (VMI) strategy, also known as *continuous replenishment*, *automatic replenishment* or *supplier managed inventory*, has become more popular in SCM recently (Daugherty et al 1999; Cetinkaya et al 2000; Disney et al 2003; Kulp et al 2004). VMI has been adopted by apparel manufacturers to replenish garments with their retailers since late 1990s.

VMI has used recent advances in computer and communication technology to provide real-time information to supply chain partners. The core concept of VMI is that the supplier monitors or forecasts the customer's demand and inventory and replenishes that inventory as necessary with little or no action on the part of the customer. The main advantages of VMI are reducing costs and increasing Customer Service Level (*CSL*) to one or both of the participating members (Waller et al 1999).

Under the traditional SCM model, the downstream member, or retailer, makes decisions on the time and the amount of replenishment to be shipped from the upstream member, or manufacturer. This information is communicated to the supplier that then provides the goods requested to the retailer. This relationship is illustrated in Figure 1-1.

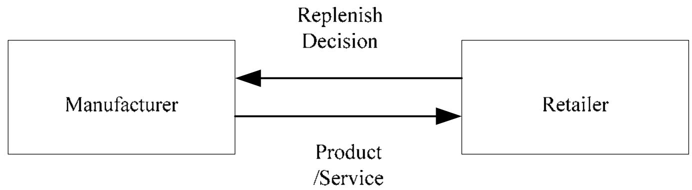


Figure 1-1: Traditional Replenishment between Manufacturer-Retailer

Under the VMI mode, decision making is different from the traditional one. Its use and benefits have been documented by several authors in the literature, with primary research conducted by Cachon et al (1997), Clark et al (1997), and Waller et al (1999). The manufacturer takes the responsibility for the decisions such as determining the stock kept by the retailer and replenishment quantity delivered to the retailer. The performance of the supply chain is influenced by these replenishment decisions. The shift in responsibility substantially changed the relationship between the manufacturer and retailer, as illustrated in Figure 1-2.

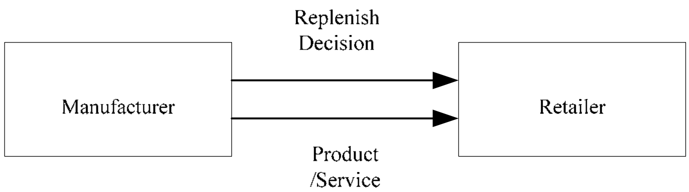


Figure 1-2: Relationship between Manufacturer-Retailer in VMI Mode

In the supply chain adopting the VMI replenishment strategy, the manufacturer makes replenishment decisions about how many products to ship to the retailer in every replenishment cycle. The replenishment quantity for each Stock keeping unit (SKU) is determined based on the Point of sales (POS) data in the past periods, seasonality trend forecasting, and promotion factors, to name but a few. The effect of the manufacturers' decisions on different replenishment strategies with their retailers (lead time, replenishment cycle and replenishment quantities) to satisfy the retailers' demand is significant to the performance of the whole supply chain. Questions of how to implement the replenishment strategies and what will be the benefits to the participating firms within the supply chain are the key issues for decision making.

However the decision-making process is inherently complex in a supply chain. The reason is that supply chain problems are often very complicated and intricate owing to the interactions between the parties, the length of the supply chain, the lead time of manufacturing and shipping, the complexities of modeling the individual parties, the stochastic nature of the demands. Few analytical models exist to represent real-world problems occurring in the supply chain.

In such instances, one alternative form of modeling supply chain is simulation. In simulation models, one can represent many realistic features. It offers a comprehensive methodology by considering the strategic, tactical, and operational elements with much more details than any other approaches do. The development of simulation models to understand issues of supply chain decision-making has gained importance in recent years (Shapiro 2001; Yao et al 2002; Simchi-Levi et al 2003; Umeda et al 2006).

In the apparel industry, the simulation model has been used extensively in handling assembly line (Whitaker 1973) , modular manufacturing systems (Wang et al 1991), and issues relating to mass production sewing lines (Tyler 1989). Some studies in the literature relevant to the simulation model in the apparel supply chain, which were initiated at the North Carolina State University (NCSU), targeted the simulation of the supply chain, along with the development of QR in the mid 1980s (Hunter et al 1996a; Nuttle et al 2001a; Nuttle et al 2001b). These simulation models have allowed retailers and importers to evaluate the effectiveness of their business strategies. Most of these simulation models in the apparel supply chain focused on evaluating the performance of the QR strategy adopted in the apparel supply chain and the improvement observed. One of the weaknesses of these studies is their limitations focusing on the retailers' benefits. Little has been done on investigating the manufacturers' replenishment strategies with the retailers.

One difficulty facing an apparel manufacturer adopting a VMI replenishment strategy is caused by uncertain demand, especially when little information about the actual demand can be acquired from the market. Owing to the fluctuating demand from the customers, the replenishment quantity from the manufacturer varies for each replenishment cycle which will directly influence the balance of production capacity. For instance, a sudden rise of replenishment to cover increasing customer demand may exceed the limitation of production capacity in one period while a decline of customers' demand may not fully utilize the production capacity. To ensure the goods to be received by the retailer on time, the manufacturer needs to set up extra production lines or require the operatives to work overtime. These strategies might cause imbalance of production of the manufacturer. The previous research linking the manufacturer's production to the demand dynamics in the apparel supply chain is limited.

With the responsibility and authority on managing replenishment given to the manufacturers, the manufacturers in the apparel supply chain are under pressure from the retailers to change their manufacturing process and search for an optimal production plan to optimize the performance of the supply chain. One challenge to the manufacturers is to set up a production strategy using the supply chain kernel which balances the benefits of different parties in the supply chain, i.e. satisfy the retailers' *CSL* and balance the manufacturers' production capacity. While research is increasing in the area of VMI, inquiries into how VMI replenishment strategies influence the manufacturers' production balance under the supply chain dynamics have received little work, and few empirical information was documented on how to integrate the VMI replenishment strategy with limited manufacturing capacity.

Based on the current situation, the motivation for this research primarily stems out from two critical issues associated with the apparel supply chain adopting the VMI replenishment strategy. Firstly, although previous studies have shown that the simulation approach is an effective means of investigating the operation of the supply chain, there are only a few studies on the VMI-based apparel supply chain. Benefits could be obtained by developing a comprehensive simulation model in investigating the VMI-based apparel supply chain performance. Specifically, the proposed simulation model will provide a tool for the retailers and the manufacturers in the apparel industry to understand how their replenishment strategy affects the performance of the apparel supply chain before actual business. Dynamic customers' demand in the apparel supply chain can be investigated using the proposed simulation model. After linking the proposed simulation model with an optimization algorithm to establish a simulation-based optimization model, optimized replenishment strategy can be generated to help the manufacturers and retailers to determine their most appropriate replenishment strategy (lead time, replenishment cycle and replenishment quantity). The performance of the VMI-based apparel supply chain in terms of *CSL*, Inventory Turnover (*IT*) and Production Capacity Balance (*PCB*) is expected to be improved under the optimized replenishment strategy.

Secondly, past research relevant to the VMI replenishment strategy did not look specifically at the production imbalance caused by the demand dynamics from the customers. There is an overall lack of empirical research on the balance of the profits between the retailers and the manufacturers in the apparel supply chain. No optimization algorithms are proposed to balance the benefits for different participants. Thus, the current exploratory research is undertaken to empirically examine and optimize the replenishment strategy in a VMI-based two-echelon apparel supply chain that links the manufacturer, the retailer and the customer.

1.2 Objectives

In this research project, a simulation-based optimization model is proposed to simulate the operation and performance of an apparel supply chain under dynamic environments in the apparel industry.

Specifically, the objectives of this research are to:

1) Develop a simulation model for simulating the apparel supply chain adopting the VMI strategy in terms of the replenishment strategy, *CSL*, *IT* and *PCB*.

2) Examine the behavior of a VMI-based apparel supply chain performance under dynamic and uncertain environments.

3) Develop a simulation-based optimization replenishment model for the apparel supply chain adopting the VMI strategy so as to improve the *PCB* of the manufacturers while maintaining the *CSL* of the retailers at a high degree.

4) Gain a better understanding and insight of the impact of various replenishment decisions in terms of replenishment cycle, lead time, and replenishment quantity on the performance of the apparel supply chain adopting the VMI replenishment strategy.

1.3 Methodology

To fulfill the research objectives, a simulation-based optimization replenishment model for the VMI-based apparel supply chain is developed in this research. The following are the steps used to establish and evaluate the proposed model.

Firstly, a VMI-based simulation model is established to investigate the VMI-based apparel supply chain. The main purpose of the simulation model is to study the relationship between the replenishment strategy and the performance of the supply chain in a VMI-based apparel supply chain. The proposed simulation model is capable of simulating the operations of a VMI-based supply chain in the existing dynamic apparel industry. Based on the replenishment strategy in terms of replenishment quantity, lead time and replenishment cycle, the VMI-based apparel supply chain simulation model generates a set of performance index, including *CSL*, *IT* and *PCB*. The performance index is also influenced by other inputs of the simulation model, such as sales forecasting and forecasting error caused by uncertain customers' demand.

The performance of *CSL* and the *IT* are the two major indicators the apparel retailers focus on the effectiveness of the replenishment strategy and supply chain performance. In the apparel industry, high level of customer service is one of the important objectives for retailers' success. At the same time, maintaining the inventory at low level is crucial for the retailers to obtain more profits. *PCB* reflects the manufacturers' production stability. For the apparel manufacturers adopting the VMI replenishment strategy with their retailers, the production imbalance caused by dynamic customers' demand may cause extra cost to the manufacturers. As managing the replenishment being shifted from the retailers to the manufacturers in the VMI mode, the decision making on the replenishment strategy by the manufacturers should consider the benefits of both participants in the two-echelon apparel supply chain, i.e. the retailers and the manufacturers. These three indicators (*CSL*, *IT* and *PCB*) are thus selected as the performance index of the proposed simulation model in this study.

The influence of dynamic and uncertain customers' demand on the performance of the apparel supply chain is identified and examined using the proposed simulation model. The fuzzy set theory is integrated into the simulation model to account for the dynamic forecasting error, which is defined as the difference between the forecasted customers' demand and actual demand. With data collected from the industry, sensitivity analyses on the relationship among the dynamic forecasting error, the replenishment strategy and performance of the apparel supply chain are conducted. Validation of the simulation model could then be made using real data collected from the reference sites.

Secondly, the VMI-based simulation model is extended to a simulation-based optimization model searching for an optimal solution for the decision makers to implement replenishment strategy and optimize the resources engaged in the apparel supply chain. This simulation-based optimization model is composed of two main parts, namely a VMI-based apparel supply chain simulation model and a Genetic Algorithm (GA)-based optimization algorithm. The simulation model developed in the first stage is employed to represent and analyze the process and performance of the VMI-based apparel supply chain. GA is employed to search for the optimized values of replenishment strategy in the apparel supply chain simulation model to optimize the performance; in other words, balance the production capacity of the manufacturer and improve the *CSL*. Figure 1-3 illustrates the architecture of the proposed simulation-based optimization replenishment model for the VMI-based apparel supply chain.

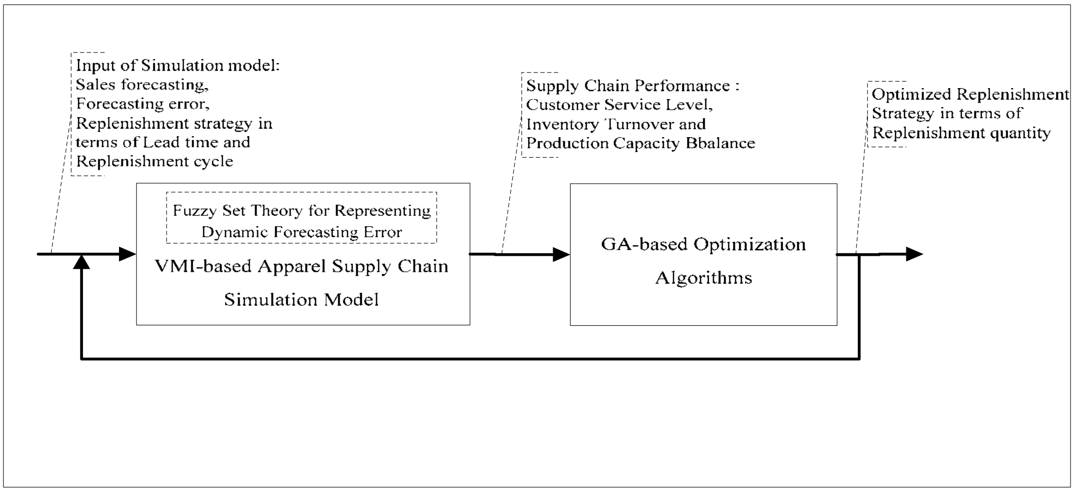


Figure 1-3: Architecture of Simulation-Based Optimization Replenishment Model for VMI-Based Apparel Supply Chain

For the optimization algorithm, GA is employed to generate an optimal replenishment solution for the decision makers in the apparel supply chain to improve the performance of the apparel supply chain. In this research, the search space for the problem is a combination of the replenishment strategy, including whether to shift the surplus part of replenishment quantity, the percentage of surplus replenishment quantity to be shifted to contiguous cycle, and the directions to be shifted (replenish the surplus part of garments in advance or delay the replenishment of garments) at each replenishment cycle. Meanwhile, evaluation of the performance of the replenishment strategy is complex. GA offers an efficient search technique suitable for large combinatorial problems, and is capable of connecting with a simulation model to evaluate the performance of the possible solutions to the optimization problem. Therefore, GA is selected as the optimization algorithm in the proposed model.

Validation of the simulation-based optimization model is undertaken by comparing the performance of the simulation-based optimization model with that of the industrial practice.

In the last part of this research, full factorial experimentation is conducted based on the proposed simulation-based optimization model for the VMI-based replenishment strategy. The results of the analyses will show the implications on the replenishment strategy of the VMI mode for both academic research and industrial processes.

1.4 Significance of this Research

While research in the area of VMI-based supply chain receives increasing attention, in-depth studies on the relationship between the performance of the two-echelon apparel supply chain adopting the VMI-based strategy and the replenishment strategy are limited. The contributions of this study are discussed as follows:

The first significant contribution of this study is to broaden the investigation and enrich our understanding on the VMI-based apparel supply chain, both from the perspective of the academic research and industrial practice.

Past studies in the apparel supply chain have mainly focused on QR strategy and the benefits it brings to retailers. This research studies the behavior and performance of the two-echelon VMI-based apparel supply chain which has not been addressed. The practice of the participants in the two-echelon apparel supply chain (including customers, retailers and manufacturers) 1s investigated. The benefits of both the manufacturers and the retailers are considered. The new optimization model proposed in this study is capable of seeking for the optimal performance and thus the optimal balance between the high *CSL* required by the retailers and balanced production capacity maintained by the manufacturers.

In the apparel industry, VMI-based replenishment strategy has been employed for quite a long time and the benefits of the VMI strategy has been reported widely. However one of the obstacles that the manufacturers involved in the VMI-based supply chain encounter is the imbalance of their production capacity. The optimization model developed in this research could provide one effective solution to this problem.

From the perspective of the research methodology, simulation, fuzzy set theory and GA are engaged in the optimization model for the VMI-based apparel supply chain. The synergistic effect of these three methods on the optimization of the performance of the VMI-based apparel supply chain is demonstrated in the optimization model. These optimization algorithms are capable of improving the performance of the two-echelon VMI-based apparel supply chain.

This research also furthers the existing SCM research by strengthening the understanding of VMI replenishment strategy adoption in the apparel industry. With full factorial experiments conducted using the simulation-based optimization model developed in this research, an investigation on the factors that may affect the performance of the VMI-based replenishment strategy is made. Suggestions on the replenishment strategy to improve the performance of the whole supply chain will be given based on the results of the experiments.

1.5 Structure of this Research

The remaining part of this research is organized as follows: Chapter 2 is a literature review on previous studies relating to apparel SCM that forms the framework for the research. An overview of the apparel supply chain, the simulation model as a research method to modeling the apparel supply chain uncertainty as well as the VMI-based replenishment strategy relating to the apparel supply chain are given. Chapter 3 explains the methodology employed in this study. Three steps including the development of a simulation model, optimization of the replenishment strategy as well as the evaluation of the factors on performance of the apparel supply chain are illustrated. Techniques involved in the model, including simulation, simulation-based optimization, fuzzy set theory and GA are described. Chapter 4 introduces the procedures of the design and implementation of the replenishment simulation model, whose purpose is to generate appropriate replenishment strategies based on the principle of satisfying the customers' demand in the apparel industry. Chapter 5 presents the fuzzy logics integrated into the simulation model (developed in Chapter 4) which is used to represent the forecasting error caused by dynamic customers' demand. Experiment to evaluate the relationship between the forecasting error degree, performance and replenishment strategies were conducted based on real data from the apparel industry. Chapter 6 proposes the simulation-based optimization model for the replenishment strategy in the VMI-based apparel supply chain. With the consideration of the production capacity constraints, a dynamic rolling optimization of the VMI replenishment strategy using simulation and GA is formulated to optimize the supply chain performance in terms of production balance of manufacturers and customer satisfaction targeted by retailers. Chapter 7 evaluates the impact of the factors on the performance of the supply chain using the simulation-based optimization model developed in Chapter 6. The last chapter summarizes the findings of this study, the limitations and recommendations for future research.

CHAPTER 2

LITERATURE REVIEW

This chapter reviews previous studies relating to Supply Chain Management (SCM) in VMI-based apparel industry that forms the framework for this research. The first section pertains to SCM in apparel industry. After providing a general overview about apparel SCM, uncertainties in the supply chain which significantly influence the performance of the apparel supply chain are then reviewed. The simulation model as one research method for investigating the uncertainties in the supply chain is presented. The second section of this chapter focuses on the Vendor Managed Inventory (VMI) replenishment strategy. After providing a general introduction of the VMI replenishment strategy and its advantages, this chapter moves on to the investigation on apparel SCM which employed the VMI replenishment strategy. The research gap is identified in the summary of the review at the end of this chapter.

2.1 Supply Chain Management (SCM) in the Apparel Industry

This section covers SCM in the apparel industry. The general overview of the apparel supply chain is first reviewed. After that, the uncertainties in the apparel supply chain are presented. A review on the supply chain simulation model which is capable of investigating the dynamic apparel supply chain is given in the last part of this section.

2.1.1 Apparel Supply Chain Management (SCM)

There is little dispute that the concept of SCM, first appeared in the early 1980s (Oliver et al 1982; Houlihan 1985; Jones et al 1985) has been an area of importance since then (Harland 1996; Cooper et al 1997). Due to the way the concept of supply chain has been developed, the definition of SCM lacks universal acceptance (Croom et al 2000). Many definitions have been used to describe this topic. Stevens (1989) described SCM as a "connected series of activities which is concerned with planning, coordinating and controlling materials, parts, and finished goods from supplier to customer. It is concerned with two distinct flows (material and information) through the organization." Oliver et al (1982), Cooper et al (1993) and Chandra et al (2001a) defined SCM as a single entity governed by strategic decision making. Their focus was on the integration, rather than on the interfaces in SCM. Some authors and practitioners from other disciplines highlighted an increasing dependence on relationships with suppliers (Sabel et al 1987; Slack 1991; Harland 1996). Still other scholars defined the SCM as strategic management of inter-business networks. For instance, Christopher (1992) defined SCM as the management of "the network of organizations that are involved, through upstream and downstream linkages, in the different processes and activities that produce value in the form of products and services in the hands of the ultimate consumer. Thus, for example, a shirt manufacturer is a part of a supply chain that extends upstream through the weavers of fabrics to the manufacturers of fibers, and downstream through distributors and retailers to the final consumers."

The apparel industry has a long supply chain from raw material suppliers (i.e. fiber manufacturers) to end-users (i.e. consumers) (Lee 2000). As defined by Dickerson (2003), the major segments in the apparel supply chain are component suppliers, finished product suppliers and retail distributors. Component suppliers refer to fabric and yarn manufacturers. Finished product suppliers include apparel and accessories manufacturers while retail distributors consist of all forms of delivering the products to the consumers. A simplified definition of the apparel supply chain was given by Hammond (1993) that the apparel chain consists of fiber producers, textile manufacturers, apparel manufacturers, retailers, and consumers.

A traditional company involved in the apparel supply chain runs its business as a separate entity, which may cause conflicts in the relationship with its partners. According to Hammond (1992), “there was very little coordination among the companies. Each segment built production schedules based on its own forecasting method, which may not accurately represent the actual demand” (Cited in Lee (2000)). The supply chain members would suffer from the long lead time and high level of inventory with consequent risks of obsolescence. In this case, the retailers would not maintain good relationship with their manufacturers. They may abuse their power to secure low prices by threatening their suppliers with order withdrawals (Aron 1998).

Today, the level of competition in the supply chain is much higher than before. Greater effort is placed on the improvement of product quality and shortening of lead time. The life cycle becomes shorter and shorter, and demand is more uncertain in growing numbers of product categories. Fill rates, inventory turns, products obsolescence and other topics in the apparel industry have received increasing attention by managers (Raman 1999).

The philosophy of SCM has been practiced in the apparel industry under the label of Quick response (QR) which was originally initiated by the need to reinforce the US domestic apparel manufacturers' competitive advantages against global competition from low labor wage countries in the 1980s. There are many definitions for QR. In the remaining part of this section, the review on apparel supply chain focuses on the definition and advantages of the QR strategy.

One consolidation of the various definitions and descriptions is given by Lowson et al (1999): "QR is a state of responsiveness and flexibility in which an organization seeks to provide a highly diverse range of products and services to a customer/consumer in the exact quantity, variety and quality, and at the right time, place and price as dictated by real-time customer/consumer demand. QR provides the ability to make demand information driven decisions at the last possible moment in time ensuring that diversity of offering is maximized and lead-times, expenditure, cost and inventory minimized. QR places an emphasis upon flexibility and product velocity in order to meet the changing requirement of a highly competitive, volatile and dynamic marketplace. QR encompasses a strategy, structure culture and set of operational procedures aimed at integrating enterprises in a mutual network through rapid information transfer and profitable exchange of activity."

Responding to customers' tastes becomes important and dealing with variability in demand has been crucial to the manufacturers competing in the apparel supply chain. The apparel manufacturing industry in the US or EU after the industrial concentration changed from the high volume-low priced to the lower volume-higher priced garments for niche markets (Dickerson 1999; Toni et al 2000).

Despite the growing interests on SCM, studies in the literature on apparel manufacturers mainly reported the benefits manufacturers have experienced through the investment on QR strategy. In a survey of the US apparel manufacturers (Kincade et al 1993), the characteristics of apparel manufacturers that adopted QR strategy were studied and discussed using statistical analyses. It was found that the size of operation and the type of retail customers were significantly related to the adoption of the QR strategy. Ko et al (1998) described the implementation of the QR strategy by a broad spectrum of the US apparel manufacturers. They examined the relationships between organizational characteristics and the implementation of QR technologies. Using the data from a survey of apparel suppliers conducted by four members of the Department of Commerce's Longitudinal Research Database, Abernathy et al (2000) concluded that suppliers that adopted comprehensive changes in their manufacturing processes performed better along a number of dimensions when compared to firms that have not.

In another report (Abernathy et al 1999), the same authors detailed the demand-driven changes by retailers in the US apparel and textile industries - lean retailing. The data collected from major textile firms, apparel producers and leading retailers showed that when “lean retailers” exchanged POS information with their suppliers and required them to replenish orders quickly, the manufacturers had to reshape their planning methods, cost models, inventory practices, production operations and sourcing strategies. One further example was provided by Lee et al (2003). In the study, the authors commented that the characteristics of the US apparel manufacturers were different in accordance with their supply chain activities. They based their argument on the data collected from the survey of a sample of US apparel manufacturers. Rollins et al (2003) developed a novel planning and control reference model for the UK apparel industry by considering the commercial environment with changing customer demand. Their model was based on twenty companies.

QR strategy combines technology and collaboration in the apparel supply chain, which in turn increases the need to manage the apparel manufacturers in a strategic way (Abernathy et al 1999; Jin 2004). The relationship between the manufacturers and retailers becomes more and more important. Along with the development of new technologies and the requirements of the demand-driven customers, the manufacturers in the apparel supply chain are under the pressure to make decisions for their proposed management systems with information sharing between the manufacturers and retailers (Kincade et al 1993).

However, little work had been done on how the apparel manufacturers' production was affected by the retailers' requirements on the replenishment strategy. King et al (1999) investigated the apparel production systems of the manufacturers that replenished garments to the retailers. The main purpose was to search for the best form of existing manufacturing systems in the manufacturers such as modular and team sewing, to best support the QR strategy. Analytic models were developed to understand the optimal manufacturing planning and control policies under a variety of operating scenarios. This research was further developed to search for the optimal production/inventory coming into and out of peak seasons in the apparel manufacturer domains (Gokce 1999). Software was developed to determine the optimal policy given the characteristics of the demand and the production system. Experimentation over a broad range of input parameters was done and the optimal policy was found nearing completion.

One difficulty facing the apparel manufacturers is caused by uncertain demand, especially when little information about the actual demand can be acquired from the market. A lack of the coordination between the participants in the apparel supply chain may lead to the stocking out of the necessary SKUs, and at the same time, the unwanted SKUs are overstocked. Even worse, the manufacturers might have difficulty in determining the right quantity and timing for production (Lee 2000). However the present work on the production and replenishment strategy is a pioneering attempt linking the manufacturers' production to the uncertainties in the apparel supply chain.

2.1.2 Uncertainties in the Apparel Supply Chain

In today's ever changing market, maintaining an efficient and flexible supply chain system is critical to every enterprise, given the prevailing volatilities in the business environment with constantly shifting and increasing customers' expectations. Various sources of uncertainties can be identified in these systems. Much work has been done in the area of supply chain uncertainty. With the integration of engineering and management into a single system, mathematical models and optimization tools were applied to solve the industrial dynamics (Forrester 1961). Southall et al (1998) developed a simulation model to study the relationship between manufacturing and distribution enterprises in the supply chain. Towill (1991, 1996) proposed a method to investigate the supply chain dynamics in which the supply chain responses over time to changes in its external environment, especially customers' demand, was considered. Philip et al (1996) formulated a time-based strategy to model supply chain behavior. Harland (1997) studied the roles of operational performance in a supply chain. These studies only represented deterministic mathematical explanation of the supply chain which considered the isolated parts of a supply chain.

There are uncertainties occurring in the apparel supply chain (Fisher et al 1994). Some of the components are fluctuating customers' demand, production lead-time, and reliability of fabric delivery. Among them, demand uncertainty has a dominating impact on profitability and customers' satisfaction. It can result in over-or under-production, leading to excessive inventories or inability to meet customer needs, respectively.

One reason for the demand uncertainty is due to the growing product variety. A trend in the apparel industry is the consumers' desire for more styles in their fashion. Though apparel items are traditionally regarded as basic goods such as men's wear, sportswear, petite and plus size goods, they are shifting to the fashion market (Feitelberg 1995).

Another phenomenon was that customers are becoming more demanding, and value-driven. They are sometimes whimsical and their demand is unpredictable. The variety of the customers' demand can be reflected from the SKUs, a term related to different catalogues of final goods offered to customers. The average number of SKUs held by the apparel business has been increasing every year, but the overall demand does not grow as well. As retailers try to carry many styles, the number of units for a given SKU in stock is getting smaller. When a customer goes to the store looking for a particular SKU, the chance of the store being out of stock tends to increase. It was reported by Bouhia (2004) that the growing product variety brought a higher coefficient variation for each SKU, hence the demand uncertainty due to the customers' demand was increasing.

As customers' demand for more fashion goods rises and competition on the market gets higher, apparel manufacturers are required to be able to produce a broad range of products. Apparel manufacturers need to either build a high level of inventory in the manufacturing sites or to make drastic changes in their use of production strategies. The case of a skiwear manufacturer was studied by Fisher et al (1997). To deal with the uncertainties in customers' demand with production capacity constraints, the solution was to produce low-risk products (i.e. basic goods) in accordance with forecasted demand far ahead of the selling season whilst postponed the production of high risk products (i.e. fashionable goods) until additional market information was gathered. In the case of Benetton (Simchi-Levi et al 2003), the conflict between the changing customers' preferences and long manufacturing lead time was addressed. The wool sweater manufacturer adjusted the manufacturing process, postponing the dyeing of the garments until the sweater was completely assembled. The revised process flow made the sweater manufacturing about 10 percent more expensive and required the purchase of new equipment and retraining of employees. However Benetton was more than adequately compensated by improved forecasts, lower inventories, and, in many cases, increased sales.

To manage uncertain demand in the apparel supply chain, many studies were related to forecasting before sales season (Fisher et al 1997). The forecasting error between customers' demand and retailers' prediction always existed. It was not unusual for both retailers and manufacturers to make a 25% error when forecasting sales (Nuttle et al 1991). Forecasting errors were very costly to make (Stratton et al 2003). It was concluded that forecasting error could be much more expensive than the savings from manufacturing offshore. If the demand was high, the store would not have the inventory to satisfy their customers. Not only would the store lose sales, they also ran the risk of turning away the customers. If the demand was low, the store would have excessive inventory. The surplus would be sold at a discount. Selling the inventory would recover part of the cost and the overall margin declined. What is more, a "cannibalization of sales" (which refers to a customer who buys two discounted items will not come in the next season to buy another one) might occur.

Some researchers devoted their study to forecasting error in the apparel industry using case study. In the case of Sports Obermeyer Company (Fisher et al 1996), the importance of forecast by experts was noted in developing a production strategy against the crisis between short life cycle and long lead time. Sales forecasts were collected from managers of different departments to determine the production strategy. Using data in the past few years, Fisher et al (1996) found that the difference between the forecasted and the actual demand was less for those items with less coefficient variation in forecasts among managers. Based on this finding, items with less coefficient variation were planned to be produced earlier before season. Stratton et al (2003) suggested an agile production strategy in which 80% of the production forecasts were manufactured offshore before sales season to lower the production cost. Only after the sales season commenced, the manufacturer might determine whether to employ the QR manufacturing strategy or not based on actual sales demand. Chandra et al (2001b) then classified the models for inventory management in the apparel supply chain into three types, namely stable level demand, time varying deterministic demand and mixture of stable and time-varying demand. The variability of demand was addressed by the variance of demand during one history period, and three different inventory models were put forward to manage each of the demand types. The above studies investigated the apparel supply chain with dynamic forecasting error. However one common issue of their models was that their strategies were based on case studies. A systematic method to represent the forecasting error was not provided.

From the view of retailers in the apparel supply chain, Aron (1998) studied the demand uncertainty and forecasting error. He claimed that regarding products with uncertain demand, retailers would prefer to make a small initial order and place reorders frequently as the selling season proceeds to reduce their inventory level in the store. With small frequent reorders, retailers reduced their risk of holding too much inventory in their store. And retailers could be more responsive to rapidly changing market trends by replenishing their store shelves with what customers want.

One method to capture random character such as consumer demand is simulation (Brooks et al 2001). Stochastic simulation models were established to manage the uncertain demand as well as the forecasting error caused by the fluctuating customers' demand in the past. By treating uncertain customers' demand as Monte Carlo model, a software called "Sourcing Simulator" was developed for planning apparel sourcing (Nuttle et al 1991). Its purely descriptive simulation approach allowed detailed representation of certain aspects of the setting, especially in the replenishment strategies and consumer behavior. Various studies based on this model validated the importance of improving demand information and the key factor for the sourcing strategies in an apparel supply chain (Hunter et al 1992; King et al 1996). Other researchers also addressed demand uncertainty in the apparel supply chain by means of a simulation model. A retailer-oriented model for managing capacity inventory and shipments was developed by Agrawal et al (2002) for an assortment of retail products produced by multiple vendors while the demand of the product is uncertain and fluctuates over time. The uncertain demand was treated as a demand scenario that has a discrete number of possible values and the model was able to optimize the production commitment that maximized the retailers' expected gross, given demand forecasts and vendors' capacity and flexibility constraints. More recently, a simulation model was employed to investigate the relationship between the uncertain forecasting error and inventory control of retailers in the apparel supply chain (Wu et al 2004). The purpose of the research was to study the impacts of uncertainties on different inventory strategies of the retailers. It was concluded that the QR strategy had high ability to handle the uncertain impacts of forecasting error on SKU mix.

It was found that all these studies on forecasting error in the apparel supply chain focused on the strategies of the retailers. When the responsibility on replenishing garments is shifted from the retailer to the manufacturer, the uncertain customers' demand greatly influences the production performance of the manufacturers and thus the replenishment frequency and quantities to the retailers. The performance of the whole supply chain (*CSL* and *IT* of the retailer, *PCB* of the manufacturer) is influenced by the uncertain customer demands. Extending the research to the upstream in the apparel supply chain (i.e. the manufacturers) is necessary.

2.1.3 Simulation Model in the Apparel Supply Chain

In simulation models, one can represent many realistic features. A simulation model offers a comprehensive methodology by considering the strategic, tactical, and operational elements with much more details than any other approaches do. The development of simulation models to understand issues of supply chain decision making has gained importance in recent years (Shapiro 2001; Simchi-Levi et al 2003).

Because of the inherent complexity of the decision-making process in the supply chains, past studies on supply chain focused on modeling methodologies. Shapiro (2001) defined two types of mathematical models in SCM, namely descriptive models and normative models. Descriptive models were those "developed to better understand the functional relationships in the company and the outside world", which included forecasting models, cost relationships, resource utilization relationships and simulation models. Normative models were those developed to help managers make better decisions, which was also termed as "optimization models". Biswas et al (2004) broadly classified the quantitative models of supply chains into optimization models, analytical performance models, and simulation models. In Truong (2002), the supply chain modeling methodology was categorized into six groups. They were linear programming-mixed integer programming, stochastic programming, network based approach, agent-based approach, discrete event simulation and system dynamic model.

Some models discussed above, such as analytical performance models, are high abstraction models for business processes under simplifying assumptions. Other models such as linear programming-mixed integer programming are widely used in the optimization of supply chain control systems. However linear programming-mixed integer programming approaches suffer from some pitfalls that limit their application to the design of supply chains. The size and complexity of a typical supply chain can involve a huge number of variables and constraints. The assumption of linearity may not hold.

In most of these models, because of complexity, stochastic relations and so on, not all real-world problems can be represented adequately. Attempts to use analytical models for such systems usually require many simplified assumptions and the solutions are likely to be inferior or inadequate for implementation. Often, in such instances, one alternative form of modeling and analysis available to the decision maker is simulation.

In the apparel supply chain, a number of research initiatives at the North Carolina State University (NCSU) applied the simulation model as a consequence of the development of QR in the mid 1980s. These simulation models focused mainly on integrating domestic resources for achieving QR in the West. Details of their research are described as follows:

Nuttle et al (1991) developed a simulation technique named Sourcing Simulator to evaluate a sourcing strategy for a retailer under a given set of input. The model allowed investigation of the effects of alternative retailing procedures on financial and other performance measures for a retail store. It modeled alternative mechanisms for supplying products to a retail store and tracked the inventory of a line of product offered in a range of SKUs. The store might issue replenishment orders to the vendor. Replenishment might be based upon the original buyer’s plan or might reflect the use of actual POS data. In this way, the selling season was played out and performance statistics was computed. Case study with the simulation system illustrated that re-estimation of demand and QR was superior to traditional retail practice.

Hewitt et al (1991) analyzed the US textile-apparel pipeline by comparing the traditional practice with QR. They examined the issues relating to various modes of supply through case study.

A novel apparel-supply system was studied compatible with QR retailing of apparel within a finite shelf life (Hunter et al 1992). The performances of both the apparel manufacturer and the retailer in the stochastic model were determined. This research expanded the capability of the simulation system to include a responsive fabric-supply component by modeling the manufacturer portion to form an apparel-supply chain system for QR retailing. The results obtained by the simulation model were that the manufacturing was seen to be capable of responding to the QR strategy over a wide range of operating conditions.

In a subsequent study, the same team (Hunter et al 1996a) used a stochastic computer-simulation model to explore the applicability and benefits of QR compared to traditional retailing procedures. The study confirmed the industrial trials as to the superiority of QR methodologies, specifically with the use of re-estimation and reorder techniques.

The simulation model was extended to include the textile industry in the apparel supply chain (Hunter et al 1993). The objective of the research was to investigate how close the fabric supply could come to QR standards. Segments of the supply pipeline such as spinning, yarn dyeing, knitting, weaving, dyeing and finishing were programmed using a stochastic simulation model. Using a variety of input variables, it was found that a selling season of less than 15 weeks put constraints on pursuing QR.

In a down stream model, the simulation system was used in a specialty retail chain and the demand re-estimation and inventory replenishment of basic apparel were investigated (King et al 1996). Their results showed that the sponsored retail chain achieved substantial reductions in inventories while improving customer service levels by adopting the reorder procedures outlined in the paper. Details can be found in subsequent publications (Lowson et al 1999; Hunter et al 2002). They showed the differences between the apparel supply chains that adopted the QR strategy and the traditional ones.

Joines et al (2002) further addressed the problem on optimizing the sourcing decisions in the apparel supply chain. Decision making was made to determine robust solutions for the order of products and/or raw materials. In this study, the simulation model was treated as a tool to evaluate the optimization algorithm using the Genetic Algorithm (GA) technique.

Some other researchers also addressed the apparel supply chain with simulation models. Belpaire et al (2000) developed a simulation model to represent a wide variety of specific logistic apparel supply chain models based on several generic modules including suppliers and manufacturers. The effects on the uses of advanced strategies such as QR and VMI were simulated. The purpose of the simulation model was to demonstrate the advantages of these strategies which could be summarized as "lead time reduction, stock level reduction, better control of production flows, increased service level and the delivery of the right products, in the right quantity and quality, at the right moment and in the right place.”

Wu et al (2004) investigated the inventory control of a retailer in the apparel supply chain using simulation models. Different retailers’ inventory strategies including QR, VMI, News boy and Target weeks supply were investigated. With the simulation results generated, the performances of different inventory strategies were analyzed. One of the implications to the actual supply chain environment was that the QR strategy was a good choice when it was needed to deal with uncertain factors on SKU mix error. Some other suggestions to retailers were avoiding markdown policy, shortening reorder lead time and increasing reorders.

These simulation models in apparel supply chain have allowed retailers and importers in the western markets to evaluate the effectiveness of their business strategies. Most of these simulation models focused on evaluating the performance of the QR strategy adopted in the apparel supply chain and the improvement observed. One of the weaknesses of these studies is their limitations focus on the retailers’ strategy. Little research has been done on investigating the manufacturers’ replenishment strategies with the retailers. The effect of the manufacturers’ decisions on different replenishment strategies with their retailers (lead time, replenishment cycle and replenishment quantities) to satisfy the retailers’ demand is significant to the performance of the whole supply chain. Both the performance of the retailers (*CSL* and *IT*) and the manufacturer (*PCB*) will be affected by the replenishment strategies.

The investigation on the relationship between the manufacturers' replenishment strategies and the performance of the whole apparel supply chain is to be explored.

2.2 Vendor Managed Inventory (VMI) Replenishment Strategy

This section reviews previous studies relating to the Vendor Management Inventory (VMI) strategy. Firstly, a general overview of VMI and its advantages are provided. Secondly, VMI replenishment strategy applied in the apparel supply chain is presented. The planning and inventory production models in the apparel industry which mainly focused on the decisions of manufacturers are reviewed. In the last part of this section, the research gap that links the VMI replenishment strategy and production model in the apparel supply chain is described.

2.2.1 Vendor Managed Inventory (VMI)

Vendor management inventory (VMI) strategy is also known as continuous replenishment, automatic replenishment or supplier managed inventory. It has become popular in SCM recently when the necessary information and communication technology are economically available (Daugherty et al 1999; Cetinkaya et al 2000; Disney et al 2003; Kulp et al 2004). It is the advances in inter-organizational information technology that has made new flows of information possible and has facilitated new SCM strategy such as the VMI replenishment strategy. The VMI strategy can be traced back to Magee (1958) in his presentation of a conceptual framework for designing a production control system.

VMI remains a largely illusive technique despite its potential impact on customer service and product availability. Part of its illusive nature stems from a lack of definition and consensus on what it is and how it differs from other tactical inventory management techniques. Some studies in the literature formulated different definitions of VMI. According to James et al (1997), VMI is “a collaborative strategy between a customer and supplier to optimize the availability of products at minimal cost to the two companies. The supplier takes responsibility for the operational management of the inventory within a mutually agreed framework of performance targets which are constantly monitored and updated to create an environment of continuous improvement.” In a subsequent publication (James et al 2000), the same authors believed that “vendor managed inventory can be generically characterized as a collaborative strategy between a customer and supplier to optimize the availability of products through a continuous replenishment approach to the management of inventory in the supply chain.”

The advantages of using VMI have been extolled in the literature. These advantages include improved customer service, reduced demand uncertainty, reduced inventory requirements and reduced costs, improved customer retention and reduced reliance on forecasting (Fox 1996). The advantages of using VMI have been well documented to the downstream member, usually a large retailer (Cachon et al 1997; Clark et al 1997; Waller et al 1999).

Other authors believed that the upstream member (manufacturers) of the supply chain can benefit as well. From the view of the manufacturers, VMI was “directly and positively related to a manufacturer’s profit margin and was significantly better at responding to volatile changes in demand such as those due to discounted ordering or price variations” (Kulp et al 2004). The shifting of replenishment from retailers to vendors will reduce the problems in production planning, since more rapid and direct sales data allow vendor greater flexibility on replenishment. As stated in Achabal et al (2000), the information of retailers’ orders are often misleading data for production planning. The orders from the retailers do not provide accurate details about which merchandises sell more rapidly and which styles stock out in mid season, for example. Relying on actual sales data such as POS data from each retailer may prevent the “bullwhip effect”. Bullwhip effect usually occurs when time lags, coupled with batch orders from the retailers, tend to amplify demand fluctuations as they go up the supply chain.

To investigate the VMI replenishment strategy, simulation models were employed as one methodology in previous studies (Cachon et al 1997; Waller et al 1999; Belpaire et al 2000). In these studies, simulation models were designed to represent a wide variety of specific logistic supply-chain models based on different generic modules (suppliers, manufacturers, etc.). The effects on the use of the VMI replenishment strategy were simulated, and results on lead times, capacities, inventory levels, information, material flows and costs were generated. It was also found that compelling economic and operational benefits were associated with VMI.

2.2.2 VMI in the Apparel Supply Chain

To gain competitive advantages, design of the supply chain has been seen as having a tremendous impact on it. Fisher (1997) developed the basic concept that supply chains should be classified by the products they produced. Products were classified as either functional or innovative. For innovative products, such as personal computers, responsive supply chains were required. With functional products, such as basic goods in the apparel industry, the chain must have been designed to minimize costs with more efficient processes that minimize inventories in the chain. Fisher noted that continuous replenishment programs, a type of VMI, were perfect for supply chain delivering functional products. This concept was reiterated by Clark et al (1997). Therefore, VMI became one of the key programs in the garment industry (Hammond et al 1990; Fisher et al 1994), as also reported in Daugherty et al (1999) and Waller et al (1999).

VMI has received considerable attention in the apparel industry. In a survey of 44 apparel companies in US, it was revealed that 25% of the subjects were willing to see an increase in VMI replenishment with their retailers in five years (Rajamanizkam et al 1998). In another study (Belpaire et al 2000), the simulation model was implemented to evaluate the performance of the VMI replenishment strategy in the apparel industry.

Most of the empirical works in the literature focused on the benefits associated with the VMI strategy using examples in a specific company. Sender (1998) reported a successful case of using a VMI-based replenishment strategy in apparel manufacturers. It was concluded that a VMI-based replenishment strategy could yield positive results in terms of sales, inventory and marketing information for soft goods. Achabal et al (2000) designed a decision support system for a major apparel manufacturer and over 30 of its retail partners. They claimed that “with the implementing of this VMI system, customer service levels improved dramatically, coupled with a significant improvement in inventory turnover.” Successful continuous replenishment program linking the manufacturing process to a network of stores and major retail was reported in Dunn (2003). The entire process studied in this research was designed to eliminate inventory and to speed up the manufacturing process. Similar case was found in Sangmoo (2004) more recently.

Some other research investigated the relationship between the negotiation variables and the retailer’s willingness when placing an item on automatic replenishments in the apparel supply chain (Dandeo et al 2004). It was concluded that merchandise driven mentality, price/value, color, design and type of merchandise category were those significant or highly related factors that affected the buyer's willingness on the negotiation variables (price, packaging, delivery and assortment) in the VMI-based apparel supply chain.

When the responsibility and the authority of managing replenishment are shifted to the manufacturers, one challenge to the supply chain adopting the VMI strategy is to set up the production model using the supply chain kernel which balances the benefits of different parties in the supply chain, i.e. satisfy the retailers' customer service level (*CSL*) and balance the manufacturers' production capacity.

SCM with production capacity has been investigated for quite a long time. For instance, Behling (1982) reported a strategic approach to balancing conflicting manufacturing objectives within the capacity limitations and introduced the techniques to be examined which addressed the critical issues of finite capacity in attaining the strategic objectives of the supply chain. More recently, Chandra et al (2001c) investigated the production model using the supply chain kernel, which balanced the coordination in the supply chain decision, while Vlachos et al (2001) analyzed a periodic review inventory system with a main and an emergency supply mode with the consideration of production capacity.

In the apparel industry, models based on management principles were established to investigate the relationship between the profits of the manufacturers and their production commitments. In Fisher et al (1996), the production quantity constraints encountered by fashion manufacturers that designed and manufactured products in a given season were looked into. The authors solved the problem by using the standard convex programming technique. The impact of working capital and inventory holding costs on a firm's stock out and markdown costs was discussed in Raman et al (2002). Peck et al (1998) developed a supply chain simulation model for the US military to evaluate a proposed military supply chain having frequent constant quantity orders to the manufacturer (the distribution centre inventory varies inversely with demand). It was confirmed that the steady flow of orders allowed retail sites to maintain low inventories with little risk of stock outage, while the manufacturer enjoyed a steady, predictable production load that reduced the manufacturing cost. King et al (1999) provided a prototype software to understand better the role of the manufacturing configuration and production planning and control system in supporting QR replenishment to retailing. They quantified the impact of the fabric supply system on the manufacturers' ability to meet retail orders. An analytical model was developed to understand optimal manufacturing planning and control policies under a variety of operating scenarios. More recently, in one study about capacity planning to optimize the profit in apparel manufacturers (Mohafiqul et al 2005), the authors dealt with the decision making of apparel firms regarding their capacity utilization during production by considering production facility as an asset to utilize in the future and using the News boy's approach (Morton 1971) to make decisions. The name of "News Boy" comes form the dilemma faced by a street corner newspaper vendor who must decide how much stock to buy from his supplier each day (Hunter et al 2002). Purchasing too little leads to lost sales while purchasing too much results in inventory obsolescence. The basic idea of this approach is to find the appropriate level such that the marginal cost of one more unit of inventory equals the marginal expected cost of lost sales .

All the above models dealt with the decision making problem of apparel firms regarding their capacity utilization during production by considering production capacity constraints. While research in the area of VMI is increasing, the problem of how the VMI replenishment strategy influences the manufacturers' production balance under the supply chain dynamics has received little work. Little empirical research studied how to integrate the VMI replenishment strategy with limited manufacturing capacity.

Waller et al (1999) examined the effect of VMI in environments with limited manufacturing capacity and partial channel adoption. The authors also reported that "suppliers are attracted to VMI because it mitigates uncertainty of demand. Infrequent large orders from buying firms force manufacturers to maintain surplus capacity or excessive finished goods inventory, which are very expensive solutions, to ensure responsive customer service. VMI helps dampen the peaks and valleys of production, allowing smaller buffers of capacity and inventory." They concluded that with the increase of the proportion of the VMI orders in the total number of production orders of a manufacturer, the production capacity utilization could be improved which contributed to stable manufacturing in the VMI strategy. This conclusion was that the replenishment cycle in the VMI strategy was much shorter than that in traditional manner, depending on the scenario. In other words, the improvement of the production utilization was caused by the shrinking of the replenishment cycle, rather than the VMI replenishment strategy itself. One of the shortcomings of this research was that the dynamic factors such as forecasting errors influencing the production balance of the apparel manufacturer under the VMI replenishment strategy was not considered in this model. In addition, no algorithms were proposed to improve or optimize the performance of the apparel supply chain in the dynamic apparel supply chain adopting the VMI replenishment strategy.

2.3 Summary

Having reviewed the literature of the relevant topics, the following remarks that inspire this research were derived.

The apparel supply chain has received considerable attention, along with the development of the QR strategy. Most of the past research in the apparel supply chain focused on the benefits of the retailers. It was shown that the manufacturers were under pressure from the retailers to change their manufacturing processes and search for an optimal production plan.

Various studies on simulation models in the apparel supply chain were reviewed. It was noted that a simulation model could provide a comprehensive supply chain modeling method with much more details than any other approaches do. However, these simulation models focused mainly on evaluating the performance of the QR strategy adopted in the apparel supply chain and the improvement observed. The effect of the manufacturers' decisions on different replenishment strategies with their retailers (lead time, replenishment cycle and replenishment quantities, etc) to satisfy the retailers is significant to the performance of the whole supply chain. Benefits could be obtained by developing a simulation model to investigate the relationship between the replenishment strategy of the apparel manufacturer and the apparel supply chain performance. The proposed simulation model can provide a tool for apparel retailers and manufacturers to better understand how their decisions on the replenishment strategy affect the performance of the apparel supply chain (*CSL* and *IT* of the retailers, *PCB* of the manufacturers) before actual business.

The benefit of the VMI replenishment strategy has been widely reported with its application in apparel SCM. The manufacturer takes the responsibility for the decisions such as determining the stock kept by the retailer and replenishment quantity delivered to the retailer. The performance of the supply chain is influenced by these replenishment decisions. However, the common phenomenon about the flexibility of the replenishment strategy by manufacturers having production capacity constraints has not been considered. Research on searching for optimal production and replenishment for apparel manufacturers to improve the performance of the supply chain was limited. Thus, the current exploratory research is undertaken in order to empirically examine and optimize the replenishment strategy in the VMI-based apparel supply chain.

CHAPTER 3

METHODOLOGY

In a VMI-based apparel supply chain, a replenishment strategy which includes the decisions of replenishment cycle, lead time and replenishment quantity significantly influences *CSL*, *IT* and *PCB* which are treated as the performance of a supply chain. Meanwhile, the uncertain factor such as forecasting error is also considered in the decision making process of replenishment. While the QR strategy mainly focuses on satisfying the retailers' *CSL* which causes the production capacity imbalance of the manufacturers, the VMI-based replenishment decisions made by manufacturers enable the decision makers to improve the manufacturers' production balance while keep the retailer's *CSL* at a certain level. The process for making decisions on the VMI-based replenishment strategy is complex. In this research, a simulation-based optimization replenishment model will be developed for the apparel supply chain adopting the VMI strategy in order to improve the *PCB* of the manufacturers while maintain the *CSL* of the retailers at a high level.

3.1 Overview

The steps for establishing a simulation-based optimization replenishment model in the VMI-based apparel supply chain are detailed as follows.

Firstly, a simulation model was designed to study the relationship between the replenishment strategy and the performance of the supply chain in a VMI-based apparel supply chain. After determining the critical performance and constraints in the apparel supply chain, a simulation program which simulated the process of the supply chain was then written. The development of the simulation software was assisted by the commercially available software MATLAB (Hanselman 2001). The simulation model was able to simulate the operations of the manufacturers, retailers and customers in the apparel supply chain under the VMI replenishment strategy. The fuzzy set theory was integrated into the simulation model in order to represent the forecasting error caused by the dynamic customers' demand. The influence of dynamic and uncertain customers' demand on the performance of the VMI-based apparel supply chain was identified and examined using the proposed simulation model. With data collected from the industry, sensitivity analyses on the relationship among the dynamic forecasting error, replenishment strategy and performance of the apparel supply chain was conducted. Based on the data collected from the industry, the output of the simulation model was generated which consisted of the replenishment strategy and performance index of the VMI-based apparel supply chain. Experimentations using real data collected from the reference sites for a feasibility study of the simulation model were conducted.

In the second part of the research, a simulation-based optimization model was derived to search for the optimal VMI replenishment strategy considering the constraints of the production capacity of the manufacturers. This proposed simulation-based optimization model for the VMI replenishment strategy was composed of two main parts, namely the simulation model and the optimization algorithms. The simulation model developed in the first part of the research was employed to simulate the supply chain process. Genetic algorithm (GA) was employed as the optimization algorithms in the simulation-based optimization model so as to generate an optimal replenishment solution for the decision makers in the apparel supply chain to improve the performance of the apparel supply chain. Validation of the simulation-based optimization model was undertaken by comparing the performance of the optimized model with that of the industrial practice. The architecture of the proposed simulation-based optimization replenishment model for the VMI-based apparel supply chain is illustrated in Figure 1-3.

The third part of this research is a detailed analysis of the factors which influence the performance of the VMI replenishment strategy both before and after optimization. The analysis is supported by full factorial experiments. The results of the analysis were expected to show implications on the replenishment strategy of the VMI mode for both academic research and industrial processes.

3.2 Simulation Model

Simulation models can provide a comprehensive supply chain modeling methodology considering the strategic, tactical, and operational elements with much more details than any other approaches do. By using simulation techniques, the performance of a supply chain model can be evaluated extensively and can be quantified, which can avoid subjective decision making (Chan et al 2005). In this research, a simulation model was designed for investigating the behavior and performance of the VMI-based apparel supply chain.

3.2.1 Overview of Simulation Model

Simulation has been so far used as a tool for supporting performance analysis of manufacturing and logistics systems since the primary work by Tocher et al (1960). The application examples are demonstrated in several publications such as Banks et al (2001), Brooks et al (2001) and Yao et al (2002). The strength of simulation is to enable users to observe and analyze the dynamic behavior in the target system, often different from mathematical programming methods. Simulation consists of building a representation of the real world and experimenting with it. The combination of model creation and experimentation enables designers and managers to “reproduce and to test different decision-making alternatives upon more possible foreseeable scenarios, in order to ascertain in advance the level of optimality and robustness of a given strategy” (Terzi et al 2004).

The important features included in a simulation model include “ability to experiment with the model by changing any part of it’ and ‘ability to collect a variety of statistics to measure the performance of the simulated system” (Brooks et al 2001). Its importance also lies in its ability to mimic the behavior of a real system through the creation of a model to represent the system and subsequent experimentations. Experimenting in real systems is seldom possible as it is both costly and time-consuming. However by experimenting with the confines of a model, important behavior and knowledge of a system can both be observed and learned. Simulation modeling therefore has the advantage of allowing the decision makers to test ideas in a virtual environment.

As stated in Pidd (1998), computer simulation involves experimentation on a computer-based model of the real system. The model is used as a vehicle for experimentation, often in a 'trial and error' way to demonstrate the likely effects of various policies. Thus, those which produce the best results in the model would be implemented in the real system. Figure 3-1 shows the basic idea.

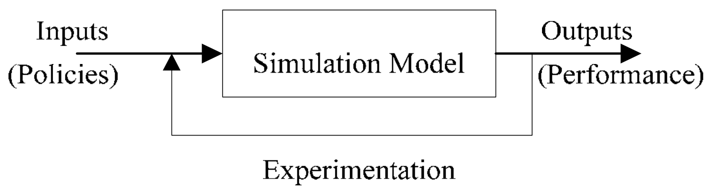


Figure 3-1: Simulation Model as Experimentation

Sometimes these experiments may be quite sophisticated, involving the use of statistical design techniques. This is due to the aspects of the real system being modeled changing from one occasion to the next in unpredictable ways. In other words, there is some inherent 'random' behavior in the system such that a given situation does not always 'play out' the same. These stochastic can be captured by computer simulation using the built-in statistical function. In most cases, the overall behavior of a variable characteristic in the long term can be described using a probability distribution. The simulation model can then simulate the characteristic by choosing a value at random from the distribution. The sampling of values at random from a distribution is done using random numbers (Brooks et al 2001).

3.2.2 Relevant Work of Simulation Model in SCM

Since the entities involved in the supply chain has complex interactions while the demand from the customers is stochastic, supply chain problems are often very large and complex to be addressed in analytical models. Even a few analytical models exist; they are often based on limiting assumptions. A simulation model was thus selected to investigate the supply chain.

The development of simulation models for understanding issues of supply chain decision-making has gained importance in recent years. A vast amount of literature presented applications of simulation into real world specific cases. Here are some examples.

In order to support designing SCM operations, generic simulation models were developed recently to represent business process activities in SCM (Schunk et al 2000; Wyland et al 2000; Chan et al 2001; Truong 2002; Hung et al 2004; Chan et al 2005; Umeda et al 2006). A few simulation models were developed to improve supply chain dynamics such as uncertain demand and external supply of raw materials with the presence of many supply chain players (Towill et al 1992; Petrovic et al 1998; Petrovic 2001). Another group of studies in the literature reported the benefits of the simulation tool designed to do business consultation from practitioners' viewpoint (Bagchi et al 1998; Heita 1998; Ingalls et al 1999; Koks et al 2003; Lee et al 2000).

Supply chain simulation has gained considerable attention and momentum in various industries. Some of the examples are electrical and communication equipment (Connor et al 1995; Persson et al 2002), food and related product (Vorst et al 2000; Weng et al 2003), automotive parts and accessories (Waller 2005). Among them, textiles and apparel industry has been one of the most important branches (Nuttle et al 1991; Hunter et al 1992; Hunter et al 1996a; King et al 1996; Nuttle et al 2001a; Nuttle et al 2001b; Raman et al 2002). Detailed review on the simulation model in the apparel supply chain is in section 2.2. However the simulation model developed in the apparel industry mainly focused on integrating resources for achieving QR. Little information can be obtained about how manufacturers evaluate themselves and benefit from these models. Studies concerning the role of the manufacturers who adopt the VMI strategy with the retailers in the apparel industry are also lacking.

3.2.3 Reasons for Using Simulation Model

To solve the replenishment problem in the VMI-based apparel supply chain, the manufacturers make decisions on the replenishment strategy between the manufacturers and the retailers in terms of different replenishment cycle, lead time, and the replenishment quantity to be shipped in each cycle. The replenishment problems have become more complicated owing to the interactions between the entities, the length of the supply chain, the lead times of manufacturing and shipping. A slight change of management strategy may affect the performance of the supply chain dramatically. Furthermore, the apparel supply chain is facing a series of dynamics both internally and externally such as the fluctuating production capacity and stochastic nature of customers' demand. These uncertain factors make the analyzing and evaluating of the supply chain performance more difficult. A powerful tool to help the decision makers test their decisions on the replenishment strategy and evaluate the outcomes of these decisions is simulation.

A simulation model is capable of capturing complexities of real-world large-scale multi-product, multi-echelon supply chain, presenting inherent features of activities in the apparel supply chain such as purchasing, manufacturing, inventory replenishment and order fulfillment. Simulation is a methodology that can be used to directly model the complexities of the entire supply chain without many assumptions.

In the replenishment model for the VMI strategy, the interactions between the individual factors are quite complicated. For instance, it is difficult to anticipate how the lost sales will be influenced by shortening the replenishment cycle from 2 weeks to 1 week and extending the lead time from 7 weeks to 8 weeks. Calculating the quantity of garments to be replenished to the retailer is also complicated since the customer service level must be maintained to a retailer-targeted degree while the IT is kept at a high level. To solve these problems, the decision makers should investigate not only the performance of an individual part, but also the system as a whole. Simulation is a tool that uses a system approach to tackle problems. The system approach of simulation is based on the fact that "even if each element or subsystem is optimized from a design or operational viewpoint, overall performance of the system may be suboptimal because of interactions among the parts" (Pegden et al 1995). With the simulation model, the significance of individual factors and the resultant consequences due to their interactions could be obtained.

3.3 Simulation-Based Optimization

It is typical that the simulation analysts and experts have to spend a considerable amount of time trying to change the original system searching for a good design and balancing several conflicting objectives simultaneously. In the proposed simulation model in this study, these conflicting objectives are production balance of the manufacturers, high customers' satisfaction, and low inventory for both manufacturers and retailers. The trial and error procedure can be avoided by coupling optimization techniques with the simulation of the supply chain (Fang et al 2003). Reviews of the current research on simulation-based optimization developments can be found in Carson et al (1997), Andradottir (1998), Fu (2002), Law et al (2002) and Tekin et al (2004).

3.3.1 Overview of Simulation-Based Optimization

This simulation-based optimization is an active area in the field of stochastic optimization. As stated in Law et al (2002), simulation-based optimization is “the orchestration of the simulation of a sequence of system configuration (each configuration corresponds to particular setting of the decision variables (factors) so that a system configuration is eventually obtained that provides and optimal or new optimal solution.”

The simulation-based optimization technique is a combination of simulation and optimization procedures with an iterative process behind it. As a first step, the structure or policies of the supply chain of interest can be optimized by using an optimization method; the optimized results are then arranged as the input to the simulation model. After that, the simulation experiments view its stochastic and dynamic behavior and feed back it to the optimization approach to continue its optimization process. This procedure will be continued until the final optimal solution is reached. The simulation-based optimization model is displayed in Figure 3-2.

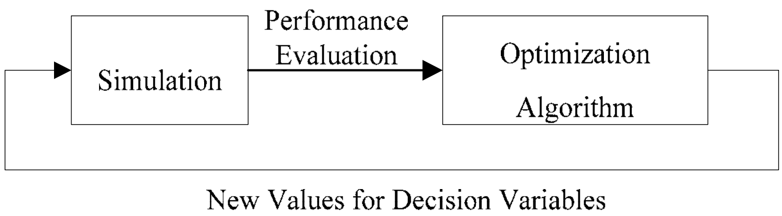


Figure 3-2: Simulation-Based Optimization Model

The output of the simulation model is used by an optimization algorithm to provide feedback on progress of the search for the optimal solution. This in turn guides further input to the simulation model.

As stated in Azadivar et al (1999) and Truong (2002), using simulation as an aid for optimization presents several advantages over conventional optimization:

- Complexity of the system being modeled does not significantly affect the performance of the optimization process.
- For stochastic system, the variance of the response is controllable by various output analysis techniques.
- Where structural optimization of system is considered, simulation provides an advantage that is often not possible in classical optimization procedures. Here, by employing appropriate techniques, the objective function or constraint can be changed from one iteration to another to reflect alternative designs for the system.

3.3.2 Relevant Work of Simulation-Based Optimization in SCM

A great deal of research has been conducted on the optimization of the supply chain with simulation for quite a long time since a good supply chain policy may improve the operational efficiency of enterprises and reduce their cost (Haddock et al 1987; Lee et al 2000; Lendermann et al 2001; Truong 2002).

In early research (Haddock et al 1987), the authors combined a simulation generator, output analysis technique and optimization procedure to consider a stochastic inventory control problem. The simulation-based optimization model was proved to be able to seek an optimal solution for the problem, simplify and accelerate the overall decision making process.

Lee et al (2000) created a supply chain model with multi-product, multi-stage, multi-production workshop and multi-distribution centre, in which the linear programming and simulation techniques are combined for optimizing its production plan and distribution plan. The cost model was created using linear programming; the objective function was the total cost of the supply chain while the constraints were production and distribution capacities. The purpose of this model was to reduce its inventory level based on the specified satisfactory index of customers. After simulation experiments, the production and distribution capacities were adjusted.

Lendermann et al (2001) suggested a new advanced framework of distributed simulation model for coordinated optimization of a supply chain with the capability of Advanced Planning and Scheduling (APS). This framework can be used for rapid optimization of total process and policies in a supply chain.

Truong (2002) applied simulation-based optimization into the supply chain configuration problem. A hybrid approach that combined Genetic Algorithm and an analytical algorithm was proposed to obtain optimal output of the supply chain.

In the apparel supply chain, Gokce (2002) developed a meta-heuristic-based optimization approach to seek for the optimal sourcing decision in several different apparel supply chains based on the simulation program. The results from the experiments showed some insights into the characteristics of the best sourcing practices in the apparel supply chain. It was concluded that for seasonal items in apparel supply chain, best performance could always be achieved by maximizing the number of reorders. Categorizing SKUs based on their volume and using a combination of presentation stock and target weeks of supply resulted in great improvement in the performance of the supply chain.

In the apparel supply chain adopting the VMI replenishment strategy, the optimization of the replenishment strategy may improve the performance of the supply chain and optimize the resources engaged in the apparel supply chain. Both the retailers and the manufacturers' benefits are considered simultaneously. So far, there is no simulation-based optimization model applied in this area.

3.3.3 Reasons for Selection of Simulation-Based Optimization

The proposed simulation model in this study is designed to describe and analyze the behavior of the apparel supply chain. It can mimic the customers' buying, retailers' stocking, and the manufacturers' replenishing for each SKU in the whole sales season.

The performance of the supply chain can also be evaluated by the simulation model through “what if” questions, such as “what will be the increase of IT if the replenishment cycle declines from four weeks to two weeks?” or “what will be the customer service level if the replenishment of 20% quantity be delayed two weeks due to the limitation of the production capacity in the manufacturers?”

However while simulation can help the decision makers understand better the supply chain, one of the disadvantages of simulation is that it is not an optimization technique but a What-If analysis tool. It is not sufficient when the question is the designing of a supply chain rather than evaluation of a given configuration.

In the replenishment problem in the apparel supply chain, practical problems facing the decision makers are those questions that may include complex combinations of inputs to the simulation model. For example, “how much of replenishment quantity could be delayed by two weeks to the retailer so as to satisfy the production capacity and what are their distributions of each SKUs?” or when there are two retailers to be supplied in VMI replenishment strategy, “which one to be satisfied when the demand and manufacture are in conflict and how to decide on the distribution of each SKU?” The decision makers might have such questions in mind in each replenishment cycle during the sales seasons when they adopt the VMI replenishment strategy.

It is very difficult to answer these questions using traditional search methods such as linear programming, differentiation, or gradient-based method. This is mainly because the simulation model proposed in this study is discrete and non-linear. A possible solution is to apply heuristic or computational methods. Several optimization algorithms can be applied in the general model presented in Figure 3-1. These optimization techniques can be categorized into two main domains based on the shapes of the response surface, namely global and local optimization. In the literature, ranking and selection, multiple comparison procedure, random search, Nelder-Mead simplex/complex search, Hooke-Jeeves pattern search and the single-factor methods were selected to optimize the discrete-parameter cases. For the continuous-parameter space case, response surface methodology, gradient-based methods (such as finite difference estimates, perturbation analysis, frequency-domain analysis and likelihood ratio estimators) and stochastic approximation methods were employed. The global search methods include the evolutionary algorithms (such as Genetic Algorithm (GA), Evolutionary Programming (EP) and Evolution Strategies (ES)), simulated annealing, tabu search , Bayesian/sampling algorithms and the gradient surface method (Tekin et al 2004). Several works have discussed the foundations, theoretical developments and applications of these techniques (Andradottir 1998; Deb 2001).

Among these optimization technologies, GA has been used in optimizing problems that arise in complex systems. In this research, GA was selected as the optimization technology to search for the optimal replenishment strategy. Details of the GA technology and the selection of GA in this research are described in section 3.5.

The simulation-based optimization model is proposed in this study so as to search for an optimal replenishment strategy in the apparel supply chain which adopts the VMI policy.

3.4 Fuzzy Set Theory Integrated into the Simulation Model

One of the tasks in the proposed simulation model in this research is to identify and investigate the influence of the dynamic and uncertain factors on the apparel supply chain performance and behavior. To address these uncertainties, one feasible tool is using the fuzzy set theory, one of the artificial intelligence (AI) techniques.

3.4.1 Overview of Fuzzy Set Theory

The fuzzy concept was initiated by Zadeh (1965). The fuzzy set theory provides a strict mathematical framework in which vague conceptual phenomena can be precisely and rigorously studied. It can also be considered as a modeling language well suited for situation in which fuzz relations, criteria, and phenomena exist. Details of the fuzzy set theory and its applications can be found in Taerno et al (1992), Klir et al (1988), and Zimmermann (2001).

A fuzzy set is a set without a crisp, clearly defined boundary. It consists of characteristic function which allows various degrees of membership for the elements of a given set. If X is a collection of objects denoted generically by x, then a fuzzy set $\tilde{A}$ in X is a set of ordered pairs:

$$\tilde{A} = \{(x, \mu_{\tilde{A}}(x)) | x \in X\} \qquad (3\text{-}1)$$

$\mu_{\tilde{A}}(x)$ is the membership function or grade of membership of x in $\tilde{A}$ to the membership space. A fuzzy set $\tilde{A}$ is characterized by its membership function $\mu_{\tilde{A}}(x)$, which maps each element of the universe X to the interval [0, 1]. $\mu_{\tilde{A}}(x)$ is a continuous function that indicates the degree to which each element belongs to the set. While a classical (crisp) set could be described using the member elements by using the characteristic function, in which 1 indicates membership and 0 non-membership, a fuzzy set could be represented using the membership function which is a continuous function with range [0, 1].

In fuzzy logic, the propositions are fuzzy propositions which are represented by fuzzy sets. The ultimate objective of the fuzzy logic is to provide the foundations for approximate reasoning with imprecise propositions using the fuzzy set theory as the principal tool. This is analogous to the role of quantified predicate logic for reasoning with precise propositions (Klir et al 1988).

Since its inception, the fuzzy set theory has advanced in a variety of ways and in many disciplines. Fuzzy set theory provides an alternative and a convenient framework for handling uncertain parameters (e.g. forecasting error caused by dynamic customers' demand), while there is a lack of certainty in data or even a lack of available historical data. According to Zadeh (1965), the possible range of a parameter and the most plausible value within that range can often be estimated and specified by experts (Wang et al 2005). This estimation is simpler than asking managers to design a probability function. They only need to estimate the values that do or do not belong to its domain (fuzzy set). Therefore, it is easy to be defined to handling uncertain parameters. Applications of this theory can be found, for example, in artificial intelligence, computer science, control engineering, decision theory, expert systems, logic, management science, operations research, pattern recognition, and robotics (Zimmermann 2001).

3.4.2 Relevant Work of Fuzzy Set Theory in SCM

There were a number of studies applying the fuzzy set theory under uncertainty in SCM in the past. A series of relevant research can be found in Petrovic et al (1996, 1998, 1999, 2001). The authors addressed uncertainties associated with customers' demand, supply deliveries along the supply chain and external or market supply by vague and imprecise phrases. Petrovic et al (1996) applied the fuzzy set theory to models for the newsboy problem. Sources of uncertainties inherent in the external environment, namely customer demand and external supply of raw material, were also identified and modeled using the fuzzy concept (Petrovic et al 1998). Interpreting and representing those uncertainties by fuzzy sets, a supply chain fuzzy model was developed to determine the order quantities at each inventory level in the supply chain (Petrovic et al 1999). A special purpose simulation tool was developed to analyze the supply chain behavior and performance in the presence of uncertainty (Petrovic

2001). Multi-criteria ranking of inventory replenishment policies was devised in the presence of uncertainty in customers' demand (Petrovic et al 2001).

Some other researchers also addressed the uncertainties in the supply chain with fuzzy concepts. Vujosevic et al (1996) considered the EOQ formulation with the imprecisely estimated inventory cost. Defining the imprecise parameters by fuzzy umbers, the approaches to determine the optimal order quantity in a fuzzy environment was developed. Giannoccaro et al (2003) presented a methodology to define a supply chain inventory management policy, which was based on the concept of echelon stock and fuzzy sets theory. More recently, Wang et al (2005) developed a fuzzy decision technique to determine the order-up-to level of SKUs in the supply chain to minimize the inventory cost and fulfill the target fill rate of finished product (Wang et al 2005).

In the textiles and apparel industry, little research has been conducted on the study of supply chain behavior and performance using fuzzy logics. Nuttle et al (2001a, 2001b) proposed a soft computing guided simulation system to provide a vehicle for soft goods supply chain modeling, analysis, and optimization incorporating the uncertainties and imprecision inherent in real system. Fuzzy logic was employed into the simulation model so as to identify whether the specific management goals (such as "we want customer service to be HIGH and inventories to be LOW") were obtained. In Fang et al (2003), a mixed integer fuzzy linear programming model was established to allocate fuzzy ship capacity to meet customers' specified due-dates in a textile supply chain. Here, the fuzzy set theory was engaged to model and capture the imprecision inherent in ‘ship capacity’ and the customers’ specified due-dates in terms of the tolerance level.

However, most of the previous research concentrated only on applying the fuzzy set theory to inventory control in SCM. Studies investigating the uncertain customers’ demand and fuzzy forecasting error in a supply chain which greatly influences the replenishment strategy in a dynamic fashion business are limited.

3.4.3 Reasons for the Selection of Fuzzy Set Theory

The supply chain simulation model can explain and deal with the uncertain factors and the model should be able to express the dynamic behaviors during the simulation run. In the proposed apparel supply chain replenishment simulation model, forecasting error, which is caused by demand uncertainty, is one of the most critical factors affecting the performance of the supply chain. Demand uncertainty can result in over- or under-production, leading to excessive inventories or inability to meet customer needs, respectively (Jung et al 2004).

To study the uncertainties systematically, two methodologies were applied to the supply chain modeling. Some researchers addressed the uncertainties using stochastic models; one of the pioneering works dealing with the stochastic nature of the supply chain was Midler (1969). In these models, the analysts usually transferred those uncertain factors into probability distribution of corresponding random variables based on past records; examples see Federgruen (1993) and Porteus (2002). However the distribution of random variables may not be obtained in the modeling process usually due to the difficulties in collecting data.

It is natural that the uncertain factors are expressed by using some inaccurate language. The reason is that there exists a need to handle different sources and kinds of uncertainties, particularly the uncertainties in judgment, and lack of evidence. In such cases, it is convenient to express uncertainties in parameters using various imprecise linguistic terms, such as “Customers’ demand is about d_m, but definitely not less than d_l and not greater than d_u”, and so on (Petrovic et al 1998). The possible range of a supply chain parameter and the most plausible value within that range can often be estimated and specified by experts.

Therefore, the fuzzy set theory, due to its conceptual and computational simplicity as a useful tool to represent approximate qualifier that corresponds to these natural language expressions, may be more appropriate to be selected for handling the uncertainty factors in the apparel supply chain model.

3.5 Genetic Algorithm (GA) for Optimization of Replenishment Strategy

Rapid developments in computing and soft technologies have given rise to the development of different types of new optimization methods. In contrast with the exact and deterministic traditional mathematical methods (for instance, linear programming, dynamic programming and gradient-based methods), genetic algorithm (GA) is a stochastic search technique. It can obtain good solutions after a number of iterations when there is sufficient computing power.

3.5.1 Overview of GA

GA is an attempt to simulate Darwin's Theory of Evolution. Darwin stipulated that more favorable characteristics in an individual would increase the individual's chance of passing those favored characteristics to the next generation via reproduction. The important struggle for life filtered out the weaker individuals and fitter individuals survived to pass on their genes to the next generation. The fitness of the population increased over the generations as individuals inherited the favored designs of their ancestors. It was recognized that this could be a very useful technique into the computer-based directed random searches (Holland 1975). Comprehensive descriptions of the concepts and techniques in genetic algorithms are presented in Goldberg (1989) and Davis (1991).

GA starts with a population of chromosomes which represents potential solutions to a problem. In real-life application, a population pool of chromosomes is installed and set initially. This can be done either randomly or by seeding. Once the initial population is generated, each individual is evaluated using the objective function. To generate the next generation, a subset of the population is selected as parent. A probabilistic selection is performed such that the fittest individuals have higher priority to be selected into the subset of the next generation. New population is generated from the parents using genetic operator. The two basic types of the genetic operators are crossover and mutation.

Through crossover, a random position on the string is selected and the segments either to the right or to the left of this point are exchanged with another string sectionalized similarly. The reproduction mechanism with crossover causes the best scheme to proliferate in the population by combining and recombining to create high quality combinations of scheme on a single chromosome. GA creates new generations of improved solutions by this reproduction mechanism in which parents that have higher fitness ratings are having greater probability to be contributors. The crossover rate, which is the ratio of the number of offspring produced in each generation to the population size, controls the expected number of chromosomes to undergo the crossover operation. Mutation operator produces spontaneous random changes in various strings by changing one or more genes. The mutation rate, which is the percentage of the total number of genes in the population, controls the rated at which new genes are introduced into the population for trial. The operations of crossover and mutation are conducted randomly.

The differences between GA and the traditional optimization search techniques were summarized in Goldberg (1989). Firstly, GA works from a population of strings, climbing many peaks in parallel; thus, the probability of find a false peak is reduced over methods that go points to points. Traditional methods usually start on a single solution, and keep iterating sequentially to other solutions. GA also does not require any auxiliary information such as derivatives in gradient techniques to work. GA only requires the fitness (objective function values) associated with individual strings. The basic procedure of GA is explained in Figure 3-3.

Let P(*g*) and C(*g*) be parents and offspring respectively in the existing generation *g*
g=0, initialize a population of chromosomes P(*g*) ;
Evaluate P(0);
g=1;
Recombine P(*g*) to generated C(*g*);
Evaluate C(*g*);
select P(*g+1*) form P(*g*) and C(*g*);
g=*g+1*;
Repeat steps of Recombination, Evaluation and Selection until some termination is reached;
Report best solution found.

Figure 3-3: Basic Procedure of GA

3.5.2 Relevant Work of GA in Supply Chain Management (SCM)

Recently, some researchers successfully used GA on the optimization problems in SCM simulation models. The optimization using GA mainly focuses on two domains. One is the optimization of the performance of a system. For example, Dengiz et al (1997) optimized an (s, S) periodic review inventory control system with stochastic lead time by GA. The result of the optimization with GA was compared with that of exhaustive search and random search method. It was reported that GA performed better than random search. Disney et al (2000) described a procedure for optimizing the performance of an industrially-designed inventory controls. GA was designed to optimize the system performance via determining the weight of appropriate “benchmark” performance characteristics. Ding et al (2004) proposed a simulation-based multi-objective optimization method for joint decision-making on strategic souring and inventory replenishment. A multi-objective genetic algorithm was developed to determine the optimal supplier portfolio and inventory control parameters in order to reach best compromise of the two conflicting criteria: costs and demand fill rate.

Another group of researchers applied GA in the field of testing or fitting of quantitative models in SCM. For instance, Azadivar et al (1999) proposed a simulation optimization method for optimizing the qualitative variables and the structure of a supply chain, such as the number of machines in a station or the in-process inventory. A GA method was suggested by the authors to continually generate the satisfactory solution to the selection of the structure of the model. It was reported that GA outperformed random search on three sample problems. GA also consistently achieved a larger fraction of the possible improvement at iteration.

However there is no research on using GA in the optimization of the replenishment strategy in the apparel supply chain.

3.5.3 Reasons for Using of GA

The optimization of the VMI-based replenishment strategy in the apparel supply chain considered in this research is complex. The optimization of the replenishment strategy includes a set of decisions to be considered each time before the replenishment is made to the retailers. These decisions include whether shifting the surplus part of replenishment quantity to the contiguous cycle, the percentage of surplus replenishment quantity to be shifted to the contiguous cycle, and the directions to be shifted (replenish the surplus part of garments in advance or delay the replenishment of garments) at each replenishment cycle. In order to ensure the practice of the proposed optimization model, this research considers the multiple retailers to be provided garments by the manufacturers under the VMI replenishment strategy. In such circumstances, apart from the above decision parameters, the parameters to be determined include the priorities of different retailers to be replenished when the production capacity of the manufacturers is less than the requirement from the retailers. All these optimization decisions of the replenishment quantities are made among contiguous replenishment cycles. In other words, in each replenishment cycle, parameters to be determined are not only for this replenishment cycle, but several contiguous cycles, for instance, three contiguous replenishment cycles. This optimization procedure is repeated for all replenishments until the end of the sales season. The size of the solution is therefore large and the solution space for the optimized replenishment strategy is not easy to search. Many solutions could be used for the optimization of the replenishment strategy, but it is difficult and time-consuming to achieve the optimal solution.

Over the past years, many researchers have proven that GA is more efficient than other optimization and search techniques for computationally complex problems. The operation research committee has reviewed the five meta-heuristic search techniques, namely simulated annealing, genetic algorithm, tabu search, target analysis, and neural network and concludes that they all have great potential to handle the real-life optimization problems (Operation Research Committee, 1988). This family of methods uses, in fact, a hyper-neighborhood technique on a population of solutions instead of on a single solution. Michalewicz (1996) compared the differences among hill-climbing search, random search and genetic search. GA is shown to be a class of general-purpose search method which combines the elements of directed and stochastic search. It can make a balance between the exploration and exploitation of the search space. The disadvantage of other two search strategies, hill-climbing search and random search, was either having the problem of only exploiting the best solution for possible improvement or exploring the search space. The comparison of GA and other search techniques was also reviewed in Tekin et al (2004).

Unlike other optimization techniques, Genetic algorithm (GA) does not make strong assumptions about the form of the objective function (Michalewicz 1996). Whereas traditional search techniques use characteristics of the problem (objective function) to determine the next sampling point (e.g. gradients, linearity, and continuity), the next sampling point in GA is determined based on stochastic sampling/decision rules, rather than a set of deterministic decision rules. Therefore, so far as the minimal requirement of the evaluation function is satisfied, many forms of the evaluation function could be employed (e.g. the simulation results of a supply chain model). This minimal requirement of the evaluation function is its ability to map the population into a totally ordered sets.

In complex problems such as the replenishment strategy in the supply chain, it is usually difficult to define one function form for measure of goodness for the solution. Therefore, evaluation functions of many forms can be used; for instance, the simulation result on performance of the supply chain such as *CSL* and *PCB* in replenishment strategy could be defined as the evaluation functions of GA. Although GA usually relies on some sort of functional form to evaluate each individual, there have been a few successful applications that used GA for simulation optimization of SCM or manufacturing systems in recent years. For example, a general framework was proposed in Tompkins et al (1995) for applying a combination of GA and discrete simulation model into a complex system with qualitative variables. It was shown that GA created a robust tool and is very promising for qualitative and structural, strategy decision variables. Other examples could be found in Azadivar et al (1999) and Gokce (2002).

One difficulty for the optimization in this study is the complexity of the evaluation of the performance of the replenishment strategy. Each one of the solution vectors has to be evaluated using the simulation program, which is time-consuming. Therefore, the large solution space should be explored efficiently. Moreover, the simulations for the solution vectors are performed in a rolling horizon. To generate the optimized replenishment strategy for each replenishment cycle, the optimization algorithms are repeated in each replenishment cycles until the end of the sales season. The efficiency therefore is significant to the performance of the algorithm.

In summary, GA offers a more efficient search technique suitable for large combinatorial problems, and is capable of connecting with a stochastic simulation program to evaluate the performance of the possible solutions.

3.6 Summary

In this chapter, a simulation model and a simulation-based optimization model applied for the optimization of the replenishment strategy in the VMI-based apparel supply chain were proposed. Two techniques (fuzzy set theory and GA) engaged into the simulation model were evaluated for solving the problems encountered in the simulation model. The related works for both the simulation-based optimization methodology and the techniques in SCM were reviewed. It was concluded that no studies have been done to date on the replenishment strategies in the apparel supply chain which adopted the VMI mode between the retailers and the manufacturers. The reasons for the selection of the research methodology and the technologies were described after analyzing the research problem. The simulation model could investigate the dynamic apparel supply chain as a whole system and the simulation-based optimization model was appropriate to solve the complex replenishment problem in the VMI-based apparel supply chain. The fuzzy set theory could be integrated into the model so as to represent the forecasting uncertainties occurred in the model. GA was selected to be the search algorithm in the optimization model.

CHAPTER 4

VMI-BASED APPAREL SUPPLY CHAIN REPLENISHMENT SIMULATION MODEL

In this chapter, a simulation model adopting the VMI replenishment strategy is developed which links the manufacturer, the retailer and the customer in the apparel supply chain. The purpose of this simulation model is to generate appropriate replenishment strategies to satisfy the customer's demand in the VMI-based apparel supply chain. With the use of data from the industry, the simulation model was experimented and the process of the simulation validated.

4.1 Problem Analysis

In the apparel supply chain, high level of customer service is one of the important objectives for success. To maintain the expected customer service level (*CSL*) at a certain level, the decision on replenishment strategies, including lead time, replenishment cycle, replenishment quantity between the retailer and the manufacturer is critical.

It is difficult to anticipate the outcome of a given change in these replenishment strategy decisions. Experimentation is seldom possible as it is both costly and time-consuming. To plan for unexpected outcomes, retailers and manufacturers must test and evaluate the outcomes of their decisions. Most of the studies in the literature on apparel supply chain discussed the use of analytical models to analyze the performance of the supply chain (Hamnant et al 1999; Abernathy et al 2000; Kincade et al 2001; Romano et al 2001; Lee et al 2003). Attempts to use analytical models usually require simplified assumptions. The solutions so obtained are likely to be inferior or impractical for implementation. In such instances, one alternative form of modeling and analysis available to decision makers is simulation. The development of simulation models for understanding issues of supply chain decision-making has gained importance in recent years (Brooks et al 2001; Shapiro 2001; Simchi-Levi et al 2003).

In this chapter, a simulation model to simulate the process of an apparel supply chain adopting the VMI replenishment strategy between the manufacturer and the retailer is proposed. This study concentrates on a two-echelon supply chain that consists of three main members: the customer, the retailer and the manufacturer. The objective of the replenishment simulation model is to generate a feasible replenishment strategy with recommended lead time, replenishment cycle, and replenishment quantity based on the CSL_t targeted by the retailer, and other pre-defined parameters, such as length of the sales season, sales forecast and the pre-defined forecasting error. The performance of each replenishment strategy is reflected by the value of predicted *CSL* and *IT*. Based on the simulation model, the relationship between the different forecasting error and various significant variables in an apparel supply chain, such as the *CSL*, the replenishment cycle, the lead time from the order release to the receipt of products by the retailer will be studied. The proposed simulation model, thus, provides a tool for apparel retailers and manufacturers to search for different replenishment strategies which are feasible to achieve the required *CSL* in the VMI-based apparel supply chain.

In the following sections, the relationship between *CSL* and replenishment strategies is firstly discussed. The simulation structure, development progress and replenishment algorithm are then introduced. Experiment results and process validation are finally presented with actual data from the industry.

4.2 Relationship between Customer Service Level (*CSL*) and Replenishment Strategies

Customer Service Level (*CSL*) is a term used in SCM. It represents the percentage of customers' demand being satisfied during the whole sales season. There are two methods to calculate the *CSL*. One is to calculate the in-stock of SKU percentage, and the other the out-of-stock of SKU percentage. In-stock means a certain SKU that customers want to buy is available when he/she comes to the shop while out-of-stock means the particular SKU is not available. However, being out of stock for one SKU does not necessarily decrease the *CSL* in a particular period if there was no demand for that SKU during that period (Lowson et al 1999). The out-of-stock situation is thus employed to measure the *CSL*, because the out-of-stock percentage is more important than the in-stock percentage. In the replenishment strategy simulation model, the variable CSL is calculated as follows:

$$CSL = (1 - \frac{sum\,of\ out\,of\ stock}{sum\,of\ actual\,demand\ of\ the\,customer})*100\% \tag{4-1}$$

In general, there are four factors influencing the variable CSL, namely, actual customers' demand (C_d), sales forecast (S_f), length of the sales season (S_S) and the replenishment strategy (R_s). The relationship between the retailer's CSL and the influential factors can be denoted by the following equation:

$$CSL = f_1(C_d, S_f, S_S, R_s) \tag{4-2}$$

The replenishment strategy (R_s) includes the replenishment algorithms (R_a), the replenishment cycle (RC), the lead time between the order released by the retailer and the receipt of products by the retailer (LT), the reliability of the replenishment (R_r) and the minimal order quantity for each SKU (L_q). Two assumptions are set in this model. Firstly, the manufacturer is supposed to be a 'capable' vendor that the replenishment quantity calculated to satisfy the customers' demand can be manufactured on time. Secondly, there should be no limitations on minimum quantity for each SKU. Equation 4-3 shows the relationship between R_s and its relevant factors.

$$R_s = f_2(R_a, RC, LT) \tag{4-3}$$

In the proposed simulation model, the actual customers' demand (C_d) is represented by sales forecast (S_f) and the error due to the difference between sales forecast and actual demand (F_e). That is,

$$C_d = f_3(S_f, F_e) \tag{4-4}$$

Linking Equations 4-2, 4-3 and 4-4 together, the variable CSL in the proposed simulation model is represented by Equation 4-5.

$$CSL = f_4(S_f, F_e, R_a, LT, RC, S_s) \tag{4-5}$$

4.3 Structure of the Simulation Model

Figure 4-1 illustrates the structure of the simulation model. Based on the CSL targeted by the retailer CSL_t, and other pre-defined parameters, such as the length of the sales season, the forecasted sales and the pre-defined forecasting error, a number of replenishment alternatives as well as the corresponding performances of the replenishment strategies will be generated by the model after applying the replenishment algorithm to be described in upcoming sections.

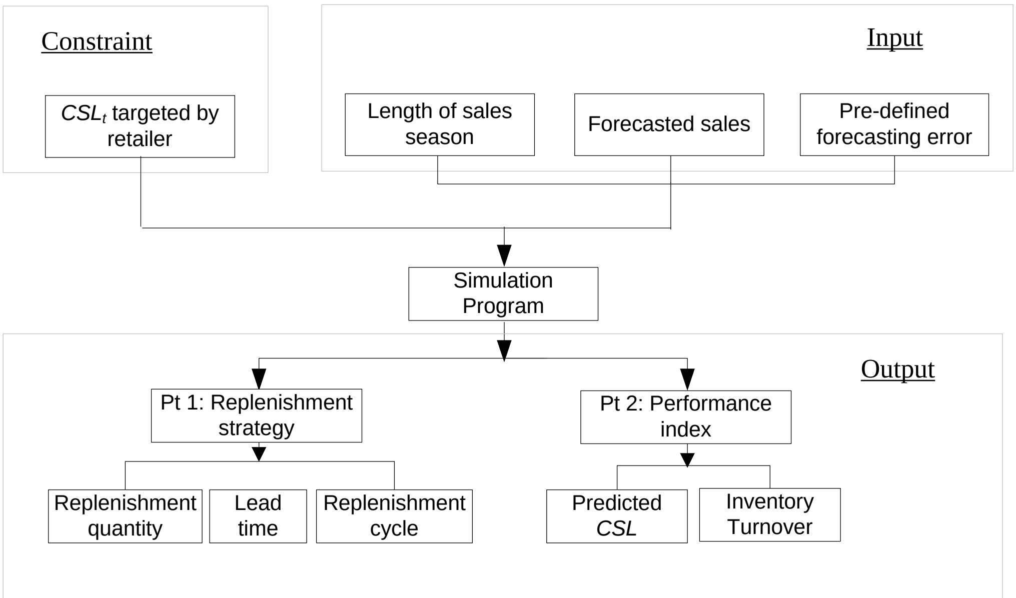


Figure 4-1: Structure of the Simulation Model

4.3.1 Constraint and Input of the Simulation Model

CSL_t targeted by the retailer is set as the constraint of the simulation model, which means the replenishment strategy generated by the simulation model should satisfy the CSL_t. A set of parameters in terms of length of the sales season, forecasted sales and pre-defined forecasting error are set as the input of the simulation model. Forecasted sales estimated by the retailer include the forecasting on total volume, SKU distribution and seasonality distribution. The SKU distribution is composed of distribution on style, color and size.

The pre-defined forecasting error is estimated by the retailers based on their experience. It is divided into volume error, SKU mix error and seasonality error. Specifically, the volume error is defined as total quantity error for all the SKUs between sales forecast and actual customers' demand in the whole sales season. SKU mix error is one that shows the difference between the actual distribution of style, color and size of the garments and the forecasted ones (Lowson et al 1999). Table 4-1 shows one example of mix color error.

Table 4-1: Example of Color Error

SKU (color)	Color 1	Color 2	Color 3	Color 4	Color 5
Forecasting distribution(%)	30	10	25	10	25
Actual demand distribution (%)	33	8	22	15	22
Absolute error(%)	3	2	3	5	3
Color error (%)	16				

In order to investigate how the different degrees of forecasting error contribute to the performance of the apparel supply chain, three degrees of pre-defined forecasting error are input to the simulation model. These degrees are high, medium and low. Among them, the medium error is estimated by the retailer. The high and low degrees of forecasting error are set as 50% higher and 50% lower of the medium error respectively.

4.3.2 Output Generated by the Simulation Model

The output generated by the simulation model consists of two parts, namely the replenishment strategy including the lead time, replenishment cycle, replenishment quantity and the performance index including the IT and predicted CSL.

1) Replenishment Strategy: The replenishment strategy in the output includes lead

time, replenishment cycle and replenishment quantity.

2) Performance Index: Based on the input parameters and the replenishment strategies, the proposed simulation model will generate the predicted CSL and IT.

In the two-echelon VMI-based apparel supply chain, CSL, IT of the retailers and the PCB of the manufacturers are significant performance indices of the replenishment policy. In this chapter, since the production capacity of the manufacturer is supposed to be sufficient enough to satisfy the customers' demand, the performance of the PCB is not considered here.

CSL is important for retailer's success, it reflects the customers' satisfactory of the retailer. CSL is one of the major factors influencing the profits of the retailer. In the overall performance of the two-echelon apparel supply chain, CSL is not the only factor which determines the supply chain performance. With high inventory held by the retailer, although the CSL may be improved, it also results in lower IT. The profit of the retailer will decline. Therefore, the simulation model developed in this study considers these two factors as the performance indices simultaneously. The IT is defined as:

$$IT = \frac{Annual \quad Sales}{Average \quad inventory \quad level} \tag{4-6}$$

4.3.3 Simulation Procedure

Figure 4-2 illustrates the procedure of the proposed simulation model. The simulation procedure is explained below:

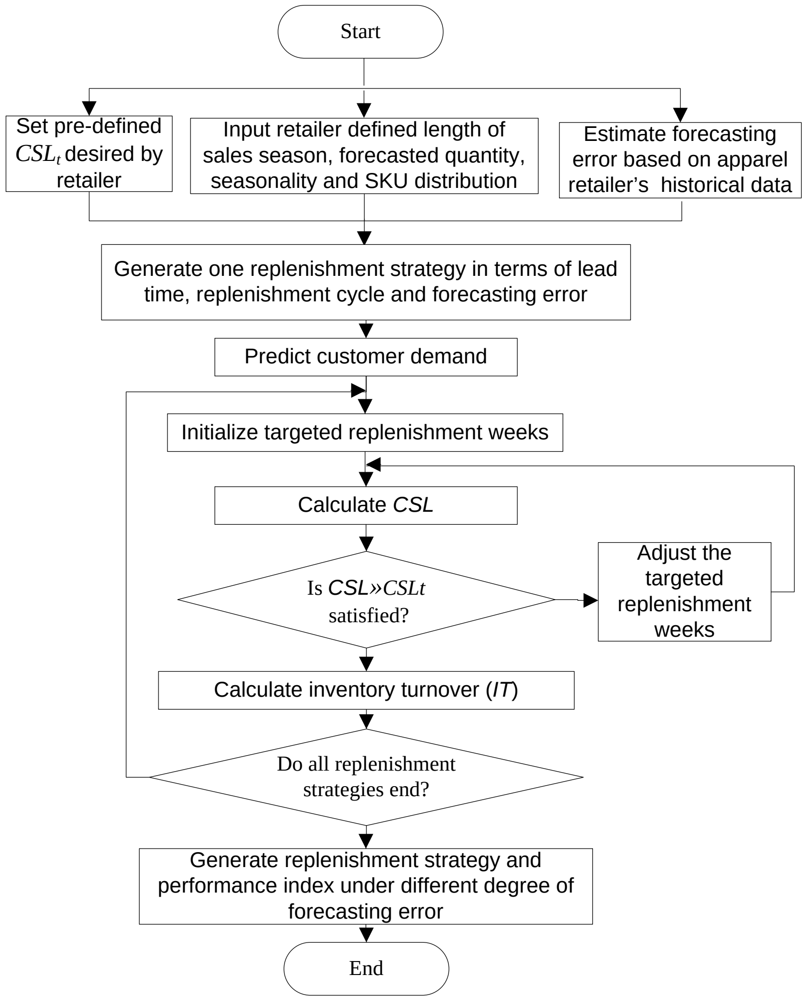


Figure 4-2: Flow Chart of Simulation Procedure

1) The retailer targets the CSL_t which is regarded as the constraint of the simulation model.

2) The retailer forecasts sales, including the total volume of garments, seasonal

distribution pattern of the sales forecast and the mix proportion of the garments in terms of style, color and size before the sales season. Approximate forecasting error at medium degrees is also estimated by the retailers based on their experience and subjective assessment. The low and high degrees of forecasting error is calculated as 50% lower and 50% higher of the medium error respectively.

3) The simulation generates a series of replenishment strategy in terms of lead time (LT) and replenishment cycle (RC). For each set of replenishment strategy with different degrees of forecasting error, the simulation procedure proceeds as follows:

a) Predict the customers' demand based on both the sales forecast and the forecasting error obtained in step 2 using Equation 4-7. Equation 4-7 denotes the relationship among forecasted sales S_f, actual customers' demand C_d and forecasting error F_e in which C_d and F_e are functions of time series and S_f is a constant predicted by the retailer before sales season. Both the sales forecast and forecasting error are in terms of total quantity of garments, seasonal distribution pattern of the sales and the mixed proportion of the garments.

$$C_d = S_f + F_e \tag{4-7}$$

b) Distribute the forecasted sales (obtained in step 2) and predicted customer demand (generated in step a) to each SKU in the sales season based on the SKU distribution and seasonal distribution pattern. Both the forecasted sales and the customers' demand for each SKU in each week of the sales period therefore are obtained.

c) Initialize the replenishment quantity using replenishment algorithm for all SKUs. The replenishment algorithm is based upon the idea that the retailer should hold inventory to meet the demands expected in the upcoming weeks. These upcoming weeks at least include the gap between the week when replenishment order released from the manufacturer and the week when the next replenishment arrives at the retailers. To overcome the demand's fluctuation, the retailer also keeps inventory to cover extra weeks of customers' demand which is called 'safety stock'. The more safety stock the retailer keeps, the higher the probability that the customer can purchase the SKU she/he wants. However, the inventory cost will increase. In general, the length of upcoming weeks is equal to the sum of lead time (LT), replenishment cycle (RC) and week of safety stock (W_{ss}). Thus, ($LT + RC + W_{ss}$) is used to denote the targeted replenishment weeks. Detailed descriptions of the replenishment algorithm can be found in section 4-4. Since the ideal situation is that the retailer needs not to keep any safety stock, targeted replenishment weeks is set as the minimal value which means W_{ss} is initiated as zero at the beginning of the simulation procedure.

d) Simulate the purchase of customers, track the inventory for each SKU, record the sales as POS data and replenish goods from the manufacturer based on the replenishment algorithm. These procedures are simulated on a weekly basis in the sales season as follows:

In the first week, the retailer keeps targeted replenishment weeks of stock based on the sales forecast. If the particular SKU the customer wants is in-stock, POS data increases and the inventory of this particular SKU decreases by one; otherwise, a lost of sales is recorded. This purchasing procedure repeats for all customers' demand in the first week. At the end of the first week, the POS data, the in-stock SKU, and the lost sales for each SKU are recorded. Replenishment quantity for each SKU is calculated using replenishment algorithms if a new replenishment is activated. This replenishment will arrive at the retailer after LT weeks. In the next week, add the new arrived garments to the inventory of the retailer if a new replenishment arrives. Repeat step d until the end of the sales season.

e) Calculate CSL using Equation 4-1.

f) If the calculated CSL is less than the targeted CSL_t, gradually increase replenishment quantity for all SKUs in terms of targeted replenishment weeks (i.e., increase the value of W_{ss} gradually) and repeat steps d-e until the CSL_t targeted by the retailer can be achieved.

g) Calculate the IT under the circumstance using Equation 4-6.

4) The simulation procedure repeats step 3 for all sets of replenishment strategies at all degrees of forecasting error and generates replenishment strategies and performance index under different degrees of forecasting error.

4.4 Replenishment Algorithm

Traditionally, the replenishment policy was controlled by the retailer. With the POS data and other information shared with the manufacturer, many retailers in the apparel industry accept VMI strategy now.

The VMI-based replenishment algorithm is based upon the idea that the retailer should hold inventory to meet the demands expected in the upcoming weeks. These upcoming weeks at least include the gap between the week when replenishment order is released and the week when the next replenishment order goods arrive at the retailer. Figure 4-3 shows an example of replenishment. At the beginning of the sales season, the retailer holds inventory to cover the demand before the first in-season replenishment arrives at the retailer. At the end of the first week, the first in-season order is released. It should cover the demand before the second in-season replenishment arrives. This covered period can be denoted as ($LT + RC$) weeks. In the example shown in Figure 4-3, the period covers (2+9) weeks. The replenishment is repeated every two weeks.

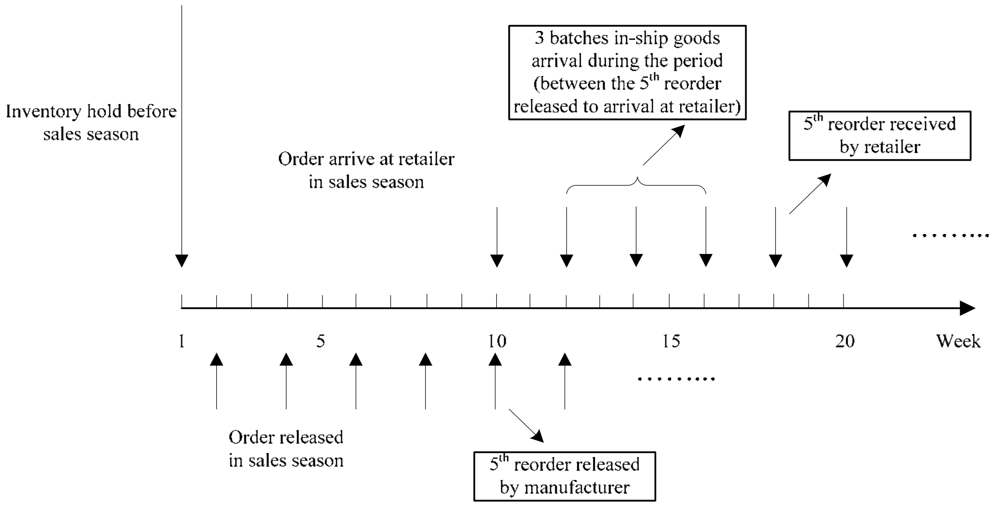


Figure 4-3: Example of Replenishment (RC =2 weeks, LT =7 weeks)

4.4.1 Safety Stock

To overcome the unexpected customers' demand, the retailer may keep several weeks' extra inventory to satisfy the fluctuation in demand. It is called 'safety stock'. The safety stock is carried forward to overcome the uncertain customers' demand. Figure 4-4 shows the safety stock to overcome fluctuation in customers' demand. The dashed line is an ideal inventory when the customers' demand is supposed to be same as the forecasted ones. The inventory kept at the beginning of the sales season is sold out exactly when the first in-season replenishment arrives. After that, each replenishment equals to the demand in the next two weeks. Therefore, no safety stock is needed.

However owing to the fluctuation in customers' demand, the actual requirement of customers may exceed the forecasted ones. The solid line in Figure 4-4 demonstrates this phenomenon. Even the retailer has prepared 10-week demand (Here 10 weeks includes 9 weeks of lead time and 1 week of initial week which means that the in-season replenishment starts at the end of the first week) based on the sales forecasting before the first in-season replenishment, the solid line declines faster than the dashed line. Therefore, to maintain the CSL at a certain value, safety stock is required; otherwise, more lost sales may occur and thus CSL may decline. In Figure 4-4, the safety stock is denoted in a dash dotting line (In practical case, the safety stock is dynamic.). The more safety stock the retailer keeps, the higher the probability that the customer will get the SKU he or she wants. However the inventory cost will increase. One difficult task for the supply chain manager is how to keep the least safety stock while the customer's demand is satisfied at the desired level.

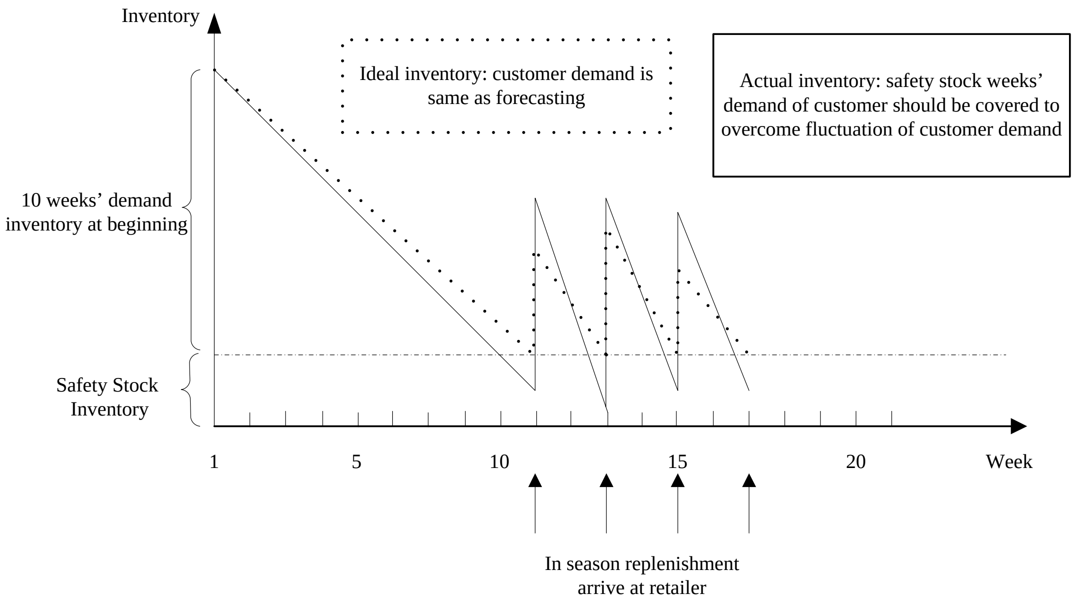


Figure 4-4: Safety Stock to Overcome Fluctuation in Customers' Demand

The safety stock defines the number of units expected to be sold over the next W_{ss} weeks. In other words, safety stock in terms of weeks (W_{ss}) should be available to overcome the fluctuating customers' demand which means the store is supposed to stock at least W_{ss} week's demand on hand. The methods to determine the W_{ss} employed in the proposed replenishment strategy simulation model are discussed as follows.

Few studies in the literature investigated the safety stock for basic goods in the apparel industry. As stated in (Lowson et al 1999), the replenishment algorithms will "attempt to maintain a 'target' inventory in each SKU equivalent to K_{DC} weeks of supply." Here K_{DC} has the same meaning as W_{ss}. One weakness of their model is that they set the K_{DC} as a fixed number during the whole sales season. This is not feasible for the supply chain since the demand from the customer is dynamic. The sales season in the VMI-based apparel supply chain is comparatively long; there are usually peak sales during the promotion and holidays. It is not surprising that with a static week of safety stock, the inventory in a peak season is not sufficient while the same safety stock in most residual weeks during the sales season has surplus to meet the customers' demand. An algorithm to generate dynamic DW_{ss} instead of the static one SW_{ss} is therefore proposed in this section. The method starts form the static DW_{ss}, and then moves to the implementation of the dynamic one.

The replenishment algorithm issues the orders attempting to maintain inventory to satisfy the next W_{ss} weeks of demand. As described in section 4.1.3, the static SW_{ss} will be set from 1 week at the beginning for each set of replenishment strategy, and it gradually increases on condition that the CSL required is not satisfied. Once the CSL is achieved or beyond the retailer's requirement, the static SW_{ss} is determined. Dynamic DW_{ss} is calculated based on the static SW_{ss} considering two factors, namely the forecasted seasonality pattern and the sales record (POS data) in previous weeks.

To link the week of safety stock to seasonality forecasted by the retailer, coefficient α is introduced. The definition of α in the i^{th} replenishment is:

$$\alpha(i) = \frac{Forecasted \;\; seasonality \;\; distribution \;\; in \;\; next \;\; (DWss) \;\; weeks}{\dfrac{DWss}{Length \;\; of \;\; sales \;\; season}} \tag{4-8}$$

The numerator part in Equation 4-8 is the percentage that the forecasted demand in next (DW_{ss}) weeks occupies in the total forecasted demand in the whole sales season while the denominator part is the ratio of DW_{ss} to the sales season.

Another factor introduced to generating the dynamic week of safety stock DW_{ss} is the actual sales record. In the apparel supply chain adopting the VMI replenishment strategy, POS data in the retailer is shared with the vendor. In the proposed simulation model, the actual sales are recorded as the POS data. Moving-average forecasting method (Simchi-Levi et al 2003) which employs the sales data occurred in the previous week to predict the sales in the following week is adopted in this study. In this study, coefficient β is employed to link the actual sales record to the dynamic week of safety stock DW_{ss}. Coefficient β in the i^{th} replenishment is defined as:

$$\beta(i) = \frac{POS\ data\ in\ week\ w}{Forecasted\ sales\ in\ week\ w} \tag{4-9}$$

Here w means the week which is one week before the manufacturer calculating replenishment quantity.

In general, the steps of generating the dynamic DW_{ss} are explained as follows:

1) Generate static week of safety stock SW_{ss} for all replenishment cycle using simulation model as stated in the simulation procedure in section 4-3.

2) For each replenishment cycle i, calculate the coefficient $\alpha(i)$ and $\beta(i)$ using Equations 4-8 and 4-9. Both factors are carefully designed so that under certain circumstances the dynamic week of safety stock DW_{ss} exactly equals the static one SW_{ss}. Particularly, if the forecasted seasonality distribution in the coming SW_{ss} weeks is equal to the ratio of SW_{ss} to the length of the sales season, α is equal to 1. This means seasonality factor has neither amplification nor reduction on the week of safety stock. For coefficient β, the same situation occurs when the actual sales in the last week exactly equals to the forecasted ones.

3) Generate Dynamic week of safety stock DW_{ss} for the i^{th} replenishment as

following:

$$DW_{ss}(i) = SW_{ss}(i) * (\alpha(i) * \beta(i)) \qquad (4\text{-}10)$$

4.4.2 Replenishment Algorithm

In general, the length of upcoming weeks the replenishment covers is equal to the sum of lead time (LT), replenishment cycle (RC) and week of safety stock (W_{ss}). Thus, ($LT + RC + W_{ss}$) is used to denote the targeted replenishment weeks.

Considering different situations in different phases of the sales season, the replenishment algorithm is divided into three parts.

1) Before the sales season, the replenishment algorithm determines the order quantity occurring over the initial targeted replenishment weeks ($LT + RC + INI_w$) using the forecasted volume, SKU distribution and seasonality curve, in which the INI_w denotes the gap between the commencement of the sales season and the first replenishment order released. These orders are supposed to arrive at the retailer before sales season.

2) During the sales season, we use the targeted replenishment weeks ($LT + RC + W_{ss}$) to denote the target demand to be satisfied in the coming weeks as described above. The actual replenishment order quantity in the whole sales season is, however, dynamic. The main reason is that there are always on-hand inventory in retailers.

Another factor to be considered is that between the gap the replenishment order is released and arrived at the retailer, there are several batches of in-transit garments which replenish in advance. For instance, there are 3 batches between the periods that the 5^{th} replenishment is released from the manufacturer to its arrival at the retailer in Figure 4-3. The replenishment quantity is revised as the maximum value of the ($0, Replenishment\ net$). The Equation of $Replenishment\ net$ is:

$$Replenishment\ net = D_m - I_n - T_s \tag{4-11}$$

$$D_m = POS\ \ in\ \ last\ \ week * \frac{forecasted\ \ seasonality\ \ in\ \ next\ \ (LT + RC + W_{ss})\ \ weeks}{forecast\ \ seasonality\ \ in\ \ last\ \ week} \tag{4-12}$$

Where D_m: Demands in the next targeted replenishment week ($LT + RC + W_{ss}$) are estimated according to the POS data of the last week and the seasonal pattern of the next targeted replenishment weeks ($LT + RC + W_{ss}$); I_n: On-hand inventory in the current week; T_s: In-transit goods that will arrive at the retailer between the current week and the week the order arrives at the retailer.

3) At the end of the sales season, the $Replenishment\ net$ is to satisfy the residual weeks of customers' demand. The Equation of $Replenishment\ net$ is revised as:

$$Replenishment\ \ net = Dm' - In - Ts \tag{4-13}$$

$$Dm' = POS\ \ in\ \ last\ \ week * \frac{forecasted\ \ seasonality\ \ in\ \ residual\ \ weeks}{forecasted\ \ seasonality\ \ in\ \ last\ \ week} \tag{4-14}$$

Where Dm': Demands in the residual weeks estimated according to the POS data of the last week and the seasonal pattern of the residual weeks; I_n: On-hand inventory in the current week; T_s: In transit goods that will arrive at retailer between the current week and the week the order arrives at the retailer.

4.5 Experimental Results and Discussion

4.5.1 Background of Industrial Data

Industrial data was collected from a two-echelon VMI-based supply chain in which a Hong Kong-based apparel manufacturer supplies garments to its overseas client (a department store who has more than a thousand department stores in the States) for testing. In the industry, as other apparel manufacturers are using the same VMI practice with their clients, the data collected from this manufacturer for model testing can reflect the typical practice of VMI strategy of the industry.

The detailed input data is shown in Table 4-2. Table 4-2 shows the percentage proportion of different styles, colors and sizes forecasted by the retailer before the sales season. The proportions of each of the five styles are 30%, 10%, 25%, 10% and 25% respectively. Similarly, the proportions for seven different colors are 20%, 15%, 20%, 5%, 20%, 10% and 10% respectively while those for six sizes are 4%, 20%, 28%, 27%, 14%, and 7% respectively.

For the seasonality pattern, there were two options for the retailer to choose. One was client defined in which the retailer input the seasonality distribution pattern based on the experience using historical data. Another option was to estimate the pattern and select one pattern out of the five provided by the simulation model, viz., early peak, late peak, flat, middle peak, and the high middle peak. Figure 4-5 illustrates theses patterns over a sales season of 36 weeks. In the experiment, the retailer selected the former one that uses the historical sales data and input them to the simulation model which is shown in Figure 4-6.

Table 4-2: Constraint and Main Input of the Simulation Model

Constraint	CSL_t target by the retailer	95%
Main input	Sales season (week)	36
	Forecasted volume of garment (unit)	56000
	Number of style	5
	Number of color	7
	Number of size	6
	Forecasted style proportion (%)	30/10/25/10/25
	Forecasted color proportion (%)	20/15/20/5/20/10/10
	Forecasted size proportion (%)	4/20/28/27/14/7
	Seasonality	Client defined
	Estimated forecasting error (%) (Volume/Style/Color/Size/Seasonality)	21.2/12/16/5/10

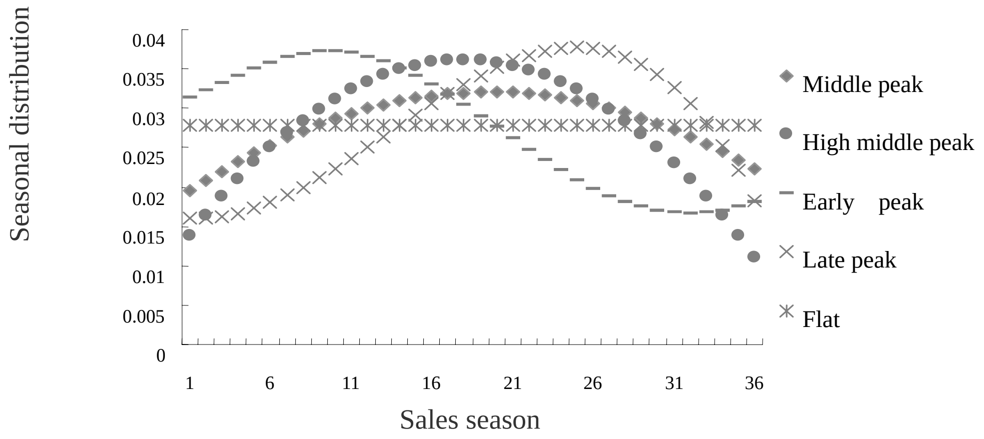


Figure 4-5: Seasonality Distribution Pattern Provided by Simulation Model

The bottom row in Table 4-2 is the forecasting error estimated by the retailer before the sales season which was set as the medium error degree in the simulation model. The quantity error is equal to 21.2%. It implies that the quantity of predicted customer demand is 21.2% above the forecasted quantity. Errors for style, color, size and seasonality are 12%, 16%, 5% and 10% respectively. These are all absolute sum of errors between the forecasting distribution and the predicted demand of customers.

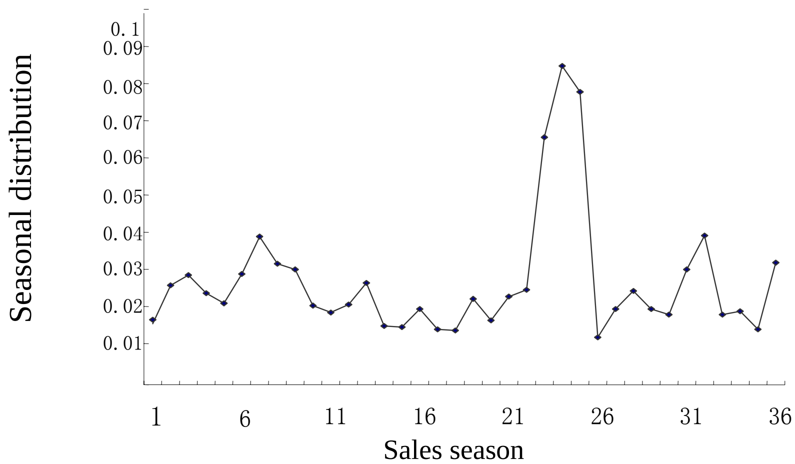


Figure 4-6: Retailer Defined Seasonality Distribution in the Experiment

Since the forecasting error, including volume error, the SKU mix error and seasonality distribution error were randomly distributed to each SKU in each week during the sales season; for each degree of forecasting error, ten different distributions were randomly generated and ten experiments based on these distributions were conducted for replications.

In the experiment, lead time (LT) was set between 7 weeks and 9 weeks based on the existing practice of the manufacturer. It included the manufacturing time and the transit time to the retailer. The length of replenishment cycle (RC) was set from 2 weeks to 6 weeks which represented different strategic policies on how the retailer replenished the goods from the manufacturer. For example, one big client that was a large chain store in the United States implemented the VMI replenishment strategy with the manufacturer; the RC was only 2 weeks. In contrast, some retailers who insisted on the traditional business practice in which the replenishments in the sales season were quite infrequent might extend the RC to 6 weeks.

4.5.2 Results

Based on the input data, the simulation model generated 27 sets of replenishment strategy as well as the corresponding performance index as shown in Table 4-3. For each set, ten experiments were conducted based on different error distributions stochastically generated. The targeted replenishment weeks ($LT + RC + W_{ss}$), the predicted CSL and the IT shown in Table 4-3 are the mean values of the ten experiments. The result provided a combination of sets in terms of replenishment strategy under different forecasting error associated with different performance indices. According to the simulation result, the retailer or the manufacturer might choose the most 'preferred' replenishment strategy among the 27 sets before the actual operation.

The results shown in Table 4-3 demonstrate the relationship among the forecasting error, replenishment strategy and performance of the supply chain. In general, increasing forecasting errors, as well as the LT and RC, would increase the replenishment quantities in order to maintain the same level of customer service.

For example, in sets 1, 10 and 19, the RC and LT are the same, while the forecasting error degrees are of low, medium and high respectively. The targeted replenishment weeks ($LT + RC + W_{ss}$) in these three sets are generated as 10, 11, and 12 respectively and the IT decreases from 9.663, 5.622 to 3.896. Another example can be found in sets 3, 6, and 9. In these three sets, both forecasting error and LT are of the same value and the RC s are 2, 4 and 6 respectively. The targeted replenishment weeks ($LT + RC + W_{ss}$) for the re-order quantity are generated as 13, 16 and 17 respectively. The IT declines from 6.947, 5.539 to 4.486. If the forecasting error degree and RC are kept constant, the influence of LT on performance of the supply chain can be identified in sets 1, 2, and 3 in which the targeted replenishment weeks ($LT + RC + W_{ss}$) increase from 10, 12 to 13 and the IT declines from 9.663, 7.892 to 6.947 respectively.

Table 4-3: Output of the Simulation Model Using Industrial Data

Set No.	Part 1	Part 2			Part 3	
	Forecasting error	Replenishment strategy			Performance index	
	Forecasting error degree	Replenishment cycle (week)	Lead time (week)	Targeted replenishment weeks ($LT+RC+W_{ss}$)	Inventory turnover (IT)	Predicted CSL
1	Low	2	7	10	9.663	0.957
2	Low	2	8	12	7.892	0.976
3	Low	2	9	13	6.947	0.970
4	Low	4	7	14	6.109	0.958
5	Low	4	8	15	6.101	0.956
6	Low	4	9	16	5.539	0.954
7	Low	6	7	15	4.964	0.963
8	Low	6	8	16	4.727	0.958
9	Low	6	9	17	4.486	0.956
10	Medium	2	7	11	5.622	0.960
11	Medium	2	8	13	5.152	0.963
12	Medium	2	9	14	4.774	0.970
13	Medium	4	7	13	5.720	0.953
14	Medium	4	8	15	4.484	0.966
15	Medium	4	9	16	4.200	0.969
16	Medium	6	7	17	3.848	0.955
17	Medium	6	8	18	3.578	0.965
18	Medium	6	9	19	2.974	0.974
19	High	2	7	12	3.896	0.961
20	High	2	8	13	3.561	0.960
21	High	2	9	15	2.904	0.955
22	High	4	7	16	3.269	0.970
23	High	4	8	17	3.143	0.968
24	High	4	9	18	2.969	0.966
25	High	6	7	17	2.470	0.967
26	High	6	8	19	2.325	0.966
27	High	6	9	20	2.603	0.953

In order to validate whether the procedure of the simulation is consistent with the actual operation in the industry, actual data from the industry was employed to test the proposed simulation model.

Since the LT, RC and the forecasting error from the industry were the same as the 12^{th} set in Table 4-3, the 12^{th} set was selected to validate the procedure of the simulation model. Industrial data of CSL_t and forecasting error were set as input of the simulation model. One set of parameters taken from actual practice of the industry are shown in the second column of Table 4-4. The parameters generated by the simulation model are shown in the third column. After the simulation procedure, the simulation model generated performance index in terms of IT and predicted CSL, which were 4.77 and 97% respectively. This shows that the parameters generated by the simulation model are very close to those of industrial practice.

Table 4-4: Comparison of the Simulation Output and Industrial Practice

	Industrial practice	Part of 12th parameters generated by simulation model
Lead time (week)	2	2
Replenishment cycle (week)	9	9
Forecasting error between sales forecast and customer demand (%) (Volume/Style/ Color/Size/Seasonality)	21.2/12/16/5/10	Medium error degree
Inventory turnover (IT)	4.05	4.77
Customer service level (CSL)	95.00%	97.00%

4.5.3 Comparison of the Static Safety Stock Week and Dynamic Safety Stock Week

As mentioned in section 4.4.1, the replenishment algorithm employed in the simulation model considers the dynamic safety stock week. In this section, an experiment was conducted using the proposed simulation model to show the comparison of the static safety stock week (SW_{ss}) and dynamic safety stock week (DW_{ss}).

Table 4-5 shows the main input to the simulation model. Figure 4-7 shows the simulation results generated for both the static and dynamic week of safety stock with the algorithms discussed in section A. For the static safety stock week algorithms, in order to achieve the 95% CSL_t, SW_{ss} is kept at 4 weeks in most of the replenishment cycles. This figure declines at the end of the season since it is not necessary to keep many goods at that time (see section 4.4.2 for the details on the replenishment algorithms at the end of the sales season). For the dynamic algorithm, DW_{ss} in most of the replenishment cycles are below the static ones while it climbs to a high level after the 16^{th} replenishments and remains for several cycles. This pattern is possibly due to the late peak seasonality applied in this simulation. At the end of the sales season, the dynamic one declines quickly as the static one.

Table 4-5: Main Input to the Simulation Model

Sales season	52
Forecasted volume of garment (unit)	50000
Number of style	3
Number of color	4
Number of size	5
Forecasted style proportion (%)	20/30/50
Forecasted color proportion (%)	10/20/30/40
Forecasted size proportion (%)	10/20/30/30/10
Seasonality	Late peak
Retail-defined CSL_t	0.95
Lead time	2
Replenishment cycle	8
Forecasting Error degree	Medium

The performance of the supply chain improves when adopting replenishment algorithm for SW_{ss} comparing to DW_{ss}. The dynamic algorithm is more flexible that the retailer may keep fewer inventories when customers' demand is low; when there is a sudden rise of demand, and the safety stock to satisfy the customer increases to a high level. The dynamic algorithm for DW_{ss} also improves the IT in the apparel supply chain. In this case, the IT are 7.90 in the dynamic case and 8.27 in the static one under the same restriction of 95% CSL_t.

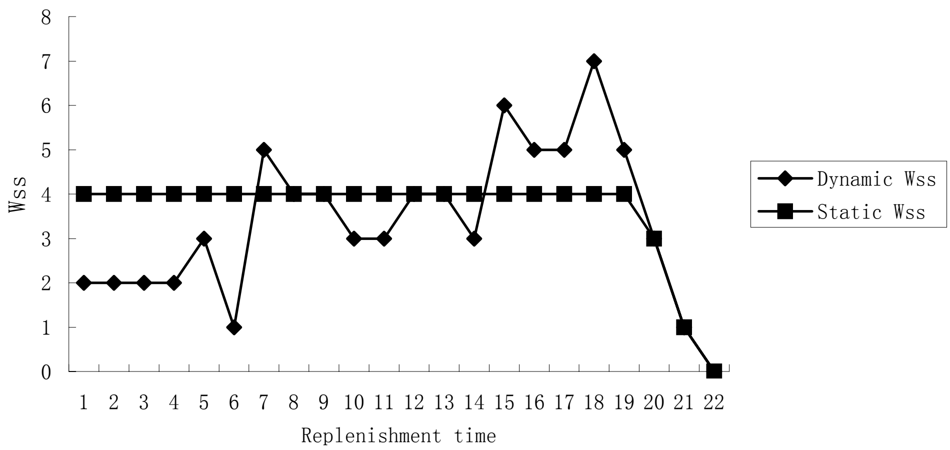


Figure 4-7: Comparison of SW_{ss} and DW_{ss}

All the experiments afterwards in this research therefore employed the dynamic algorithm for calculating the week of safety stock.

4.6 Summary

In this chapter, a simulation model that integrates customers, retailers and manufacturers along the supply chain for the apparel industry is proposed. The simulation model provides a tool for the apparel supply chain to generate a set of replenishment strategies under different forecasting error to satisfy CSL_t required by the retailer. Firstly, the desired CSL_t was determined by the retailer. Other pre-defined parameters, such as length of the sales season, forecasted sales and pre-defined forecasting error were input to the simulation model. After simulating the operation of the apparel supply chain and applying the replenishment algorithms, the simulation model generated a set of outputs in terms of the degree of forecasting error, replenishment strategy and performance index.

The simulation model was shown to be an effective tool enabling the retailer and the manufacturer adopting the VMI replenishment strategy to understand how the various factors affect the performance of the apparel supply chain before actual business. When discussing the forecasting error in this chapter, the medium degree of forecasting error was obtained from the industry while the low and high degree errors were set as 50% lower and higher than that of the medium degree. This assumption will be released with data from the industry and the fuzzy set theory is to be integrated into the proposed simulation model in Chapter 5.

The simulation model also provides a fundamental platform for the proposed optimization replenishment model. With the release of the constraints in the manufacturer’s production limitation, this simulation model will be further developed and integrated into the optimization model, which will be discussed in Chapter 6.

CHAPTER 5

FUZZY FORECASTING ERROR IN REPLENISHMENT SIMULATION MODEL FOR APPAREL SUPPLY CHAIN

In this chapter, the fuzzy set theory is proposed to investigate the uncertainties of forecasting error in the VMI-based replenishment simulation model for the apparel supply chain. The relationship between the forecasting error, performance and replenishment strategies is evaluated with the experiment based on real industrial data of the apparel industry.

5.1 Problem Analysis

Managing an apparel supply chain effectively to satisfy the CSL_t required by the retailer is very difficult, since various sources of uncertainties and complex interrelationships at various levels between various entities exist in the supply chain. Among the factors relevant to CSL, forecasting error between the forecasted sales and the customers' demand, which is caused by demand uncertainty, is one of the most critical ones affecting the performance of the supply chain. However, forecasting is always uncertain and imprecise. The retailer and the manufacturer are not able to predict with certainty the value of forecasting error.

A systematical method is proposed in this chapter to investigate the forecasting error. Particularly, retailers in the apparel supply chain are required to estimate the scope of forecasting error in different degrees based on their experience. The fuzzy set theory is then proposed to represent the uncertainty of forecasting error. After determining the expected value of the fuzzy estimation of the forecasting error, the fuzzified forecasting error will be integrated into a replenishment simulation model for the VMI-based apparel supply chain proposed in Chapter 4. The relationship between the forecasting error, performance and replenishment strategies is then evaluated with the experiment based on real industrial data of the apparel industry using the simulation model.

5.2 Fuzzified Forecasting Error

Forecasting error is caused by demand uncertainty. Demand uncertainty can result in over- or under-production, leading to excessive inventories or an inability to meet customers' needs respectively (Jung et al 2004). To study the uncertainties systematically, two methodologies are applied to the supply chain models. Some researchers address the uncertainty using stochastic models; one of the pioneering works dealing with the stochastic nature of the supply chain is credited to Midler (1969). In these models, uncertain demand was incorporated with normal probability function based on past records (see Porteus (1990) and Federgruen (1993)) for examples); Other scholars treat uncertainty using the fuzzy set theory (Petrovic et al 1999; Petrovic et al 2001; Wang et al 2005). The reason is that there exists a need to handle different sources and kinds of uncertainties, particularly uncertainties in judgment, lack of evidence and lack of certainty in evidence. The general approach was originally initiated by (Zadeh 1965).

Forecasting accuracy is the most significant factor affecting the performance of the replenishment strategy adopted by both manufacturers and retailers. Retailers and manufacturers usually forecast customers' demand before the sales season in terms of total quantity (or the total volume), SKU mix (which includes style, color, and size), and seasonality distribution (percentage of customer volume in each week during the sales season) (Nuttle et al 1991; Lowson et al 1999), in which five categories are included. However forecasting is always uncertain and imprecise. The difference between actual market demand and forecasted demand is called the forecasting error. The forecasting error is considered in terms of the total quantity of garments, the SKU mix of the garments, and seasonality distribution pattern of the sales, each corresponding to the forecasted customers' demand. Detailed forecasting error in different categories in the apparel supply chain is explained as follows:

Suppose the forecasted quantity is 100000 units and actual customer demand is 120000 units, the error on quantity is 20%. For the SKU mix errors, Hunter et al (1996b) shows an example on the size distribution. Suppose there are four sizes, Small, Medium, Large and Extra-Large. The expected or forecasted percentage distribution of sizes is 10%, 35%, 40% and 15% respectively. The actual demand percentage, however, turn out to be 10%, 30%, 30% and 30% respectively. The size error is defined as the sum across all sizes of the absolute difference between the expected and actual demand percentages. Thus, the difference for the Small size is $|10-10|=0$, $|35-10|=5$ for Medium, $|40-30|=10$ for Large, and $|15-30|=15$ for Extra-Large. Summing these values gives a total of $0+5+10+15=30\%$, the total size error. For the seasonality distribution, the forecasted seasonality distribution is defined as the percentage of total demand that the forecasted customers' demand in each week occupied. The actual seasonality distribution is the percentage of total demand the actual customers' demand in each week occupied. The seasonality distribution error is thus defined as the sum across all weeks of the absolute difference on the seasonality percentage between the expected and actual demand.

Equation 5-1 denotes the relationship among sales forecasting S_f, actual customers' demand C_d and forecasting error F_e in which C_d and F_e are functions of time series and S_f a constant predicted by the retailer before the sales season. The forecasting error is in terms of the total quantity of garments, seasonal distribution pattern of the sales and the mixed proportion of the garments.

$$C_d = S_f + F_e \tag{5-1}$$

Though the retailer and manufacturer are not able to predict with certainty the value of the forecasting error, they usually predict the degree of forecasting error within a range of value based on their experience. They may divide the forecasting error into three degrees, i.e. low, medium and high. For each degree, the error range can be expressed in linguistic terms. For instance, a low degree of forecasting error of 20% with respect to volume may range between 5% and 30%. This simplified representation can be approached by using the possibility concept of fuzzy events. A fuzzy set is characterized by fuzzy boundaries: unlike crisp sets in which a given element does or does not belong to a given set, each element in a fuzzy set belongs to a set with a certain membership degree. The function that returns the membership degree of each fuzzy set element is called membership function.

In this chapter, triangular membership functions have been adopted because they are considered the most suitable form to model market demand (Katagiri et al 2000; Giannoccaro et al 2003). Based on the relationship between the forecasting error and market demand denoted in Equation 5-1, the forecasting error is treated as a triangular membership function. Figure 5-1 depicts a possible percentage of forecasting error on volume in a triangular membership function. The linguistic description for this forecasting error on volume is “about 40%, possibly ranging from 20% to 60%”.

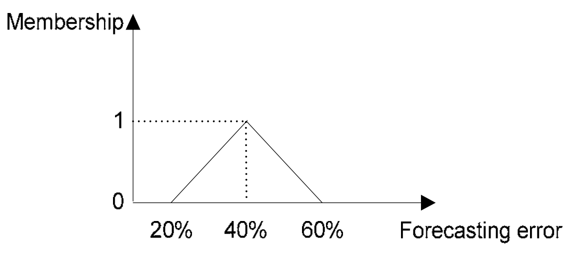


Figure 5-1: Example of Fuzzy Membership

Once the forecasting error can be formulated as membership function, the next step is to input the estimated forecasting error which has been fuzzified into the supply chain simulation model. In order to simplify the manipulation of fuzzy numbers, they can be represented by one or two values instead of a set of values even though this simplified representation frequently loses part of the original meaning (Lee et al 1998). Heilpern (1992) introduced a method of denoting the expected value of fuzzy numbers in the problem of ranking or comparing fuzzy numbers, in which the expected interval is defined as the expected value of an interval random set generated by the fuzzy number and the expected value of this number is defined as the centre of the expected interval.

The method can be summarized as below.

1) Firstly, the membership function $\mu_A(x)$ of the fuzzy number A is described as:

$$m_A(x) = \begin{cases} 0 & for \quad x < a, \\ f_A(x) & for \quad a \le x < c, \\ 1 & for \quad c \le x < d, \\ g_A(x) & for \quad d \le x < b \\ 0 & for \quad x > b, \end{cases} \tag{5-2}$$

where the functions f_A and g_A are located between the left and the right sides of A. f_A and g_A are increasing and decreasing functions. This fuzzy set can be denoted as $N(a,c,d,b)$.

2) The expected interval of a fuzzy number A is denoted by $EI(A)$.

3) The centre of the expected interval of a fuzzy member A is called the expected value of this number and denoted by $EV(A)$, i.e.

$$EV(A) = \frac{1}{2}(Es_1 + Es_2) \tag{5-3}$$

where,

$$Es_1 = c - \int_a^c f_A(x)dx \tag{5-4}$$

$$Es_2 = d + \int_d^b g_A(x)dx \tag{5-5}$$

Figure 5-2 illustrates the step of integrating the fuzzy set in the proposed replenishment strategy model to represent different degrees of forecasting error between the sales forecast before the sales season and the actual demand of the customers. Detailed descriptions are as follows:

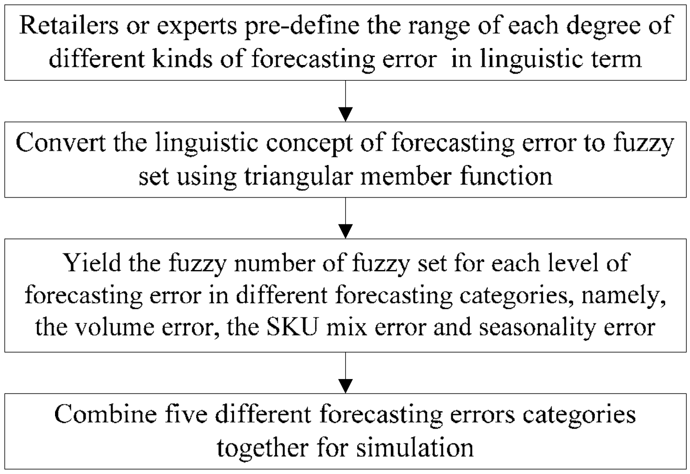


Figure 5-2: Procedures of Integrating Fuzzy Forecasting Error into the Simulation Model

1) Pre-define the range of each degree of forecasting error in linguistic terms by retailers or experts

The forecasting error in the supply chain is made up of errors due to the total volume, SKU mix and seasonality of sales. Usually the retailers or experts divide each kind of forecasting error into three degrees, i.e. low, medium and high. For each degree of different kind of forecasting error, the experts predict the forecasting error within a range of value based on their experience and historical data. These ranges of error are expressed in linguistic terms. For example: “The medium forecasting error on total volume is about 40%, ranging from 30% to 50%.”

2) Convert the linguistic description of the forecasting error into a triangular member function of fuzzy numbers

The representations in the linguistic term for each kind forecasting error in different degrees are approached by using the vague concept of fuzzy set theory. A fuzzy set is characterized by fuzzy boundaries: unlike crisp sets in which a given element does or does not belong to a given set, each element in a fuzzy set belongs to a set with a certain membership degree. The function that returns the membership degree of each fuzzy set element is called membership function. In this study, the forecasting error is considered as a triangular membership function for each kind of forecasting error at different degrees. The triangular membership function is obtained with the help of the veteran in fashion forecasting. The veteran in the supply chain is asked to estimate the range of forecasting error by using the concept of "approximation", and the beginning point and ending point of the range. For each set, there are three parameters given by the retailer. Their membership functions are set as 1, 0, and 0. Figure 5-1 shows the relationship between the estimated range of forecasting error and its triangular membership function.

3) Yield the expected value of fuzzy number of fuzzy set for each forecasting error degree

Applying the method of (Heilpern 1992), and denoting the membership function in Equation 5-1 with triangular ones generated in step 2, the expected value of fuzzy number of fuzzy set for each forecasting error degree for different forecasting categories can be obtained.

4) Merge five types of forecasting error for simulation

There are five types for forecasting error, each with three levels of error, namely high (H), medium (M) and low (L). Altogether there are 3^5 combinations. Table 5-1 demonstrates 15 typical examples of them. H, M and L are abbreviations of the high, medium, and low degrees of the forecasting error in fuzzy concept.

Table 5-1: Examples of Different Combinations of Forecasting Error Degrees

No. of Combinations		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
		Forecasting error degree														
Quantity		H	H	H	H	H	M	M	M	M	M	L	L	L	L	L
SKU mix	Style	H	M	H	H	H	H	M	M	M	M	L	L	L	M	L
	Color	H	H	M	H	H	M	H	M	L	M	L	L	M	L	L
	Size	H	H	H	M	H	M	H	M	M	M	L	M	L	L	L
Seasonality		H	H	H	H	M	H	M	M	M	L	M	L	L	L	L

These forecasting error degrees will be transferred into fuzzy numbers using the algorithm discussed above. Together with different replenishment strategies in terms of LT and RC, the model will generate the performance of each set. The relationship between forecasting error and performance as well as the replenishment strategy can then be studied after the simulation procedure.

5.3 Empirical Study

5.3.1 Features of Industrial Data

Table 5-2 illustrates the real industrial data, which was collected from a two-echelon apparel supply chain consisting of an apparel manufacturer and its overseas client (retailer), to be input in the model for experimental testing.

The percentage proportions of different styles, colors and sizes forecasted by the retailer before the sales season are pre-defined. The proportions of each of the five styles are 30%, 10%, 25%, 10% and 25% respectively. Similarly, the proportions for seven different colors are 20%, 15%, 20%, 5%, 20%, 10% and 10% respectively while those for the six sizes are 4%, 20%, 28%, 27%, 14%, and 7% respectively.

Table 5-2: Experimental Data for Empirical Study

Constraint	CSL_t targeted by the retailer	95%
Main input	Sales season (week)	52
	Forecasted quantity of garment (unit)	100,000
	Number of styles	5
	Number of colors	7
	Number of sizes	6
	Forecasted style proportion in (%)	30/10/25/10/25
	Forecasted color proportion in (%)	20/15/20/5/20/10/10
	Forecasted size proportion in (%)	4/20/28/27/14/7
	Seasonality	Retailer defined

Figure 5-3 illustrates the seasonal patterns over a sales season of 52 weeks as the input forecasting seasonality which is based on historical sales data.

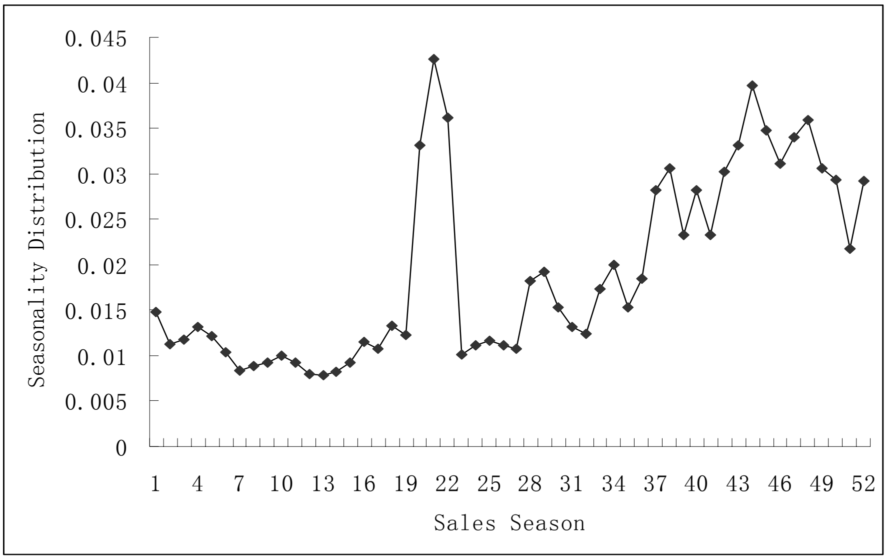


Figure 5-3: Retailer-Defined Seasonality Distribution in the Experiment

In the experiment, LT was set between 7 weeks and 9 weeks based on the existing practice of the apparel manufacturers. It included the manufacturing time and the transit time to the retailer. The length of RC varied from 1 week to 6 weeks depending on different strategic policies adopted by the parties of supply chain.

5.3.2 Numerical Representation of the Forecasting Error

Table 5-3 demonstrates the expert-estimated range for different forecasting error degrees. These figures are based on the statistics of historical records from the retailer, after investigating the differences between the forecasting and actual sales for more than 1000 of SKUs.

Table 5-3: Estimation of the Range for Different Types of Forecasting Error Degrees

		Low degree of forecasting error (Percentage)			Medium degree of forecasting error (Percentage)			High degree of forecasting error (Percentage)		
		Appro-ximate	Start point of range	End point of range	Appro-ximate	State point of range	End point of range	Appro-ximate	Start point of range	End point of range
Quantity		10	5	20	25	20	35	50	30	65
SKU mix	Style	10	5	15	18	10	34	55	30	60
	Color	20	5	35	35	30	60	80	55	105
	Size	30	20	40	50	40	70	100	70	125
Seasonality		5	3	8	10	5	25	30	20	50

Figures 5-4 to 5-8 depict the membership function for the fuzzy forecasting error based on the data shown in Table 5-3.

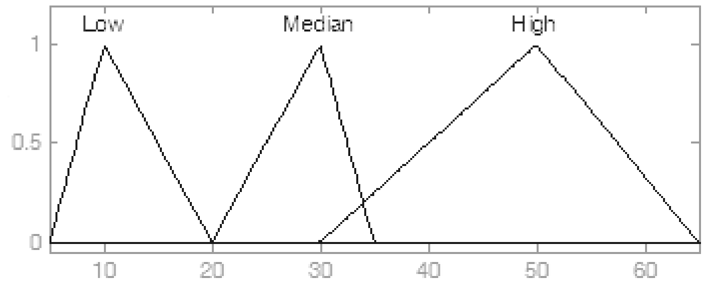


Figure 5-4: Membership Function of Quantity Error

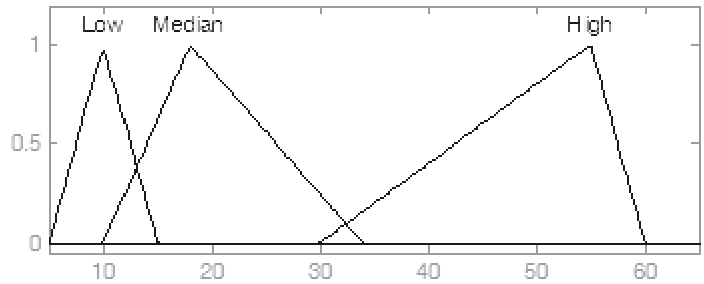


Figure 5-5: Membership Function of Style Forecasting Error

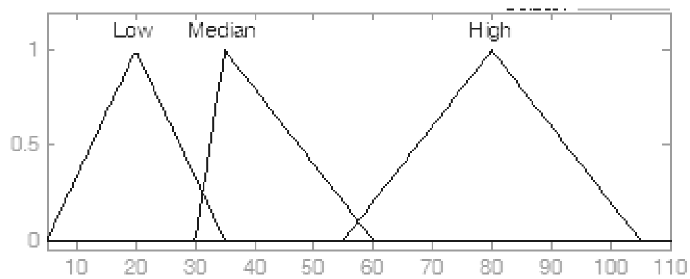


Figure 5-6: Membership Function of Color Forecasting Error

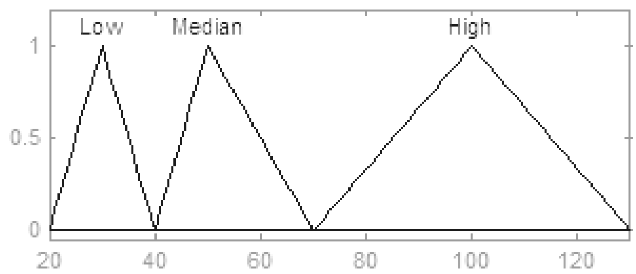


Figure 5-7: Membership Function of Size Forecasting Error

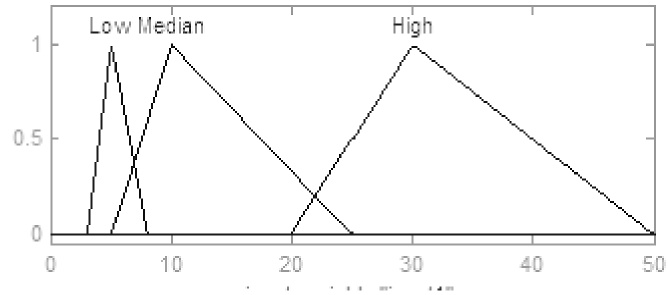


Figure 5-8: Membership Function of Seasonality Forecasting Error

The membership functions for low degree, medium degree and high degree for the five types of forecasting error can be denoted as:

$$\mu(x) = \begin{cases} 0, & x < b_1 \\ \dfrac{x - b_1}{b_2 - b_1}, & b_1 \le x \le b_2 \\ \dfrac{b_3 - x}{b_3 - b_2}, & b_2 \le x \le b_3 \\ 0, & x > b_3 \end{cases} \tag{5-6}$$

And the b_1, b_2 and b_3 for each degree of different forecasting error see Table 5-4.

Table 5-4: Value of b_1, b_2 and b_3 for Each

Degree of Different Forecasting Error

		Low degree of forecasting error (Percentage)			Medium degree forecasting error (Percentage)			High degree of forecasting error (Percentage)		
		b_1	b_2	b_3	b_1	b_2	b_3	b_1	b_2	b_3
Quantity		5	10	20	20	25	35	30	50	65
SKU mix	Style	5	10	15	10	12	35	30	55	60
	Color	5	20	35	30	16	60	55	80	105
	Size	20	30	40	40	50	70	70	105	125
Seasonality		3	5	8	5	10	25	20	30	50

Comparing Equation 5-6 with Equation 5-2, a, b, c and d in Equation 5-2 are substituted with b_1, b_2, b_2 and b_3 respectively in Equation 5-6. Equations 5-4 and 5-5 are now revised as:

$$Es_1 = b_2 - \int_{b_1}^{b_2} \frac{x - b_1}{b_2 - b_1} dx = \frac{b_1 + b_2}{2} \tag{5-7}$$

$$Es_2 = b_2 + \int_{b_2}^{b_3} \frac{b_3 - x}{b_3 - b_2} dx = \frac{b_3 + b_2}{2} \tag{5-8}$$

The expected value in Equation 5-2 can be simplified as:

$$EV(A) = \frac{1}{2}(Es_1 + Es_2) = \frac{b_1 + 2b_2 + b_3}{4} \tag{5-9}$$

Based on the b_1, b_2 and b_3 represented in Table 5-4, the expected values of fuzzy number of forecasting error is calculated in Table 5-5.

Table 5-5: Expected Value of Fuzzy Degree of Forecasting Error

		Expected value of Low degree of forecasting error (Percentage)	Expected value of Medium degree of forecasting error (Percentage)	Expected value of High degree of forecasting error (Percentage)
Quantity		11.25	28.75	48.75
SKU mix	Style	10	20	50
	Color	20	40	80
	Size	30	52.5	100
Seasonality		5.25	12.5	32.5

5.3.3 Experiment and Results

To simplify the analysis, only three combination sets, 1, 8 and 15 at high, medium and low degrees of forecasting error, in Table 5-1 were chosen. With the combination of LT and RC, a total of 36 sets of experiment results were generated, as shown in Table 5-6.

Since the forecasting error, including volume error, the SKU mix error and seasonality distribution error were randomly distributed to each SKU in each week during the sales season; for each degree of forecasting error, ten different distributions were randomly generated and ten experiments based on these distributions were conducted for replications. For each set, ten experiments were conducted based on different error distributions which were stochastically generated. The targeted replenishment weeks in terms of $LT + RC + W_{ss}$, the IT and the predicted CSL shown in Table 5-6 are the mean values of the ten experiments.

According to the results shown in Table 5-6, the retailer or manufacturer may choose the most 'preferred' one among the 36 sets as all these replenishment strategies can achieve the targeted CSL_t.

The result shown in Table 5-6 demonstrates the relationship among the forecasting error, replenishment strategy and performance of the supply chain. In general, increasing forecasting errors, as well as the LT and RC will increase the replenishment quantities in order to achieve the minimum 95% of CSL_t.

Table 5-6: Simulation Result Generated by the Proposed Replenishment Strategy Simulation Model

Set No.	Part 1	Part 2			Part 3	
	Forecasting error	Replenishment strategy			Performance index	
	Forecasting error degree	Replenish-ment cycle (week)	Lead time (week)	Targeted replenishment weeks ($LT+RC+W_{ss}$)	Inventory Turnover (IT)	Predicted CSL
1	Low	1	7	8	12.5	0.951
2	Low	1	8	10	10.73	0.959
3	Low	1	9	11	9.43	0.961
4	Low	2	7	11	9.64	0.954
5	Low	2	8	13	7.86	0.972
6	Low	2	9	14	6.92	0.961
7	Low	4	7	14	6.61	0.961
8	Low	4	8	15	6.1	0.952
9	Low	4	9	16	5.52	0.955
10	Low	6	7	17	4.96	0.961
11	Low	6	8	18	4.71	0.952
12	Low	6	9	19	4.45	0.954
13	Medium	1	7	9	8.72	0.951
14	Medium	1	8	10	7.72	0.952
15	Medium	1	9	11	6.82	0.955
16	Medium	2	7	11	5.61	0.958
17	Medium	2	8	12	5.15	0.961
18	Medium	2	9	13	4.77	0.954
19	Medium	4	7	13	5.07	0.952
20	Medium	4	8	15	4.48	0.953
21	Medium	4	9	16	4.2	0.961
22	Medium	6	7	15	3.85	0.965
23	Medium	6	8	16	3.58	0.955
24	Medium	6	9	17	2.95	0.971
25	High	1	7	11	5	0.956
26	High	1	8	12	4.32	0.95
27	High	1	9	14	3.33	0.958
28	High	2	7	13	3.7	0.956
29	High	2	8	14	3.32	0.953
30	High	2	9	16	2.7	0.965
31	High	4	7	17	3.01	0.963
32	High	4	8	19	2.84	0.958
33	High	4	9	20	2.62	0.959
34	High	6	7	18	2.37	0.962
35	High	6	8	20	2.11	0.956
36	High	6	9	22	1.92	0.963

For example, in sets 1, 13 and 25, the RC and LT are the same, while the error degrees are low, medium and high respectively. The targeted replenishment quantities in terms of targeted replenishment weeks $LT+RC+W_{ss}$ in these three sets are generated as 8, 9, and 11 respectively and the IT decreases from 12.5, 8.72 to 5.00. Another example can be found in sets 3, 6, 9 and 12. In these four sets, both forecasting error and LT are of the same value and the RCs are 1, 2, 4 and 6 respectively. The targeted replenishment quantities in terms of targeted replenishment weeks $LT+RC+W_{ss}$ are generated as 11, 14, 16 and 19 respectively. The IT declines from 9.43, 6.92, 5.52 to 4.45. If the forecasting error degree and RC are kept constant, the influence of LT on performance of the supply chain can be identified in sets 1, 2, and 3 in which the target replenishment weeks $LT+RC+W_{ss}$ increase from 8, 10 to 11 and the IT declines from 12.5, 10.73 to 9.43 respectively.

5.3.4 Sensitivity Analyses

In order to investigate the impact of different forecasting error degrees on the supply chain performances and replenishment strategy, sensitivity analyses were conducted.

Figure 5-9 shows the relationship between forecasting error LT and IT. The points in the figure is the relative change of IT when LT shrinks one unit, that is from 9 weeks to 8 weeks, or from 8 weeks to 7 weeks. The relative change of IT is defined as $\frac{\Delta\ Inventory\ turnover}{Inventory\ turnover}$. The result is calculated as the average value of different LT whose forecasting error is at the same degree in Table 5-6.

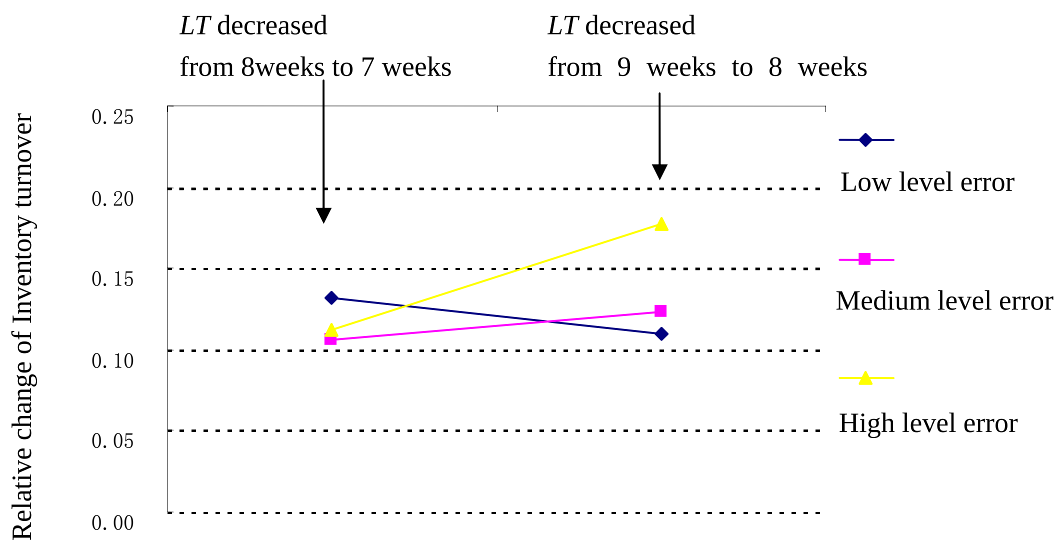


Figure 5-9: Results of Sensitivity Analyses on Relationship between Forecasting Error Degree, LT and IT

It can be seen that all the points in Figure 5-9 are positive, which means the IT will increase with the decrease of the LT, regardless of the extent of the forecasting error degree. Secondly, the relative increase of IT is quite trivial when the LT decreases for each degree of the forecasting error, that is, the range of variation for IT is quite narrow. When LT declines, the relative increase of inventory for all the forecasting error is similar to each other. The maximum one is 0.18, and the minimum one 0.11; the difference between the different forecasting error degrees is not clear.

These findings have shown that shrinking LT may increase the IT while maintaining the minimum CSL_t required by the retailer, no matter whether the forecasting error is high, medium or low. However the improvement of the performance on IT is not significant.

Figure 5-10 illustrates the results of the sensitivity analyses on the relationship between forecasting error degree, relative *IT* and *RC*. The values plotted in Figure 5-10 are obtained by averaging the value of the relative increase of *IT* of the different *RC* whose forecasting error is at the same degree in Table 5-6. As the values of all the points are positive, the *IT* will increase with the increasing replenishment frequency at different degrees of the forecasting error. Regarding the impact of the different degrees of forecasting error, the lower the forecasting error, the higher the increased *IT* can achieve when increasing the frequency of replenishment.

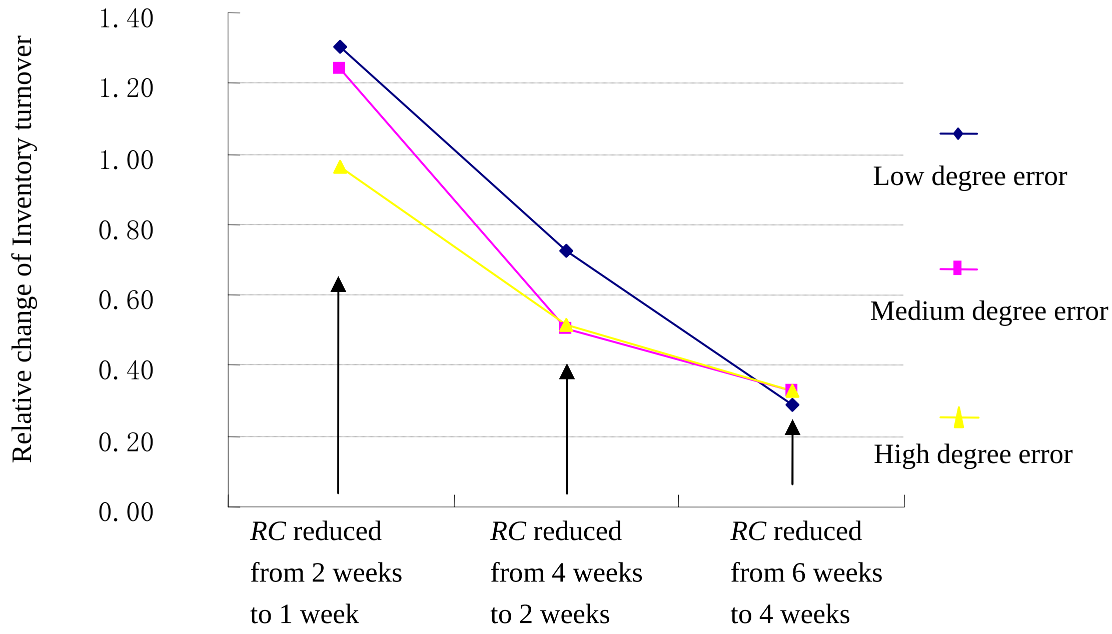


Figure 5-10: Results of Sensitivity Analyses on Relationship between Forecasting Error Degree, *RC* and *IT*

Comparing with Figures 5-9 and 5-10, it can be concluded that the *IT* is more sensitive by reducing the RC (from 0.3 to 1.38) than reducing the LT (from 0.11 to 0.18) at all degrees of forecasting error. The results of these sensitivity analyses provide a reference for the industry to improve the IT. It may be more effective to achieve a higher IT by improving the replenishment frequency instead of shrinking the LT.

5.4 Summary

This chapter addresses the uncertainties associated with the forecasting error, which significantly affects the performance of the apparel supply chain. The proposed methodology addresses the uncertainties through the fuzzy set theory, which is more appropriate than stochastic techniques, especially when the environment is complex and turbulent. With the integration of the fuzzy forecasting error to the VMI-based apparel supply chain replenishment simulation model, the replenishment strategy in the simulation model is linked with the forecasting error. An experiment based on real industrial data of the apparel industry was presented to evaluate how the forecasting error degree influenced the relationship between the performance and replenishment strategies in the VMI-based supply chain.

The proposed supply chain replenishment strategy model integrating with the fuzzy concept contributes to the scientific approach of the supply chain practitioners to deal with uncertainties in a dynamic market environment. The results generated by the model provide a feasible replenishment strategy to achieve the required CSL_t and also improve the performance of the supply chain.

The replenishment strategy as well as the performance of the retailer and the manufacturer in a VMI-based apparel supply chain was investigated using the simulation model. The retailer required CSL_t was achieved under different combinations of forecasting error and replenishment strategy in terms of RC and LT. In the proposed simulation model, it was assumed that the replenishment quantity generated by the replenishment algorithm was 100% delivered to the retailer. In real life apparel supply chain, there is limitation in the production capacity of manufacturers who cannot deliver 100% what the retailer requires. The simulation model proposed in this chapter will be extended by considering the production capacity limitation of the manufacturer and an optimized replenishment model will be proposed in Chapter 6.

CHAPTER 6

SIMULATION-BASED OPTIMIZATION MODEL FOR REPLENISHEMNT STRATEGY IN VMI-BASED APPAREL SUPPLY CHAIN

In this chapter, the simulation model developed in chapters 4 and 5 for generating the VMI-based replenishment strategy in apparel supply chain is further developed with the consideration of the manufacturer's production capacity. A simulation-based optimization model is proposed for the coordination of the interests of manufacturers and retailers in the apparel supply chain. With the consideration of the production capacity constraints, a dynamic rolling optimization of the VMI replenishment strategy using simulation and GA is formulated to optimize the supply chain performance in terms of *PCB* of manufacturers and customers' satisfaction targeted by retailers. The experimental results demonstrated that the proposed optimization replenishment strategy can benefit the manufacturer with balanced production and maintain the CSL at a certain degree. The impact of the optimized replenishment strategy on the supply chain performance is finally presented with a case study.

6.1 Problem Analysis

In a supply chain adopting the VMI replenishment strategy, the manufacturer makes replenishment decisions on the quantity of products to be shipped to the retailer in every replenishment cycle. With the responsibility and authority on managing the replenishment given to the manufacturer, one challenge to the supply chain adopting the VMI strategy is to set up the production model using the supply chain kernel which balances the benefits of different parties in the supply chain, i.e. satisfy the retailer's CSL and balance the manufacturer's production capacity.

The replenishment quantity for each SKU is determined based on the POS data in the previous weeks, seasonality trend forecasting, promotion factors, to name but a few. Owing to the fluctuating customers' demand, the replenishment quantity from the manufacturer varies for each replenishment cycle which directly influences the balance of production capacity. For instance, a sudden rise of replenishment to cover increasing customers' demand may exceed the original production capacity in one period while a decline in customers' demand may make it impossible for the utilization of the production capacity. To ensure the goods to be received by the retailer on time, the manufacturer needs to deliver products by air after production, set up extra production lines or require the operatives to work overtime. All these strategies will cause extra cost to the manufacturer.

In this chapter, an optimized VMI replenishment strategy is devised to generate appropriate replenishment quantity of each replenishment cycle so as to satisfy different parties' interests in terms of CSL_t targeted by the retailer, balance of production capacity of the manufacturer, and high IT of the retailer. The key idea is moving the exceeding part of replenishment quantity to the succession periods provided that there is sufficient production capacity in these periods. These adjustments include two directions: one is replenishing the exceeding quantities in advance and another one is postponing the delivery of extra garments to the retailer in the next replenishment cycles.

The simulation approach has been used extensively in the literature for the selection and evaluation of policies for controlling and managing the supply chain dynamic behaviors (Nuttle et al 1991; Towill et al 1992; Mason-Jones et al 1997). The advantage of using the simulation approach over the analytical approach is that the former facilitates the investigation of the effects of the supply chain operations such as replenishment strategies, inventory policy and production plan (Fisher et al 1997; Cetinkaya et al 2000).

In complex problems such as using the replenishment strategy in the supply chain, it is usually difficult to define one function form for the measure of goodness for the solution. Unlike other optimization techniques, Genetic algorithm (GA), first introduced by Holland (1975), does not make strong assumptions about the form of the objective function (Michalewicz 1996). Whereas traditional search techniques use characteristics of the problem (objective function) to determine the next sampling point (e.g. gradients, linearity, and continuity), the next sampling point in GA is determined based on stochastic sampling/decision rules rather than a set of deterministic decision rules. Therefore, the evaluation functions of many forms can be used; for instance, the simulation result on performance of the supply chain such as CSL and Production Capacity Balance in the replenishment strategy could be defined as the evaluation functions of GA. There have been a limited number of studies in recent years on supply chain or manufacturing systems using GA in simulation-based optimization (Joines et al 2002; Onoyoma et al 2002; Ding et al 2004).

In order to investigate the optimized replenishment strategy and its impact on the performance of the VMI supply chain, a simulation-based optimization replenishment model is established. This model is developed using both GA and simulation techniques to search for the optimal replenishment quantity for each replenishment in rolling horizon.

The proposed simulation-based optimization replenishment model is established based on the real operation of one two-echelon apparel supply chain. The apparel manufacturer is located in China while the customers are overseas retailers in US. Besides adopting the VMI replenishment strategy, the manufacturer also produces garments for the traditional retailer under the Order-Based (OB) business agreement.

The manufacturer generates initial replenishment plans with the retailer who adopts the VMI strategy before the sales season. After that, the manufacturer arranges the orders from the traditional retailer according to the production capacity. Once the quantity and delivery time of these orders are determined, they cannot be changed and the products must be delivered to the retailer on time. Under the VMI strategy, the actual customers' demand fluctuates and it is always different from the initial plans although the forecasting on customers' demand has been done. In order to satisfy the actual demand during the sales season, the balance of the production capacity is broken. A simulation-based optimization model of the VMI replenishment strategy is thus introduced to solve the problem.

In the remainder parts of this chapter, the simulation-based optimization model is discussed in details. Section 6.2 presents the formulation of the proposed replenishment model. Section 6.3 is about the simulation-based optimization model of the VMI-based replenishment strategy in which the structure of the model, the dynamic rolling simulation procedure and the optimization algorithm of the replenishment strategy are presented. Experiments of the replenishment model and discussion of the results are reported in section 6.4. Finally, conclusions are outlined.

6.2 Formulation in Simulation-Based Optimization Model

In order to develop a more realistic simulation-based optimization model, a simplified model for manufacturers providing garments to one retailer and a practical model for manufacturers running business with multiple VMI-based retailers are proposed. Experiments on both types of model were conducted in this research.

One simple case considered in the proposed simulation-based optimization model is that the manufacturer supplies garments to one retailer based on the VMI replenishment strategy. The key idea for the optimization for this situation is moving the exceeding part of replenishment quantity for the VMI orders to the succession periods provided that there is sufficient production capacity in these periods. These adjustments include two directions: one is replenishing the exceeding quantities in advance and another one is postponing the delivery of extra garments to the retailer in the next replenishment cycles.

A more complicated but practical case is that the manufacturer provides garments to more than one retailer under the VMI mode with different requirements on CSL_t. For instance, one retailer may require 95% of CSL_t and another one 90% of CSL_t. In such a situation, the replenishment model should not only be able to move the exceeding replenishment quantity under the VMI strategy to the successive periods provided that there are sufficient production capacities in these periods, but it should also determine the priorities of the replenishment quantity belonging to different retailers when the replenishments for them conflict with each other, i.e. in a condition when the limited production capacity could only satisfy part of the retailers' demand.

In the following subsection, the notations being employed, the assumptions being satisfied, the objectives to be satisfied and the performance to be evaluated in the simulation-based optimization replenishment model for both the single order and multiple orders are given.

6.2.1 Nomenclature

The following notations are used in the simulation-based optimization replenishment model for both single order and multiple orders:

SS :	No. of weeks in the sales season
i :	Replenishment time, $i = 1\ to\ n$, where n is the total replenishment time in the sales season
PL_i :	Production capacity limitation in the i^{th} replenishment
OB_i :	Order-Based quantity in the i^{th} replenishment
St :	Product style, $St = 1\ to\ ST$
Co :	Product color, $Co = 1\ to\ CO$
Sz :	Product size, $Sz = 1\ to\ SZ$

The following notations are used in the simulation-based optimization replenishment model for single order:

PV_i :	VMI replenishment quantity in the i^{th} replenishment before optimization
OV_i :	Optimized VMI replenishment quantity in the i^{th} replenishment after optimization
EPV_i :	Surplus quantity of PV_i beyond the production capacity in the i^{th} replenishment
λ_i :	The state that part of EPV_i being adjusted to the $(i-1)^{th}$ or $(i+1)^{th}$ replenishment

$$l_i = \begin{cases} 1 & \text{if part of } EPV_i \text{ being adjusted to } (i-1)^{th} \text{ or } (i+1)^{th} \text{ replenishment} \\ 0 & \text{otherwise} \end{cases}$$

$P(i,i-1)$: Percentage of EPV_i being adjusted to the $(i-1)^{th}$ replenishment

$P(i,i+1)$ Percentage of EPV_i being adjusted to the $(i+1)^{th}$ replenishment

$PV(St,Co,Sz)_i$: Replenishment quantity for the VMI strategy in the i^{th} replenishment for certain SKU (style= St ,color= Co ,size= Sz) before optimization

$OV(St,Co,Sz)_i$: Optimized replenishment quantity in the i^{th} replenishment for certain SKU (style=St, color=Co, size=Sz) after optimization

$LOS(St,Co,Sz)_j$: Lost sales in week j for certain SKU (style=St, color=Co, size=Sz), $j=1$ to SS

$DEM(St,Co,Sz)_j$: Customers' demand in week j for certain SKU (style=St, color=Co, size=Sz), $j=1$ to SS

$SAL(St,Co,Sz)_j$: Sales in week j for certain SKU (style=St, color=Co, size=Sz), $j=1$ to SS

$INV(St,Co,Sz)_j$: Inventory in week j for certain SKU (style=St, color=Co, size=Sz), $j=1$ to SS

The following notations are used in the simulation-based optimization replenishment model for multiple orders:

ORD: Order of different retailers adopting the VMI replenishment strategy, $ORD = A$ or B

V_i: Maximum VMI replenishment quantity in the i^{th} replenishment cycle, $V_i = PL_i - OB_i$

PV_{Ai}: VMI replenishment quantity in the i^{th} replenishment cycle before optimization for order A

PV_{Bi}: VMI replenishment quantity in the i^{th} replenishment cycle before optimization for order B

OV_{Ai}: Optimized VMI replenishment quantity in the i^{th} replenishment cycle after optimization for order A

OV_{Bi}: Optimized VMI replenishment quantity in the i^{th} replenishment cycle after optimization for order B

EPV_{Ai}: Surplus quantity of PV_{Ai} beyond the production capacity in the i^{th} replenishment cycle

EPV_{Bi}: Surplus quantity of PV_{Bi} beyond the production capacity in the i^{th} replenishment cycle

$P_A(i,i)$: Percentage of PV_{Ai} being replenished in the i^{th} replenishment cycle

$P_B(i,i)$: Percentage of PV_{Bi} being replenished in the i^{th} replenishment cycle

$P_A(i,i-1)$: Percentage of EPV_{Ai} being adjusted to the $(i-1)^{th}$ replenishment cycle

$P_B(i,i-1)$: Percentage of EPV_{Bi} being adjusted to the $(i-1)^{th}$ replenishment cycle

$P_A(i,i+1)$: Percentage of EPV_{Ai} being adjusted to the $(i+1)^{th}$ replenishment cycle

$P_B(i,i+1)$: Percentage of EPV_{Bi} being adjusted to the $(i+1)^{th}$ replenishment cycle

$LOS(St,Co,Sz)_{Aj}$: Lost sales in week j for certain SKU (style=St, color=Co, size=Sz) in order A, $j=1$ to SS

$LOS(St,Co,Sz)_{Bj}$: Lost sales in week j for certain SKU (style=St, color=Co, size=Sz) in order B, $j=1$ to SS

$DEM(St,Co,Sz)_{Aj}$: Customers' demand in week j for certain SKU (style=St, color=Co, size=Sz) in order A, $j=1$ to SS

$DEM(St,Co,Sz)_{Bj}$: Customers' demand in week j for certain SKU (style=St, color=Co, size=Sz) in order B, $j=1$ to SS

$SAL(St,Co,Sz)_{Aj}$: Sales in week j for certain SKU (style=St, color=Co, size=Sz) in order A, $j=1$ to SS

$SAL(St,Co,Sz)_{Bj}$: Sales in week j for certain SKU (style=St, color=Co, size=Sz) in order B, $j=1$ to SS

$INV(St,Co,Sz)_{Aj}$: Inventory in week j for certain SKU (style=St, color=Co, size=Sz) in order A, $j=1$ to SS

$INV(St,Co,Sz)_{Bj}$: Inventory in week j for certain SKU (style=St, color=Co, size=Sz) in order B, $j=1$ to SS

6.2.2 Assumptions

The following assumptions are to be satisfied in the proposed simulation-based optimization replenishment model for single order:

AS1: The VMI replenishment quantities above the upper bound of the production capacity in the i^{th} replenishment could be shifted to the contiguous replenishments, i.e. the $(i-1)^{th}$ replenishment or the $(i+1)^{th}$

replenishment.

AS2: SKU distribution in EPV_i in the i^{th} replenishment is unchanged when these garments are shifted to the $(i-1)^{th}$ replenishment or the $(i+1)^{th}$ replenishment.

The following assumptions are to be satisfied in the proposed simulation-based optimization replenishment model for multiple orders:

AM1: The VMI replenishment quantity in the i^{th} replenishment before optimization PV_{Ai} and PV_{Bi} should be replenished to order A and B so far as the sum of PV_{Ai} and PV_{Bi} is less than the space for the VMI replenishment which equals the difference between the production limitation PL_i and Order-Based quantity OB_i.

AM2: The VMI replenishment quantities above the upper bound of the production capacity in the i^{th} replenishment could be shifted to the contiguous replenishments, i.e. the $(i-1)^{th}$ replenishment or the $(i+1)^{th}$ replenishment.

AM3: In the i^{th} replenishment cycle, the replenishment priority of PV_{Ai} and PV_{Bi} was higher than that of the $EPV_{A(i+1)}$, $EPV_{B(i+1)}$, $EPV_{A(i-1)}$, and $EPV_{B(i-1)}$.

AM4: SKU distribution in EPV_{Ai} and EPV_{Bi} in the i^{th} replenishment is unchanged when these garments are shifting to the $(i-1)^{th}$ replenishment or the $((i+1)^{th}$ replenishment.

6.2.3 Objective Function

The objective functions of the proposed simulation-based optimization replenishment model for single order are:

Objective 1: The proposed optimization model minimizes the imbalance of production capacity of the manufacturer. The imbalance of the production capacity of the manufacturer is defined as the absolute difference between production limit and the sum of production quantity of VMI and OB replenishment strategies, i.e.

$$Minimize \quad \sum_{i=1}^{n} \left| PL_i - (OV_i + OB_i) \right| \tag{6-1}$$

Objective 2: It minimizes the lost sales percentage under the VMI strategy. The lost sales percentage is defined as the ratio of total lost sales to customers' demand for all SKUs during the whole sales season, i.e.

$$Minimize \quad \frac{\sum_{ST,CO,SZ,SS} LOS(St,Co,Sz)_j}{\sum_{ST,CO,SZ,SS} DEM(St,Co,Sz)_j} \tag{6-2}$$

s.t

$$\begin{cases} P(i,i+1) \le 100\% & i = 1 \\ P(i,i\text{-}1) + P(i,i+1) \le 100\% & i = 2 \text{ to } n-1 \\ P(i,i-1) \le 100\% & i = n \end{cases} \tag{6-3}$$

The maximum percentage for shifting the surplus production quantity of the i^{th} replenishment to the $(i-1)^{th}$ and $(i+1)^{th}$ replenishment is 100%.

$$OV_i = \min(PV_i, (PL_i - OB_i)) + \lambda_{i-1} \times EPV_{i-1} \times p(i-1, i) + \lambda_{i+1} \times EPV_{i+1} \times p(i+1, i) \quad i = 1 \text{ to } n \tag{6-4}$$

The actual replenishment quantity in the i^{th} replenishment comprises three parts: the VMI replenishment quantity in the i^{th} replenishment under the production capacity, and the quantity shifted from the $(i-1)^{th}$ and $(i+1)^{th}$ replenishment.

$$OV_i + OB_i \leq PL_i \qquad i = 1 \quad to \quad n \tag{6-5}$$

The constraint of production capacity should be satisfied.

The objective functions of the proposed simulation-based optimization replenishment model for multiple orders are:

Objective 1: The proposed model minimizes the imbalance of production capacity of the manufacturer. The imbalance of the production capacity is defined as the absolute difference between the production limit and sum of production quantity of the VMI and OB replenishment strategies, i.e.

$$Minimize \quad \sum_{i=1}^{n} \left| PL_i - (OV_{Ai} + OV_{Bi} + OB_i) \right| \tag{6-6}$$

Objective 2: It minimizes the lost sales percentage under the VMI strategy. The lost sales percentage is defined as the ratio of total lost sales to customers' demand for all SKUs during the whole sales season for both Order A and Order B, i.e.

$$Minimize \quad \frac{\sum_{ST,CO,SZ,SS} LOS(St,Co,Sz)_{Aj} + LOS(St,Co,Sz)_{Bj}}{\sum_{ST,CO,SZ,SS} DEM(St,Co,Sz)_{Aj} + DEM(St,Co,Sz)_{Bj}} \tag{6-7}$$

s.t

$$\begin{cases} P_X(i,i+1) \le 100\% & i = 1, X = A \quad or \quad B \\ P_X(i,i\text{-}1) + P_X(i,i+1) \le 100\% & i = 2 \ to \ n-1, X = A \quad or \quad B \\ P_X(i,i-1) \le 100\% & i = n, X = A \quad or \quad B \end{cases} \tag{6-8}$$

The maximum percentage for shifting the surplus production quantity of the i^{th} replenishment to the $(i-1)^{th}$ and $(i+1)^{th}$ replenishment is 100%.

$$OV_{Ai} = P_A(i,i)*PV_{Ai} + P_A(i\text{-}1,i)*PV_{A(i-1)} + P_A(i+1,i)*PV_{A(i+1)} \tag{6-9}$$

$$OV_{Bi} = P_B(i,i)*PV_{Bi} + P_B(i\text{-}1,i)*PV_{B(i-1)} + P_B(i+1,i)*PV_{B(i+1)} \tag{6-10}$$

The actual replenishment quantity in the i^{th} replenishment for both Order A and

Order B comprise three parts respectively: the VMI replenishment quantity in the i^{th} replenishment under the production capacity, and the quantity shifted from the $(i-1)^{th}$ and $(i+1)^{th}$ replenishment.

$$OV_{Ai} + OV_{Bi} + OB_i \leq PL_i \qquad i = 1 \quad to \quad n \tag{6-11}$$

The constraint of production capacity should be satisfied.

6.2.4 Performance Evaluation

In this chapter, the CSL and IT of the retailer, as stated in section 4.3.2, is evaluated using the simulation model to represent the performance of the retailer. Besides, PCB of the manufacturer is also considered. In the VMI-based apparel supply chain, the imbalance of the production caused by the dynamic customers' demand is a heavy burden to the manufacturer and the optimization model proposed in this chapter is expected to improve the balance of the manufacturer's production capacity. Apart from the CSL and IT, PCB is included to be one of the index to evaluate the performance of the two-echelon VMI-based supply chain.

The following performance index is to be evaluated in the proposed simulation-based optimization replenishment model for single order:

(1) Customer Service Level (CSL)

As mentioned in section 4.2, CSL represents the percentage of customers' demand being satisfied during the whole sales season and the out-of-stock situation is thus employed to measure it. In the proposed simulation-based optimization replenishment model for single order, CSL defined in Equation 4-1 is detailed as follows:

$$CSL = (1 - \frac{\sum_{St,Co,Sz,SS} LOS(St,Co,Sz)_j}{\sum_{St,Co,Sz,SS} DEM(St,Co,Sz)_j})*100\% \tag{6-12}$$

(2) Inventory Turnover (IT)

Inventory Turnover (IT) represents the ratio of annual sales over the average inventory level (See Equation 4-6). In the proposed model for single order, IT is defined in details as follows:

$$IT = \frac{(\sum_{St,Co,Sz,SS} SAL(St,Co,Sz)_j)*\frac{52}{SS}}{\frac{\sum_{St,Co,Sz,SS} INV(St,Co,Sz)_j}{SS}} \tag{6-13}$$

(3) Production Capacity Imbalance Coefficient (PBC)

PBC represents the average ratio that the actual production exceeds the production capacity comparing to production capacity. It reflects the PCB of the manufacturer. The higher the PBC, the more fluctuating is the production in the manufacturer. In the proposed simulation-based optimization replenishment model for single order, PBC is defined as follows:

$$PBC = \begin{cases} \dfrac{\sum_{i=1}^{RC}(PV_i + OB_i\text{-}PL_i)}{\sum_{i=1}^{RC} PL_i} *100\% & \textit{Before Optimization} \\ \dfrac{\sum_{i=1}^{RC}(OV_i + OB_i\text{-}PL_i)}{\sum_{i=1}^{RC} PL_i} *100\% & \textit{After Optimization} \end{cases} \tag{6-14}$$

The following performance index is to be evaluated in the proposed simulation-based optimization replenishment model for multiple orders:

(1) Customer Service Level for multiple orders (CSL_A & CSL_B)

In the proposed simulation-based optimization replenishment model for multiple orders, CSL_A and CSL_B represent the percentage of customers' demand for orders A and B being satisfied during the whole sales season respectively. CSL_A and CSL_B are defined as follows:

$$CSL_A = (1 - \frac{\sum_{ST,CO,SZ,SS} LOS(St,Co,Sz)_{Aj}}{\sum_{ST,CO,SZ,SS} DEM(St,Co,Sz)_{Aj}})*100\% \tag{6-15}$$

$$CSL_B = (1 - \frac{\sum_{ST,CO,SZ,SS} LOS(St,Co,Sz)_{Bj}}{\sum_{ST,CO,SZ,SS} DEM(St,Co,Sz)_{ABj}})*100\% \tag{6-16}$$

(2) Inventory Turnover for multiple orders (IT_A & IT_B)

IT_A and IT_B represent the ratio of annual sales over the average inventory level for orders A and B respectively. In the proposed model, IT_A and IT_B are defined respectively as follows:

$$IT_A = \frac{(\sum_{St,Co,Sz,SS} SAL(St,Co,Sz)_{Aj}) * \frac{52}{SS}}{\frac{\sum_{St,Co,Sz,SS} INV(St,Co,Sz)_{Aj}}{SS}} \tag{6-17}$$

$$IT_A = \frac{(\sum_{St,Co,Sz,SS} SAL(St,Co,Sz)_{Bj}) * \frac{52}{SS}}{\frac{\sum_{St,Co,Sz,SS} INV(St,Co,Sz)_{Bj}}{SS}} \tag{6-18}$$

(3) Production Capacity Imbalance Coefficient for two orders (PBC_{AB})

PBC_{AB} represents the average ratio that the actual production exceeds the production capacity comparing to production capacity. The higher the PBC_{AB} , the more fluctuating is the production in the manufacturer. In the proposed replenishment model for multiple orders, PBC_{AB} is defined as follows:

$$PBC_{AB} = \begin{cases} \dfrac{\sum_{i=1}^{RC}(PV_{Ai} + PV_{Bi} + OB_i - PL_i)}{\sum_{i=1}^{RC} PL_i} * 100\% & \text{Before Optimization} \\ \dfrac{\sum_{i=1}^{RC}(OV_{Ai} + OV_{Bi} + OB_i - PL_i)}{\sum_{i=1}^{RC} PL_i} * 100\% & \text{After Optimization} \end{cases} \tag{6-19}$$

6.3 Simulation-Based Optimization Model of the VMI Replenishment Strategy

The simulation-based optimization replenishment model described above links the apparel supply chain VMI replenishment with *PCB* in manufacturers. It, however, substantially increases the decisions to be determined by the vendor.

Specifically, for the single order case, the decisions in the i^{th} replenishment cycle include whether to shift the surplus part of the VMI replenishment quantity EPV_i, how much to shift and which direction $(i-1)$ or $(i+1)$ to shift and so on.

In the multiple orders case, the decisions are more complicated. Take the i^{th} replenishment cycle as an example. The optimization procedures to determine replenishment quantity under the VMI strategy for multiple orders include:

1) Calculate the difference between PL_i and Order-Based quantity OB_i.

2) Determine the percentages of PV_{Ai} and PV_{Bi} to be replenished in the i^{th} replenishment cycle $P_A(i,i)$ and $P_B(i,i)$, particularly in a condition when the sum of PV_{Ai} and PV_{Bi} is greater than the difference between the production limitation PL_i and Order-Based quantity OB_i.

3) Determine the percentages of $EPV_{A(i+1)}$, $EPV_{B(i+1)}$, $EPV_{A(i-1)}$ and $EPV_{B(i-1)}$ to be

shifted into the i^{th} replenishment $P_A(i+1,i)$, $P_B(i+1,i)$, $P_A(i-1,i)$ and $P_B(i-1,i)$.

4) Obtain the optimal replenishment quantity under the VMI strategy in the i^{th} replenishment cycle for orders A and B OV_{Ai} and OV_{Bi} as presented in Equations 6-9 and 6-10.

In both models for single order and multiple orders, the impacts of the proposed optimization replenishment strategy on supply chain performance are to be examined using the simulation model.

6.3.1 Structure of the Simulation-Based Replenishment Model

The structure of the simulation-based replenishment model for both single order and multiple orders is shown in Figure 6-1. Specifically, the procedure could be divided into two sub-stages. In stage 1, the replenishment simulation program generates the VMI replenishment strategies which satisfy the CSL_t defined by the retailer. In stage 2, simulations employing GA are devised to search for the optimized replenishment strategies that meet the manufacturer's *PCB* and the retailer's targeted service level. Detailed explanations are as follows.

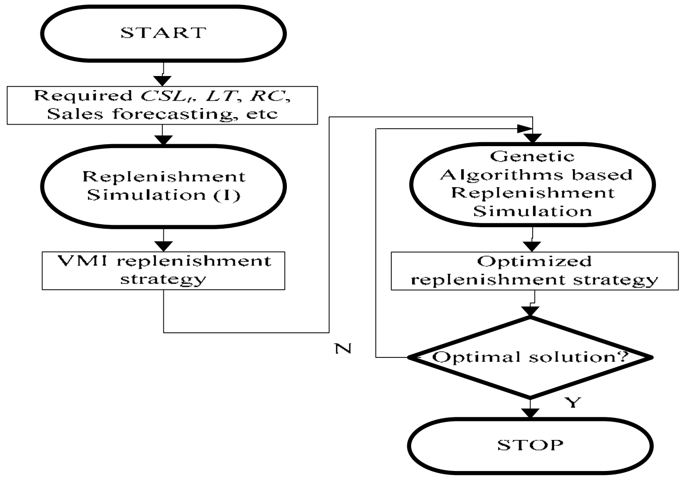


Figure 6-1: Structure of the Simulation-Based Optimization Model for the VMI-Based Replenishment Strategy

6.3.2 Stage 1: Generation of the VMI-Based Replenishment Strategy before Optimization

In this stage, the replenishment simulation model developed in Chapter 4 is revised to Replenishment Simulation (I). Comparing with the replenishment simulation model proposed in Chapter 4, this revised Replenishment Simulation (I) is simplified. The replenishment strategy generated using the simulation model is relevant to one set of lead time (LT) and replenishment cycle (RC), i.e. the retailer and the manufacturer are supposed to have made their decisions on the selection of LT and RC.

The replenishment simulation (I) imitates customers buying at a retail store and records the inventory held by the retailer. The VMI scheme ensures that the vendor captures the information of the sales record (POS data), seasonality trend and distribution of SKUs. The manufacturer regularly replenishes goods for the retailer based on this information. The VMI replenishment strategies generated by the Replenishment Simulation (I) will determine the replenishment quantity of all SKUs based on the retailer targeted CSL_t and other pre-defined parameters, such as length of the sales season, sales forecast and the pre-defined forecasting error. In the single order case, the replenishment quantity before optimization PV_i is thus calculated. In the multiple orders cases, the replenishment quantity before optimization for order A and order B, namely, PV_{Ai} and PV_{Bi} are calculated. Figure 6-2 depicts the structure of Replenishment Simulation (I).

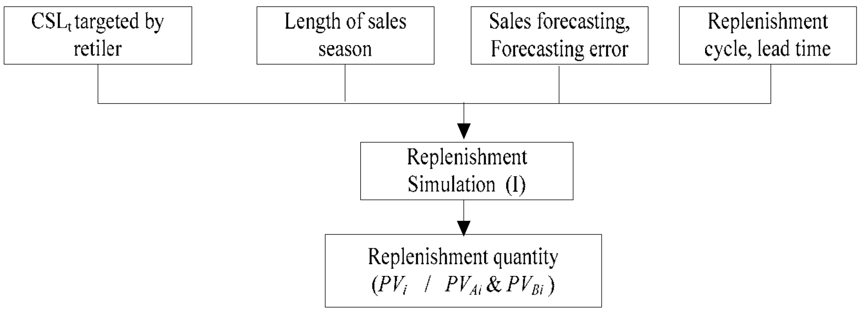


Figure 6-2: Structure of Replenishment Simulation Model (I)

Till now, the manufacturer is supposed to be capable of replenishing all the garments generated by the replenishment algorithm to satisfy the retailer when the production capacity constraints of the manufacturer are not considered.

6.3.3 Stage 2: Optimization of VMI Replenishment Strategy

Figures 6-3 and 6-4 show the procedures of optimization of the VMI replenishment strategy for single order and multiple orders respectively. Take the single order for example. In each replenishment cycle, two simulation programs and one GA-based optimization will be executed. The function of Replenishment Simulation (II) is to predict the upcoming replenishment quantity based on the VMI replenishment strategy, POS data, forecasting. An optimization applying GA is devised to find the optimal solution which satisfies the benefits of different parties in the VMI apparel supply chain. Performance (objective) evaluation is produced using simulation (III). The schemes of Replenishment Simulation (II) and (III) are similar to that of Replenishment Simulation (I) in stage 1. The procedure of the multiple orders is similar to that of single order but the details are different.

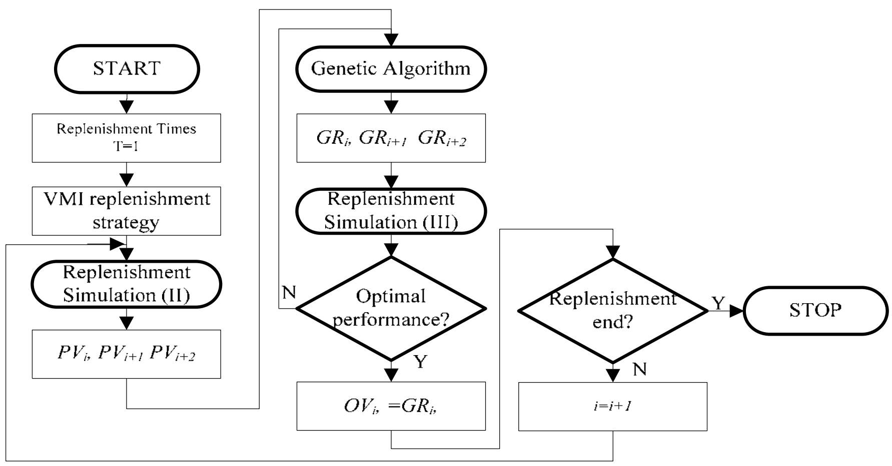


Figure 6-3: Optimization of the Replenishment Strategy for Single Order

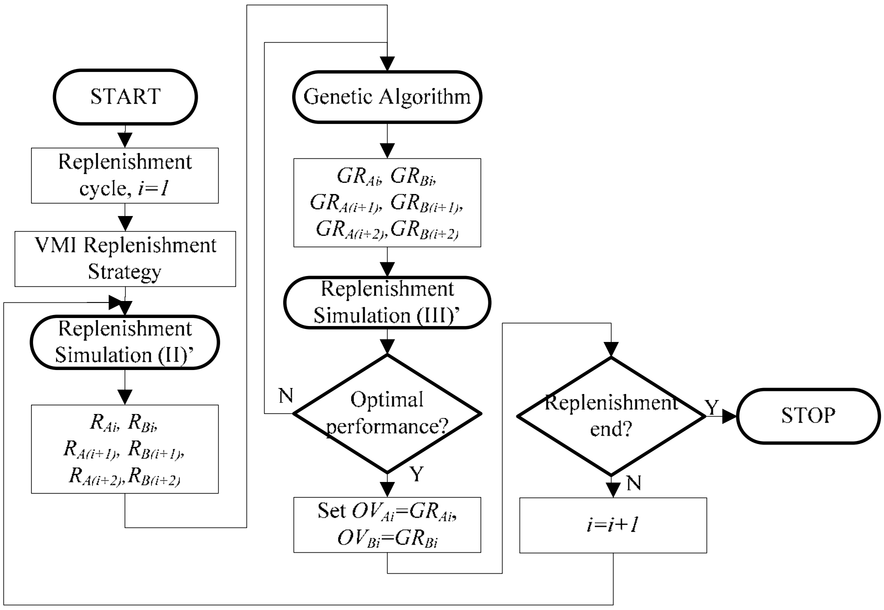


Figure 6-4: Optimization of the Replenishment Strategy for Multiple Orders

The detailed procedures in stage 2 for single order and multiple orders are explained separately as follows:

Detailed procedures in stage 2 for single order:

1) Predict replenishment quantity of three contiguous periods for each SKU using Replenishment Simulation (II). The summarizations of all SKUs are denoted as PV_i, PV_{i+1} and PV_{i+2}.

2) With the consideration of constraints of Equations 6-5, 6-6 and 6-7 in the proposed model, adjust PV_i, PV_{i+1} and PV_{i+2} to intermediate variable GR_i, GR_{i+1} and GR_{i+2} which are the optimal solution to satisfy the model objectives using the GA.

The evaluation of the objectives is implemented in Replenishment Simulation (III).

3) Set the upcoming optimized replenishment quantity $OV_i = GR_i$ and distribute OV_i to individual SKUs based on the SKU distribution and seasonality distribution, obtaining $OV(St,Co,Sz)_i$. In this study, the rolling horizon method (Baker 1977) is adopted in which only the upcoming VMI replenishment quantity GR_i rather than the total 3 intermediate variables GR_{i+1} and GR_{i+2} is set as the optimized VMI replenishment quantity. This rolling procedure is reasonable because it is identical with the practical replenishment procedure in the apparel supply chain. Once a certain quantity OV_i is shipped to the retailer, the POS data and the replenishment quantity for the next cycles are changed compared with those of PV_i. For example, suppose that for one certain SKU, customer demand is greater than $PV(St,Co,Sz)_i$. If $OV(St,Co,Sz)_i$ is greater than $PV(St,Co,Sz)_i$ and the lost sales caused by the shortage of goods decrease, the replenishment quantity for the next 2 cycles is no longer the previous $PV(St,Co,Sz)_{i+1}$ and $PV(St,Co,Sz)_{i+2}$ Hence, the total replenishment quantity PV_{i+1} and PV_{i+2} are updated. The optimization should be conducted based on the most updated situation.

4) Input the optimized replenishment quantity $OV(St,Co,Sz)_i$ to Replenishment Simulation (II) to generate the prediction of replenishment quantity PV_{i+1}, PV_{i+2} and PV_{i+3} for the next 3 replenishment cycles, after imitating customers buying and POS data recording at the retailer.

5) Repeat steps 1-4 until the end of the sales season.

Till now, the optimized replenishment quantity for individual SKUs $OV(St,Co,Sz)_i$ and their summarization OV_i in each replenishment cycle is obtained.

Detailed procedures in stage 2 for multiple orders:

1) Predict replenishment quantity of 3 continuous periods using the replenishment simulation program. The replenishment quantity for order A and order B are denoted as RV_{Ai}, RV_{Bi}, $RV_{A(i+1)}$, $RV_{B(i+1)}$, $RV_{A(i+2)}$ and $RV_{B(i+2)}$. In the first replenishment cycle, these 6 variables are equal to the replenishment quantity generated before optimization, i.e. PV_{Ai}, PV_{Bi}, $PV_{A(i+1)}$, $PV_{B(i+1)}$, $PV_{A(i+2)}$ and $PV_{B(i+2)}$.

2) Adjust RV_{Ai}, RV_{Bi}, $RV_{A(i+1)}$, $RV_{B(i+1)}$, $RV_{A(i+2)}$ and $RV_{B(i+2)}$ to intermediate variable GR_{Ai}, GR_{Bi}, $GR_{A(i+1)}$, $GR_{B(i+1)}$, $GR_{A(i+2)}$, and $GR_{B(i+2)}$ which are the optimal solution to satisfy the model objectives using GA.

3) Set optimal replenishment quantity $OV_{Ai} = GR_{Ai}$, $OV_{Bi} = GR_{Bi}$. The rolling horizon method is adopted in which only the upcoming VMI replenishment quantity GR_{Ai} and GR_{Bi} rather than the total six intermediate variables GR_{Ai}, GR_{Bi}, $GR_{A(i+1)}$, $GR_{B(i+1)}$, $GR_{A(i+2)}$, and $GR_{B(i+2)}$ are set as the optimized VMI replenishment quantity OV_{Ai} and OV_{Bi}. The reason is the same as that stated for single order.

4) Input the optimized replenishment quantity OV_{Ai} and OV_{Bi} to the replenishment simulation program to generate the prediction of replenishment quantity $RV_{A(i+1)}$, $RV_{B(i+1)}$, $RV_{A(i+2)}$, $RV_{B(i+2)}$, $RV_{A(i+3)}$ and $RV_{B(i+3)}$ for the next 3 replenishment cycles, after imitating customers buying and POS data recording at the retailer.

5) Repeat steps 1-4 until the end of the sales season.

The optimized replenishment strategy for multiple orders is thus obtained.

6.3.4 Genetic Algorithm (GA) for Replenishment Strategy Optimization

In this subsection, the design in GA for replenishment strategy optimization for both single order and multiple orders is explained in details, which includes the representation of code, the definition of fitness function, as well as the selection, crossover and mutation.

A. Code and fitness function in GA

Code and Fitness Function for Single Order:

The proposed GA is real coded and the individuals are coded in floating point numbers. Figure 6-5 illustrates the chromosomes used in models for single order. The chromosomes in Figure 6-5 comprise real numbers representing the percentage of i^{th} exceeding replenishment quantity EPV_i to be adjusted to the contiguous replenishment cycle $(i-1)$ or $(i+1)$.

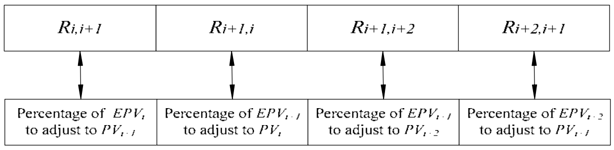


Figure 6-5: Representation of GA chromosomes for Single Order

The GA operates on a population of chromosomes. In this study, each chromosome is randomly initialized by assigning each gene a real number. Since not all combinations of the decision variables constitute a feasible solution, infeasible solutions are repaired using a repair function before they are input to the simulation procedures as below:

1) Set the $R_{i,x} = 0$ in the condition that $EPV_i = 0$; $x = i-1 \text{ or } i+1$

2) Set the $R_{i,x} = 100\%$ in the condition that $EPV_i > 1$; $x = i-1 \text{ or } i+1$

3) If $R_{i+1,i} + R_{i+1,i+2} > 1$, discard the chromosome and randomly generate another one until the population size is satisfied.

Fitness function is defined as the fitness of each chromosome so as to determine which will reproduce and survive into the next generation. Given a particular chromosome, the value of fitness function and fitness represents its probability to survive. In this study, the objective functions generated by Replenishment Simulation

(III) of the proposed model (Equations 6-3 and 6-4) are the basis of the fitness function. The less the fitness of a chromosome is, the greater the probability to survive. Since each optimization procedure includes 3 replenishment cycles, periods of performance evaluation are also set as 3 replenishment cycles. Fitness of each chromosome is defined as follows:

$$f_1 = \frac{\sum_{i=j}^{j+2} \left| PL_i - (OV_i + M_i) \right|}{\sum_{i=j}^{j+2} \left| PL_i - (PV_i + M_i) \right|} \qquad j = 1 \quad to \quad n-2 \tag{6-20}$$

$$f_2 = \frac{\sum_{i=j}^{j+2} LOS(St,Co,Sz)_i}{\sum_{i=j}^{j+2} DEM(St,Co,Sz)_i} \qquad j = 1 \quad to \quad n-2 \tag{6-21}$$

Code and Fitness for Multiple Orders:

Figure 6-6 illustrates the chromosome segmented in two parts used in the i^{th} optimization procedure in the proposed model.

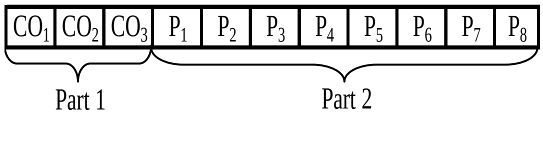


Figure 6-6: Representation of GA chromosomes for multiple orders

The first part of the chromosome is composed of three coefficients CO_1 to CO_3 to determine the proportion of replenishment quantity for orders A and B in each replenishment cycle. Take CO_1 as an example. It reflects the weight of PV_{Aj} and PV_{Bj} occupying in the i^{th} replenishment cycles. Considering the production capacity constraints, these three coefficients should be subject to:

$$\begin{cases} \begin{cases} CO_i = \dfrac{PV_{Ai}}{PV_{Ai} + PV_{Bi}} \\ CO_j * PV_{Ai} + (1 - CO_i) * PV_{Bi} \le V_i \end{cases} & if\ PV_{Ai} + PV_{Bi} \le V_i \\ \begin{cases} 0 \le CO_i \le \dfrac{PV_{Ai}}{PV_{Ai} + PV_{Bi}} \\ CO_i * PV_{Ai} + (1 - CO_i) * PV_{Bi} \le V_i \end{cases} & otherwise \end{cases} \tag{6-22}$$

In the second part, eight real numbers P_1 to P_8 are employed to represent the percentage of exceeding replenishment quantity of orders A and B in the i^{th}, $(i+1)^{th}$ and $(i+2)^{th}$ replenishment cycle, to be adjusted to their contiguous replenishment cycles. Specifically,

P_1: percentage of EPV_{Ai} to be adjusted to $(i+1)^{th}$ replenishment cycle

P_2: percentage of EPV_{Bi} to be adjusted to $(i+1)^{th}$ replenishment cycle

P_3: percentage of $EPVA_{(i+1)}$ to be adjusted to i^{th} replenishment cycle

P_4: percentage of $EPV_{B(i+1)}$ to be adjusted to i^{th} replenishment cycle

P_5: percentage of $EPVA_{(i+1)}$ to be adjusted to $(i+2)^{th}$ replenishment cycle

P_6: percentage of $EPV_{B(i+1)}$ to be adjusted to $(i+2)^{th}$ replenishment cycle

P_7: percentage of $EPVA_{(i+2)}$ to be adjusted to $(i+1)^{th}$ replenishment cycle

P_8: percentage of $EPV_{B(i+2)}$ to be adjusted to $(i+1)^{th}$ replenishment cycle

Owing to the limitation of production capacity, these eight percentages should be subject to:

$$\begin{cases} EPV_{Aj} = PV_{Aj} - PV_{Aj}*CO_j & j = i \text{ to } i+2 \\ EPV_{Bj} = PV_{Bj} - PV_{Bj}*(1-CO_j) & j = i \text{ to } i+2 \end{cases} \tag{6-23}$$

$$\begin{cases} PV_{Aj}*CO_j + PV_{Bj}*(1-CO_j) & \\ + P_3 * EPV_{A(j+1)} + P_4 * EPV_{B(j+1)} \le V_j & j = i \\ PV_{Aj}*CO_j + PV_{Bj}*(1-CO_j) + P_1 * EPV_{A(j-1)} + P_2 * EPV_{B(j-1)} & \\ + P_5 * EPV_{A(j+1)} + P_6 * EPV_{B(j+1)} \le V_j & j = i+1 \\ PV_{Aj}*CO_j + PV_{Bj}*(1-CO_j) & \\ + P_7 * EPV_{A(j-1)} + P_8 * EPV_{B(j-1)} \le V_j & j = i+2 \end{cases} \tag{6-24}$$

The GA operates on a population of chromosomes. In this study, each chromosome is randomly initialized by assigning each gene a real number. Since not all combinations of the decision variables constitute feasible solutions to ensure that the range of adjustment of the surplus quantity to the contiguous replenishment cycles is from 0% to 100%, infeasible solutions are repaired as follows:

1) Set $P_i = 0$ in the condition that $P_i < 0$, $i = 1 \text{ to } 8$

2) Set $P_i = 100\%$ in the condition that $P_i > 1$, $i = 1 \text{ to } 8$

3) If $P_3 + P_5 > 100\%$, or $P_4 + P_6 > 100\%$ discard the chromosome and randomly generate another one until the population size is satisfied.

Fitness function is defined as the fitness of each chromosome so as to determine which will reproduce and survive into the next generation. Given a particular chromosome, the value of fitness function and fitness represent its probability to survive. Since each optimization procedure includes 3 replenishment cycles, the periods of performance evaluation are set as 3 replenishment cycles. These fitness functions are calculated using the simulation program. Fitness of each chromosome is defined as follows:

$$f_1 = \frac{\sum_{i=j}^{j+2} \left| PL_i - (OV_{Ai} + OV_{Bi} + OB_i) \right|}{\sum_{i=j}^{j+2} \left| PL_i - (PV_{Ai} + PV_{Bi} + OB_i) \right|} \quad j = 1 \ \ to\, n-2 \qquad (6\text{-}25)$$

$$f_2 = \frac{\sum_{i=j}^{j+2} LOS_{Ai} + LOS_{Bi}}{\sum_{i=j}^{j+2} DEM_i} \qquad j = 1 \ \ to \ \ n-2 \qquad (6\text{-}26)$$

B. Selection, crossover and mutation in GA

In this study, the strategy on selection, crossover and mutation for single order and multiple orders is identical.

The selection strategy of GA is based on the natural law of survival of the fittest in which the chromosomes are selected for the next generation in terms of their fitness. In this study, the Roulette-wheel-selection (Goldberg 1989) scheme is utilized. This selection chooses parents by simulating a roulette wheel, in which the area of the section of the wheel corresponding to a chromosome is proportional to the chromosome's expected fitness. The algorithm uses a random number to select one of the sections with a probability equal to its area.

Crossover options specify how the GA combines two individuals, or parents, to form a crossover child for the next generation. The procedure for computing offspring from two parents in this study for both single order or multiple orders is based on Simulated Binary Crossover (SBX) (Deb et al 1995). Firstly, a random value μ_i between 0 and 1 is created. Based on a specified probability distribution function, the ordinate $f(\mu_i)$ is found such that the cumulative probability for ordinate $f(\mu_i)$ is equal to μ_i. After finding the ordinate $f(\mu_i)$, the offspring are calculated using the following equations:

$$C1 = 0.5[(1 + f(u_i))P1 + (1 - f(u_i))P2] \tag{6-27}$$

$$C2 = 0.5[(1 - f(u_i))P1 + (1 + f(u_i))P2] \tag{6-28}$$

where $C1$ and $C2$ are children solutions after applying the crossover operator and $P1$ and $P2$ are the parents. The probability distribution is given as follows:

$$P(x) = \begin{cases} 0.5(\eta + 1)x^{\eta} & if \quad x \le 1; \\ 0.5(\eta + 1)\dfrac{1}{x^{\eta+2}} & otherwise \end{cases} \tag{6-29}$$

In the above equation, the distribution index η is a non-negative real number. A large value of η gives a higher probability for creating 'near parent' solutions and a small value of η allows distant solutions to be selected as offspring. In order to maintain diversity in a population from one generation to the next, a mutation operator is normally applied. In this study, this mutation is implemented based on (Deb 2001) which is similar to SBX for crossover. First, a random number γ_i between 0 and 1 is created. Then, from a specified probability distribution function, the ordinate $f(\gamma_i)$ is found that the cumulative probability for ordinate $f(\gamma_i)$ is equal to γ_i. After computing $f(\gamma_i)$, the offspring is calculated using the following equation:

$$C = P + (P_U - P_L)f(r_i) \tag{6-30}$$

where C is denoted as a child, P is a parent, P_U and P_L are the upper and lower bounds of the parents respectively.

Both the genetic operators of crossover and mutation are randomly used. In the proposed replenishment strategy optimization approach, a crossover rate of 0.7 and mutation rate of 0.04 are chosen after testing.

The process of selection, crossover and mutation repeats in each generation with the objective of reaching the global optimal solution.

6.4 Simulation Experiments and Discussions

Simulation-based optimization models for both single order and multiple orders were evaluated via experiments. Simulation experiments were conducted on the basis of the practical procedure from a manufacturer in South China adopting typical VMI strategy and providing apparel products to a retailer who has more than a thousand department stores in the States.

6.4.1 Simulation Experiments for Single Order

Ten simulation experiments were conducted to evaluate the optimization model for single order. Table 6-1 shows the input parameters of these simulation experiments. The major input parameters of the simulation experiments (including the sales season, lead time, replenishment cycle, forecasted SKU distribution, forecasted seasonality distribution as well as the forecasting error) were set at two different levels. Experiments 1 to 5 were set at one level while Experiments 6 to 10 were set at another level. These settings of the input parameters reflect two common industrial practices. Particularly, the predicted SKU distribution and seasonality distribution of actual customers' demand were different in each experiment. They were randomly predicted based on the forecasted distribution and the forecasting error of the customers' demand. Detailed relationship among the forecasting error, the forecasted customers' demand and the predicted actual customers' demand sees Chapter 4.

Table 6-1: Input Parameters for Single Order

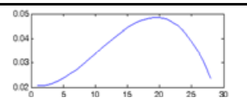
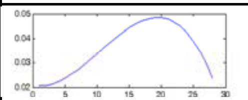
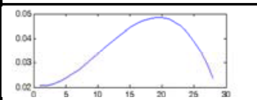
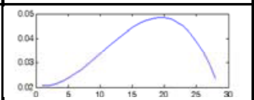
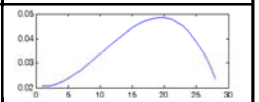
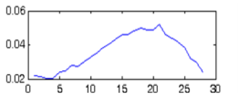
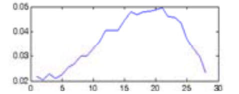
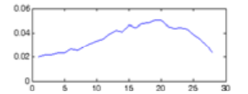
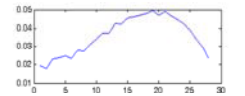
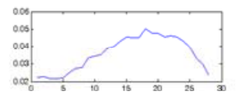
Input		Experiment 1	Experiment 2	Experiments 3	Experiments 4	Experiments 5
Sales season (week)		28	28	28	28	28
SKU (Style/Color/Size)		3/4/5	3/4/5	3/4/5	3/4/5	3/4/5
Forecasting error (Quantity/Style/color/Size /Seasonality Distribution)		(0/20/20/10/3)	(0/20/20/10/3)	(0/20/20/10/3)	(0/20/20/10/3)	(0/20/20/10/3)
Replenishment cycle (week)		2	2	2	2	2
Lead time (week)		7	7	7	7	7
Required CSL_t		95%	95%	95%	95%	95%
Forecasted SKU distribution	Style	20/30/50	20/30/50	20/30/50	20/30/50	20/30/50
	Color	10/20/30/40	10/20/30/40	10/20/30/40	10/20/30/40	10/20/30/40
	Size	10/10/20/30/30	10/10/20/30/30	10/10/20/30/30	10/10/20/30/30	10/10/20/30/30
Predicted actual SKU distribution	Style	13/40/47	16/40/44	30/30/40	15/40/45	10/40/50
	Color	5.21/23.14 /36.84/34.79	14.96/15.35 /35.04/34.65	21.1/26.5 /33.5/37.89	17.8/18.56 /32.2/31.44	16.6/11.37 /33.4/38.63
	Size	11.47/8.42/20.09 /33.53/26.50	12.3/7.66/20.57 /32.13/27.34	12.55/7.88/21.1 /31.35/27.12	6.61/8.73/22.46 /32.54/29.66	9.4/6.11/22.41 /32.59/29.49
Forecasted seasonality distribution						
Predicted actual seasonality distribution						

Table 6-1: Input Parameters for Single Order (Continued)

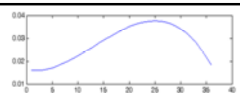
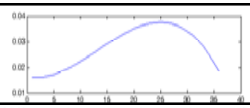
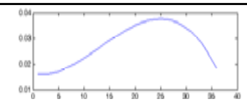
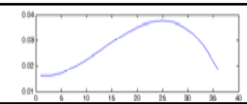
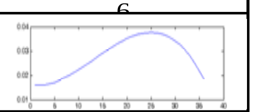
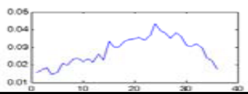
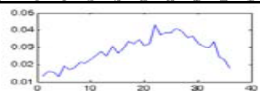
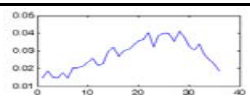
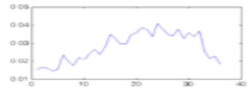
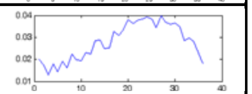
Input		Experiments 6	Experiments 7	Experiments 8	Experiments 9	Experiments 10
Sales season (week)		36	36	36	36	36
SKU (Style/Color/Size)		5/6/7	5/6/7	5/6/7	5/6/7	5/6/7
Forecasting error (Quantity/Style/color/Size /Seasonality Distribution)		(5/10/10/10/3)	(5/10/10/10/3)	(5/10/10/10/3)	(5/10/10/10/3)	(5/10/10/10/3)
Replenishment cycle (week)		4	4	4	4	4
Lead time (week)		7	7	7	7	7
Required CSL_t		95%	95%	95%	95%	95%
Forecasted SKU distribution	Style	30/10/25/10/25	30/10/25/10/25	30/10/25/10/25	30/10/25/10/25	30/10/25/10/25
	Color	4/20/28/27/14/7	4/20/28/27/14/7	4/20/28/27/14/7	4/20/28/27/14/7	4/20/28/27/14/7
	Size	20/15/20/5 /20/10/10	20/15/20/5 /20/10/10	20/15/20/5 /20/10/10	20/15/20/5 /20/10/10	20/15/20/5 /20/10/10
Predicted actual SKU distribution	Style	31.97/8.07/27 /11.03/21.93	32.43/6.24/26.17 /11.4/23.76	31.84/7.36/24.26 /13.16/23.38	28.23/12.18/26.37 /11.45/21.77	30.31/13.91/21.91 /11.09/22.78
	Color	2.06/21.97/27.63 /26.29 /17.03/5.01	2.47/18.34/27.89 /29.19/16.81/5.3	1.9/19.79/30.74 /24.12/16.47/6.98	6.98/20.34/25.45 /25.48/16.02/5.73	1.47/21.08/30.57 /25.18/15.34/6.35
	Size	19.4/17.45/17.07 /5.48/20.29/12.55/7.76	18.66/16.66/18.21 /6.05 /21.92/10.37/8.13	18.95/17.8/21.6 /4.89/17.72/10.6/8.44	18.03/18.38/20.78 /5.23/18.42/10.62/8.54	15.45/14.85/22.84 /6.18/19.59/11.13/9.96
Forecasted seasonality distribution						
Predicted actual seasonality distribution						

Figure 6-7 shows the experimental procedure of the dynamic rolling optimization in Experiment 1. Both the objective functions on *PBC* and *CSL* (Equations 6-9 and 6-10) were conducted in this experiment. The Production capacity limitation (*PL*) was set at 6000 for each replenishment cycle. The initial plan for the VMI strategy and the production quantity for OB retailers are shown in the first and second rows in Figure 6-7 respectively. The replenishment quantity for the VMI strategy before optimization which was generated using Replenishment Simulation (I) are shown in the third row. The GA was activated in each optimization cycle to generate 3 intermediate replenishment quantity variables, followed by a rolling prediction on replenishment quantity for the next 3 cycles using Replenishment Simulation (II). Take the objective function for maximization of *PCB* (i.e. minimization of the *PBC*) as an example. The 1300/2991/3400 in the forth line of 5 shows the first three intermediate replenishment quantities. In the fifth line, the 1300 is the first optimal replenishment quantity generated by the rolling optimization model and 2821/3829/3059 are the predictions for the next 3 cycles. The procedures of optimizing and rolling were repeated until the end of the sales season. The final optimal replenishment quantities for all cycles (i.e. 1300/2988/3400/3099/3020/3770/3600/3500/2900/2106) are shown in the last line.

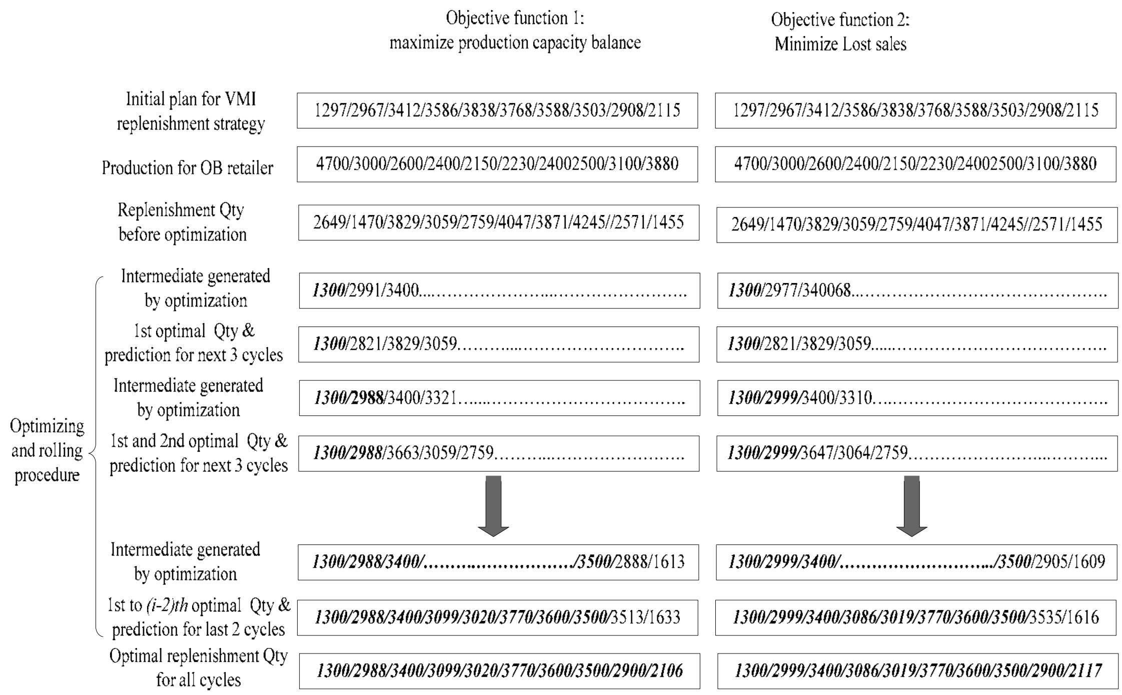


Figure 6-7: Dynamic Rolling Optimization of the Replenishment Procedure

in Experiment 1 for Single Order

Table 6-2 illustrates the performance comparison of the VMI replenishment strategy and the optimized one in this simulation experiment. It is obvious that the optimized replenishment strategy can eliminate the exceeding production quantity which is about 10% of the total quantity for the VMI strategy and the *CSL* only declines about 2%.

Table 6-2: Performance Evaluation of Experiment 1 for Single Order

	Objective Function: Improve *CSL*		Objective Function: Improve Production Capacity Balance	
Performance	Pre-optimized Strategy	Optimized Strategy	Pre-optimized Strategy	Optimized Strategy
CSL (*)	0.961	0.945	0.961	0.942
IT (*)	12.00	12.71	12.00	12.69
PBC (*)	10.26%	0	10.26%	0

*: Performance of *CSL* was evaluated according to Equation 6-12; *IT* was evaluated according to Equation 6-13; *PBC* was evaluated according to Equation 6-14.

In this experiment, the result on performance evaluation is closer to each other when the objective functions are set as eliminating the lost sales and improving the *PCB* respectively. For simulation experiments in the latter part, the objective function is set to improve the *PCB*.

Table 6-3 shows the comparison of performance of the VMI replenishment strategy before and after optimization in the ten simulation experiments. Since the major input parameters of the simulation experiments were set at two different levels for all experiments, the performance evaluated in this study was divided into two parts, each corresponding to one level on the input parameters. Specifically, the figures in Table 6-3 are the mean values and standard deviations of each five simulation experiments.

It is obvious that in both cases, the improvement on the *PCB* is significant. In Experiments 1 to 5, over 10% of the total production quantity exceeding the production capacity limitation can be shifted to the continuous replenishment cycles while in Experiments 6 to 10, this figure is about 18%. Meanwhile, CSL and IT are kept at a high level. The decline rates of the CSL are around 3% to 5% in all experiments. These results show that the optimized replenishment strategy can work well to balance the different profits for participants in the supply chain. Specifically, for the manufacturer, the cost for imbalanced production was saved; and for the retailers, the CSL declined a little.

Table 6-3: Summary on Performance Comparison for Single Order

Performance Evaluation	Experiments 1 to 5			
	Pre-optimized Strategy		Optimized Strategy	
	Mean value	SD	Mean value	SD
CSL (*)	0.962	0.002	0.931	0.022
IT (*)	12.4	0.57	12.7	0.01
PBC (*)	10.20%	0.03	0	0
Performance Evaluation	Experiments 6 to 10			
	Pre-optimized Stragtegy		Optimized Strategy	
	Mean value	SD	Mean value	SD
CSL (*)	0.965	0.008	0.917	0.007
IT (*)	9.11	0.51	11.33	0.71
PBC (*)	18.22%	0.03	0	0

*: Performance of CSL was evaluated according to Equation 6-12; IT was evaluated according to Equation 6-13; PBC was evaluated according to Equation 6-14.

6.4.2 Simulation Experiments for Multiple Orders

Using the proposed simulation-based optimization model for multiple orders, ten simulation experiments were conducted on the basis of the industrial practice. Table 6-4 shows the major input parameters of the model for these ten simulation experiments. Orders A and B were two orders adopting the VMI replenishment strategy with different CSL_t requirements. For order A, the retailer-defined CSL_t was 95%; for order B, this figure was 90%. Like the experiments for single order, the major input parameters of the 10 simulation experiments (including the sales season, lead time, replenishment cycle, forecasted SKU distribution, forecasted seasonality distribution as well as the forecasting error) were set at tow different levels. Experiments 1 to 5 were set at one level while Experiments 6 to 10 were set at another level. These settings of the input parameters reflect two common industrial practices.

Table 6-4: Input Parameters for Multiple Orders

Input	Experiments 1 to 5		Experiments 6 to 10	
Sales season (week)	Order A	Order B	Order A	Order B
Replenishment cycle (week)	2		2	
Lead time (week)	7		7	
SKU (Style/Color/Size)	3/4/5	5/6/7	3/4/5	5/6/7
Forecasting Error (Volume/Style Mix /Color Mix/Size Mix/Seasonality)	0/20/20/10/5	20/25/25/15/2	5/10/10/10/3	15/20/15/9/8
Required CSL_t	95%	90%	95%	90%

Tables 6-5 and 6-6 illustrate the performance comparison of the VMI replenishment strategy and the optimized one in the ten experiments. The results shown in Tables 6-5 and 6-6 are the mean values and standard deviations of Experiments 1 to 5 and 6 to 10 respectively.

In all the ten simulation experiments, the improvements on the *PCB* were significant. In Experiments 1 to 5, over 21% of the total production quantity exceeding the production capacity limitation could be shifted to the continuous replenishment cycles while in Experiments 6 to 10, this figure was about 17%. Meanwhile, *CSL* could be kept at a high level. In Experiments 1 to 5, the decline rates of the *CSL* for orders A and B were 1.7% and 3.7% respectively. In Experiments 6 to 10, the decline rates of *CSL* in orders A and B were 1.3% and 3.6% respectively. These results show that the optimized replenishment strategy works well to balance the different profits for participants in the supply chain. Specifically, for the manufacturer, the cost for imbalanced production was saved; and for the retailer, the *CSL* declined a little.

Table 6-5: Summary on Performance Comparison for Multiple Orders

(Part 1: Experiments 1 to 5)

Performance Evaluation	Order A (Statistical result of Experiments1 to 5)			
	Before optimization		After optimization	
	Mean value	SD	Mean value	SD
CSL_A (*)	0.957	0.002	0.94	0.002
IT_A (*)	12	0.56	12.7	0.31
Performance Evaluation	Order B (Statistical result of Experiments 1 to 5)			
	Before optimization		After optimization	
	Mean value	SD	Mean value	SD
CSL_B (**)	0.908	0.008	0.871	0.007
IT_B (**)	7.21	0.61	7.92	0.45
PBC (***)	21.91%	0.03	0	0

Table 6-6: Summary on Performance Comparison for Multiple Orders

(Part 2: Experiments 6 to 10)

Performance Evaluation	Order A (Statistical result of Experiments 6 to 10)			
	Before optimization		After optimization	
	Mean value	SD	Mean value	SD
CSL_A (*)	0.961	0.002	0.948	0.005
IT_A (*)	11	0.45	11.5	0.31
Performance Evaluation	Order B (Statistical result of Experiments 6 to 10)			
	Before optimization		After optimization	
	Mean value	SD	Mean value	SD
CSL_B (**)	0.908	0.008	0.872	0.001
IT_B (**)	8.41	0.51	9.22	0.42
PBC (***)	17.76%	0.02	0	0

*: Performance of CSL_A was evaluated according to Equation 6-15; IT_A was evaluated according to Equation 6-17; **: Performance of CSL_B was evaluated according to Equation 6-16; IT_B was evaluated according to Equation 6-18; ***: PBC was evaluated according to Equation 6-19.

6.5 Impacts on the Performance of the Supply Chain

In order to study the relationship between the simulation-based optimization replenishment strategy and the performance of the supply chain in details, an impact analysis on the performance of the supply chain was done with a case study. To simplify the analysis, only the investigation results of single VMI order are reported in this section.

6.5.1 Variation of the Customer Service Level (CSL)

In the previous simulation experiments, the CSL was kept at a high level in the replenishment strategy after optimization. As the CSL was evaluated by the mean lost sales in the whole sales season in the proposed model (Equation 6-12), one of the possible reasons for it to be kept so well was that some of the replenishment shipped in advance in some cycles and parts of the goods might be delayed by one replenishment cycle in other cycles. Replenishing the garments in advance would increase the inventory and more customers were lost in certain periods, compared with the VMI replenishment strategy; for delaying the replenishment by one replenishment cycle, the situation was the reverse. Figures 6-8 and 6-9 show the comparison of the VMI replenishment strategy before and after optimization in Experiment 1 on replenishment quantity and lost sales in the whole sales season respectively.

Compared with the VMI replenishment strategy before optimization, the variation of the lost sales after optimization was correlative to the change of the replenishment quantity. Owing to the reduction of the replenishment from week 9 to 13, the lost sales increased during week 17 to 22 in the optimized replenishment strategy. Since transportation time was required to ship the replenishment goods from the manufacturer to the retailer, the lost sales increased during this period. In this case, the period was around 7 weeks. Opposite phenomena could be found in the other two periods: replenishment quantity increased from week 15 to 17 while lost sales decreased during week 22 to 25.

Some changes of the lost sales in certain periods may lead to retailers' dissatisfaction.

Although the reduction of the average *CSL* in the whole sales season is limited, as shown in Table 6-2, the lost sales increased over 50% in week 18 in this case. This amplification of the lost sales occurred after 3 successive lack of replenishment compared with the replenishment before optimization. This simulation result reveals some relationship between the intensification of lost sales and consecutive decrease of replenishment quantity.

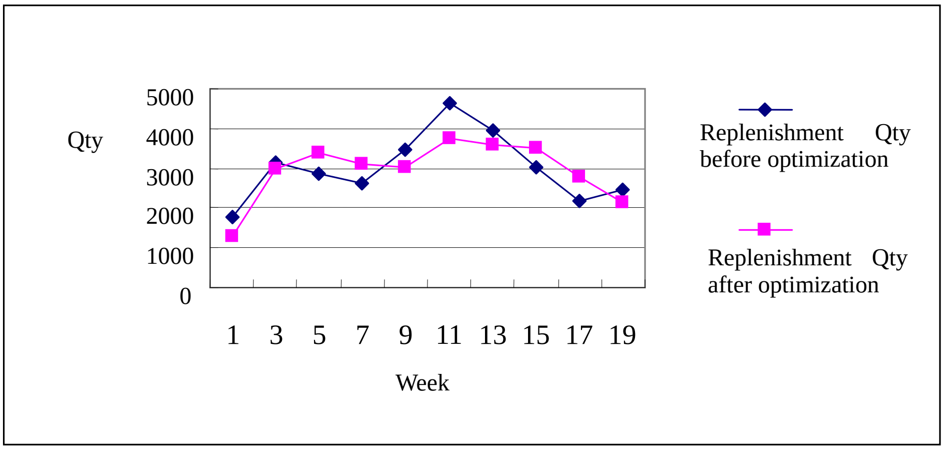


Figure 6-8: Comparison of Replenishment Quantity

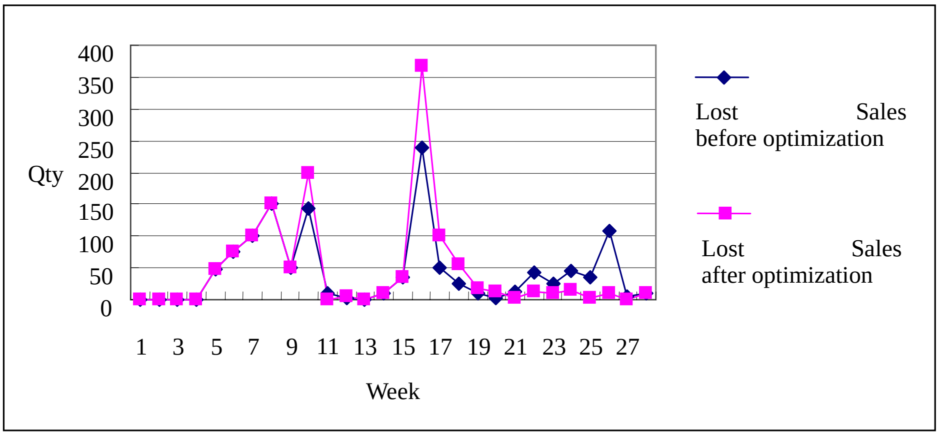


Figure 6-9: Comparison of Variation of Lost Sales

6.5.2 Relationship between the Forecasting Error and the Supply Chain Performance

In the VMI supply chain model, the imbalance of production capacity is mainly caused by the forecasting error on the customers' demand. In order to investigate the relationship between the forecasting error and the performance of the proposed optimized replenishment strategy, the forecasting error shown in Table 6-1 was increased to a higher degree which was input to the simulation-based optimization model for experimental study.

Table 6-7 summarizes the change of the supply chain CSL when the forecasting error increases. The figures in the table are in the form of means and standard deviations. In all of the simulation experiments, the CSL declines dramatically along with the increase in the forecasting error. Around 10% more customer sales will be lost if the optimized strategy is utilized when the forecasting error increases.

Based on the above results, it could be found that the forecasting error would influence the performance of the supply chain. A possible suggestion is that more resources should be put on maximizing the forecasting accuracy. With the improvement in forecasting customers' demand, the proposed optimization replenishment model would benefit the industry to improve the performance of the supply chain.

Table 6-7: Impact of Forecasting Error on *CSL*

	Experients 1 to 5 for single order							
Forecasting error	0/20/20/10/3				20/25/25/15/5			
	Before optimization		After optimization		Before optimization		After optimization	
	Mean value	SD	Mean value	SD	Mean value	SD	Mean value	SD
CSL	0.962	0.002	0.931	0.022	0.961	0.002	0.852	0.021
	Experiments 6 to 10 for single order							
Forecasting error	5/10/10/10/2				11.25/10/20/30/5.25			
	Before optimization		After optimization		Before optimization		After optimization	
	Mean value	SD	Mean value	SD	Mean value	SD	Mean value	SD
CSL	0.965	0.008	0.917	0.007	0.954	0.009	0.852	0.002

All these findings might give some reference to the VMI-based apparel supply chain participants, especially for the manufacturer who dominates the replenishment strategy. Generally, the optimized replenishment model for the VMI strategy could work well since it could improve the *PCB* of the manufacturer significantly while only a small amount of lost sales was sacrificed. The performance of the optimized replenishment strategy would be affected by the increase in the forecasting error.

6.6 Summary

In this chapter, using the VMI-based replenishment model and GA, a simulation-based optimization model was proposed to investigate the replenishment strategy and improve the performance of the apparel supply chain. The simulation-based optimization model was developed in rolling horizon. This model incorporated the production capacity of manufacturer and the *CSL* of the retailer. In the replenishment model for the VMI strategy in the supply chain, two situations were considered. One was for single order and the other was for multiple orders with different targeted CSL_t requirements.

With the development of the simulation program and genetic optimization algorithm, the proposed model was validated and its impact on the supply chain performance was investigated. Simulation experimental results indicate that the proposed optimization replenishment strategy could maintain the retailer's CSL while improving the PCB of the manufacturer significantly under the condition that the forecasting error in the customers' demand is at a low degree.

At the end of this chapter, the impact on the variation of the CSL and the relationship between the forecasting error and the CSL were investigated with simulation experimental studies.

CHAPTER 7

IMPACT FACTOR ANALYSIS IN VMI-BASED REPLENISHMENT MODEL

In this chapter, in-depth simulation experiments were conducted on the basis of the simulation-based optimization model developed in Chapter 6. The purposes of the simulation experiments are to thoroughly understand the current industrial practice of the apparel supply chain adopting the VMI-based replenishment strategy and its performance as well as investigate how the factors in the optimized replenishment strategy affect the performance of the supply chain. Specifically, six factors in the simulation-based optimization model were selected to conduct a two level-full factorial simulation experimentation. These six factors were overtime production to cover the surplus requirements, lead time, replenishment cycle, forecasting error, ratio of VMI orders occupying total production capacity and the number of SKUs. ANOVA was used to find out the significant levels of different variables. Implications in the aspects of the manufacturer’s policy, the retailer’s policy, agreements between the manufacturer and the retailer, and uncontrollable parameters were presented. Based on these implications, possible suggestions were given to the manufacturer and the retailer involving in the VMI-based apparel supply chain so as to benefit the whole supply chain.

7.1 Problem Analysis

In Chapter 6, a simulation-based optimization model for the VMI-based replenishment strategy was proposed to balance the manufacturer's production capacity while keeping the retailer's CSL at a certain value. Specific scenarios from industrial practice were chosen for experimental evaluation and the simulation-based optimization model was proved to be successful in coordinating the benefits of the manufacturer and retailer in the apparel supply chain. The application of the proposed simulation-based optimization model for the VMI-based replenishment strategy will be explored in this chapter.

In each scenario of the simulation experiments conducted in Chapter 6, the replenishment strategy in terms of the replenishment cycle and lead time was determined based on the industrial practice. Values of other variables in the experiments, including the number of SKUs, the forecasting error between the forecasted customers' demand and the actual one were acquired from the industrial practice. In other words, values of these factors were fixed in each experiment. This method of setting the factors at fixed values could demonstrate the improvement of the supply chain performance of the proposed simulation-based optimization model when comparing with the industrial practice. In order to understand thoroughly the current practice of the apparel supply chain adopting the VMI-based strategy, in-depth simulation experiments were conducted in this chapter. The performance of the VMI-based replenishment model was further evaluated after optimization using the simulation-based optimization model developed in Chapter 6.

The remaining parts of this chapter are organized as follows: after elaborating the factors included in the simulation experimentation and the performance index to be evaluated in the experimentation, detailed procedure of the experimentation will be explained in section 7.2. Results generated from the simulation experimentation are analyzed and discussed in section 7.3. The implications from the results of the replenishment model adopting the VMI strategy and suggestions to the participants in the VMI-based supply chain (retailers and manufacturers) for improving the performance of the whole supply chain are introduced in section 7.4, followed by a summary.

7.2 Simulation Experiments

The experiments were mainly based on the simulation-based optimization model for the VMI-based replenishment strategy developed in Chapter 6 except for releasing the constraints on production limitation and the ratio of VMI orders occupying total production capacity. Details of the constraints release are explained as follows:

In the experiments conducted in Chapter 6, it was assumed that the production quantity of the manufacturer was under production limitation. In other words, the CSL obtained in the optimization model was based on the assumption that there was no overtime production. This assumption set a strict limitation for acquiring the performance of CSL in the optimization model. In this chapter, the assumption on production limitation was released based on the industrial process. In practice, the manufacturer may set a tolerance of overtime production to cover the surplus requirements from the retailer, i.e. operators may work longer than their normal working time at a certain percentage when there is a surplus requirement for production. With the setting of the tolerance of overtime production, the sacrificed CSL in the optimization model will be reduced. Another purpose of this study is the examination of the effect of overtime production on the optimization model for the VMI-based replenishment strategy.

Most of the apparel manufacturers adopting the VMI strategy with their retailers produce garments for both Order-Based (OB) retailers and the VMI-based ones. The ratio of VMI-based orders occupying total production capacity varies from time to time in different supply chains. The investigation of the effect of the ratio of VMI orders occupying total production capacity was made in this chapter.

The simulation-based optimization model developed in Chapter 6 therefore was slightly revised so that the factors of overtime production and ratio of VMI orders occupying total production capacity were included.

7.2.1 Factors and Performance Index

Six factors were selected for evaluating their impacts on the performance of the replenishment model. These factors included overtime production to cover the surplus requirements, lead time, replenishment cycle, forecasting error, ratio of VMI orders occupying total production capacity and the number of SKUs. One of the reasons for selecting these six factors is that they can be set at different levels in different apparel supply chains. In order to explore the scope of implementation of the proposed optimization model, it is necessary to conduct experiments according to different degrees of these factors. Secondly, these factors are critical to the performance of the replenishment model as the alternation of these factors may cause a change in the performance of the replenishment model in the apparel supply chain. These six factors therefore were selected in the experiments. Table 7-1 shows the nomenclature of the six factors to be represented in the remaining parts of this chapter.

Table 7-1: Nomenclature of Factors

Factor	Nomenclature
Over time production	*OT*
Lead time	*LT*
Replenishment cycle	*RC*
Forecasting error	*FE*
Ratio of VMI orders occupying total production capacity	*Ratio of VMI*
Number of SKUs	*No. of SKU*

For each factor, two levels were chosen based on the industrial practice. The simulation experiments were covered with full factorials. Three replications of the experiments were conducted considering the stochastic procedure of the simulation. A total of 192 ($3*2^6$) simulation experiments were conducted. Table 7-2 shows the design of experiments for the evaluation of the replenishment model. Detailed descriptions of the factor setting are explained as follows:

Table 7-2: Experimental Design

Factor	*OT*	*LT* (weeks)	*RC* (weeks)	*FE*	*Ratio of VMI*	*No. of SKU*
Level 1	10%	7	3	L	1:2	3*4*5
Level 2	15%	9	6	M	4:5	4*5*5

Overtime production (OT) is the tolerance to cover the surplus production which exceeds the production limitation in each replenishment cycle i (PL_i). (See Section 6.2 for the definition of PL_i). The maximum production in each replenishment cycle i might reach $PL_i*(1+OT)$. 10% and 15% of OT are typical setting according to the industrial experience.

The definitions of lead time (LT) and replenishment cycle (RC) see Chapter 4. The levels of the two factors shown in Table 7-2 were set based on the industrial practice.

Forecasting error (FE) refers to the degree of forecasting error between the forecasted customers' demand and the actual one. Each degree of FE is composed of error regarding the total volume, SKU mix (including style mix, color mix and size mix) and seasonality of sales, each represented in linguistic terms on their scopes. A set of fuzzy number is generated from the linguistic terms using the fuzzy set theory (see Chapter 5 for details of forecasting error in the replenishment model). In the experiments conducted in this study, the fuzzy number of FE in low degree (L in Table 7-2) was (10/10/10/5/3) and the fuzzy number of FE in medium degree (M in Table 7-2) was (20/20/20/10/5).

The definition of the ratio of VMI orders occupying total production capacity ($Ratio\ of\ VMI$) is $\frac{Produciton\ quantity\ of\ VMI\text{-}based\ orders}{Total\ production\ capacity} = \frac{\sum PV_i}{\sum PL_i}$. The residual part of the production capacity is occupied by OB orders. The two levels for Ratio of VMI were set as 1:2 and 4:5 respectively.

The number of SKUs ($No.of\ SKU$) stated in Table 7-2 is the combination of style, color and size. For combination set as (3*4*5), the $No.of\ SKU$ was 60; for combination of (4*5*5), the $No.of\ SKU$ was 100.

The performance index for evaluation consisted of Customer Service Level (CSL), Inventory Turnover (IT) and Production Capacity Imbalance Coefficient (PBC) which were defined in section 6.2. The performance of the VMI-based replenishment model was evaluated both before optimization and after optimization.

7.2.2 Experimental Procedure

The following steps were used to calculate the performance of the VMI-based replenishment model.

1) Select one combination of levels in Table 7-2 as the initialized value of the six factors defined in section 7.2.1.

2) Input the forecasting on customers' demand in the VMI replenishment strategy in terms of total quantity, SKU distribution and seasonality distribution.

3) Generate the initial replenishment quantity in each replenishment cycle for the VMI strategy by supposing that the customers' demand is equal to the forecasted one using Replenishment Simulation (I) developed in Chapter 6 and then calculate the production quantity for OB retailers.

4) Generate the replenishment quantity for the VMI strategy by inputting the error between customers' demand and the forecasted demand using Replenishment Simulation (I). Calculate supply chain performances before optimization in terms of CSL, IT and PBC using Replenishment Simulation (II) developed in Chapter 6.

5) Generate the replenishment quantity for the optimized VMI strategy using the simulation- based optimization model. Calculate supply chain performance after optimization in terms of CSL, IT and PBC.

6) Adjust the combination of the six factors and repeat steps 2 to 5 until the performance of the replenishment model with the combination of factors are obtained.

7.3 Results and Discussion

The performance of the replenishment model adopting the VMI strategy in terms of CSL, IT and PBC generated in section 7.2 is evaluated in this section. Minitab Release 14 (Mathews 2005) was employed for data analysis. ANOVA was performed for analyzing the significant levels of different variables. In the ANOVA table indicating which factors are statistically significant, one should look at the F value or p value associated with each factor. F values are calculated as the ratio of mean square for the factor divided by the mean square error and are compared to the $F_{critical}$. $F_{critical}$ is the tabulated F value for the same number indicating the degree of freedom at the chosen significant level α. For all the tests in this study, α was set as 0.05. If the calculated F value is greater than the $F_{critical}$, the factor is statistically significant at the α level. One can also look at p value for deciding on the significance of any factor. p value shows the probability that F value may be attained by pure chance. It is usually a common practice to compare p values to 0.05. If a p value is higher than 0.05, we rule that the associated factor is not statistically significant.

Pareto chart was plotted in determining the order of significance for the factors. Main effect plot and interaction plot were used to demonstrate how the different factors as well as their combination affected the performance of the replenishment model applying the VMI strategy.

7.3.1 Performance Evaluation of the Replenishment Strategy before Optimization

In the simulation-based optimization model, the manufacturer was assumed to be capable of providing the retailer with the garments generated using the replenishment algorithms before adopting the optimization strategy. In other words, CSL required by the retailer was supposed to be satisfied no matter how long OT is employed for production. Since there is no limitation on the production over time, in this section, the factor of OT was not included as the evaluation factors. For the performance being evaluated, CSL was not considered since it was set as the constraint of the replenishment model.

1) Production Capacity Imbalance Coefficient before optimization (PBC_{pre})

ANOVA was performed on the performance measure of PBC before optimization (PBC_{pre}). The results of ANOVA presented in Tables 7-3 and 7-4 include factors up to two-way interactions. Tables 7-3 and 7-4 show that FE, $Ratio\,of\,VMI$, LT, RC, and 2 interactions (FE and $Ratio\,of\,VMI$; LT and RC) are statistically significant to influence the production balance. Their p values are less than 0.05 which indicate the significance of their impacts on the performance of PBC_{pre}. Figure 7-1 elaborates the Pareto chart of PBC_{pre}. It was found that FE and $Ratio\,of\,VMI$ are the two most important factors influencing the PBC_{pre}.

Table 7-3: p Values of Main Effect for PBC_{pre}

Factor	p value
LT	0.000
RC	0.000
FE	0.000
Ratio of VMI	0.000
No. of SKU	0.863

Table 7-4: p Values of Two-Way Interactions for PBC_{pre}

Factor	p value
FE*Ratio of VMI	0.000
LT*RC	0.035
FE*No. of SKU	0.091
RC*No. of SKU	0.242
LT*FE	0.349
LT*Ratio of VMI	0.361
Ratio of VMI*No. of SKU	0.391
LT*No. of SKU	0.595
RC*FE	0.857
RC*Ratio of VMI	0.869

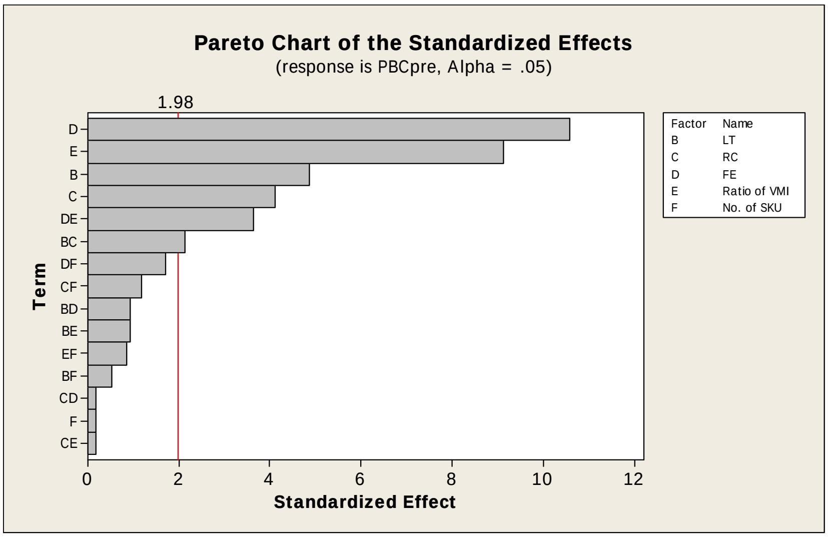


Figure 7-1: Pareto Chart for PBC_{pre}

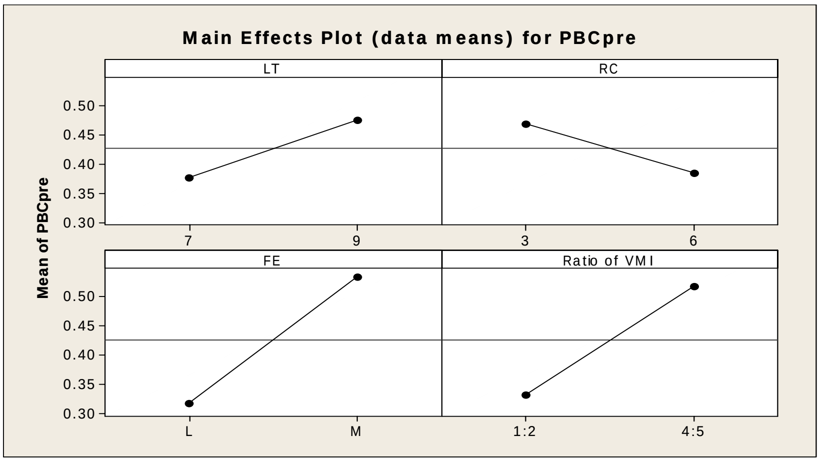


Figure 7-2: Statistically Significant Main Effects for PBC_{pre}

Figure 7-2 shows the main effects that are statistically significant for the performance of PBC_{pre}. It indicates that the frequent replenishment strategy resulted in higher production imbalance before using the optimization strategy. The definition of PBC_{pre} is the sum of imbalanced quantity percentage occupying total production capacity. This imbalance is caused by the fluctuating customers' demand. When RC is equal to 6 weeks, each replenishment covers 18 weeks' demands of the customers. In contrast, when RC is equal to 3 weeks, each replenishment covers 9 weeks' demands of customers. The former leads to lower imbalance because it covers more weeks and more variations with two directions counteracting each other.

Figure 7-3 illustrates the interactions between the different factors on the performance of PBC_{pre}. The parallel lines indicate that there is no interaction while the intersection lines suggest interactions between the relevant factors (Mathews 2005). Take interaction between RC and LT as an example. The points in the figure are the mean value of the PBC_{pre} in experiments satisfying the condition listed in its corresponding axis. For example, the upper-left point in the interaction of LT and RC is the average PBC_{pre} in simulation experiments in which RC is equal to 3 weeks while LT is equal to 9. This interaction reveals that the production imbalance caused by the replenishment frequent will decrease along with the extension of LT. A similar phenomenon was found between the factors of FE and $Ratio\,of\,VMI$.

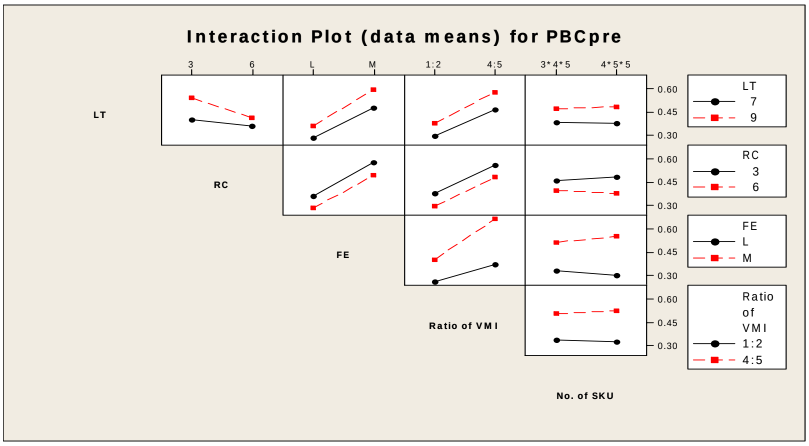


Figure 7-3: Interaction Effects for PBC_{pre}

2) Inventory Turnover before optimization (IT_{pre})

ANOVA was performed on the performance measure of IT before optimization IT_{pre}. The ANOVA table presented in Tables 7-5 and 7-6 are factors up to two-way interactions. Table 7-5 shows that the p values of 4 out of 5 main effects are less than 0.05, which indicates their statistical significance in determining IT_{pre}. The statistically significant main effects include FE, RC, LT and $No.\,of\,SKU$. Table 7-6 shows that the p values of 2 out of 10 two-way interactions are less than 0.05, i.e. interactions between LT and RC, as well as LT and $No.\,of\,SKU$ are statistically significant in determining IT_{pre}. The results regarding the significance of factors in Tables 7-5 and 7-6 are consistent with that in Pareto chart shown in Figure 7-4.

Figure 7-5 reflects a trend that the statistically significant factors affect the performance of IT_{pre}. Generally speaking, IT_{pre} will increase along with the decrease of FE, shortening of LT, increase of replenishment frequency and reduction of the $No. of\ SKU$. It is a common understanding that the average inventory definitely decreases with shorter LT, frequent replenishment, lower FE estimated by the retailer and fewer $No. of\ SKU$ since fewer safety stocks are required to be stored in the retailer when the same level of customers' satisfaction is required under such circumstances.

Table 7-5: p Values of Main Effect for IT_{pre}

Factor	p value
LT	0.000
RC	0.000
FE	0.000
No. of SKU	0.019
Ratio of VMI	0.360

Table 7-6: p Values of Two-Way Interactions for IT_{pre}

Factor	p value
LT*RC	0.000
LT*NO. of SKU	0.032
FE*NO. of SKU	0.060
FE*Ratio of VMI	0.135
RC*FE	0.224
LT*FE	0.232
RC*Ratio of VMI	0.402
LT*Ratio of VMI	0.427
Ratio of VMI*NO. of SKU	0.641
RC*NO. of SKU	0.932

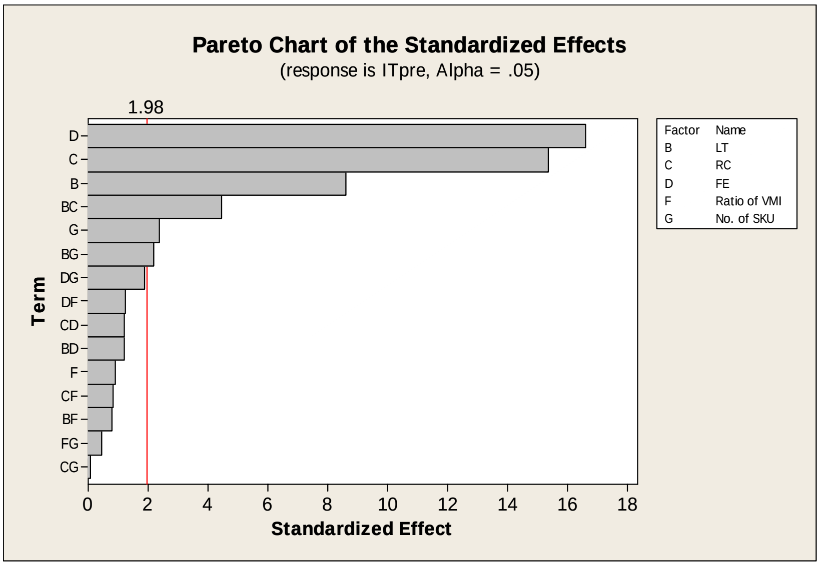


Figure 7-4: Pareto Chart for IT_{pre}

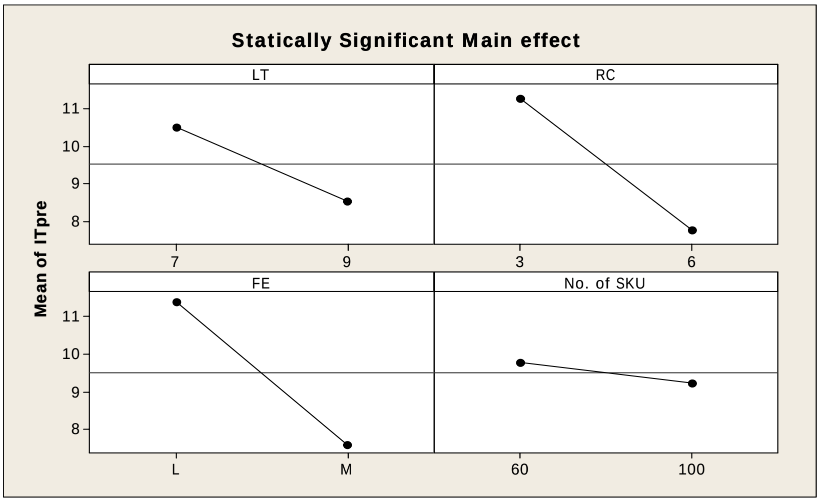


Figure 7-5: Statistically Significant Main Effects for IT_{pre}

Figure 7-6 depicts the interaction effects between the different factors. It is obvious that the interactions between LT and RC, LT and $No. of\ SKU$ are significant to the performance of IT_{pre}.

The only factor which was found insignificant to the performance of IT_{pre} is the

$Ratio\ of\ VMI$. Furthermore, none of the interaction relevant to this factor is significant. The reason is mainly because IT_{pre} was calculated for those orders applying the VMI replenishment strategy before optimization. Since all these VMI orders were supposed to be satisfied no matter whether they exceeded the limitation of production capacity or not, it is reasonable that the $Ratio\ of\ VMI$ was found to be irrelevant to the performance of IT_{pre}.

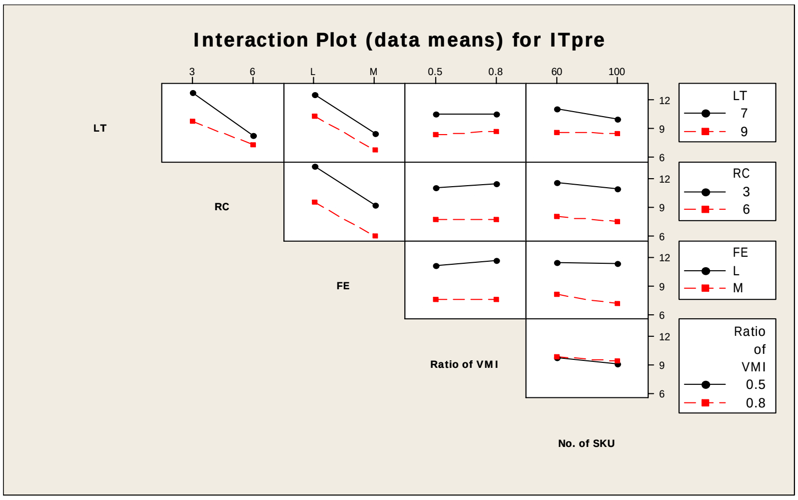


Figure 7-6: Interaction Plot for IT_{pre}

7.3.2 Performance Evaluation of the Replenishment Strategy after Optimization

For performance evaluated after the optimization, six factors, including OT, LT, RC, FE, $Ratio\ of\ VMI$, and $No.\ of\ SKU$ were analyzed.

1) Production Capacity Imbalance Coefficient after optimization PBC_{post}

ANOVA was performed on the performance measure of Production Capacity Imbalance Coefficient after optimization (PBC_{post}). Table 7-7 presents the ANOVA results of the main effects while Table 7-8 shows the two-way interactions of ANOVA results. Table 7-7 shows that five out of six main effects whose p values are less than 0.05 are statistically significant in determining PBC_{post}. Main effect of $No.\,of\ SKU$ is the only one which is not significant. 4 out of 15 two-way interactions in Table 7-8 are statistically significant. They are the interactions between RC and $No.\,of\ SKU$, RC and $Ratio\,of\ VMI$, OT and $Ratio\,of\ VMI$, as well as RC and FE. The results of significance in Tables 7-7 and 7-8 are consistent with those in Pareto chart shown in Figure 7-7.

Table 7-7: p Values of Main Effect for PBC_{post}

Factor	p value
OT	0.000
RC	0.000
Ratio of VMI	0.000
FE	0.003
LT	0.014
No. of SKU	0.235

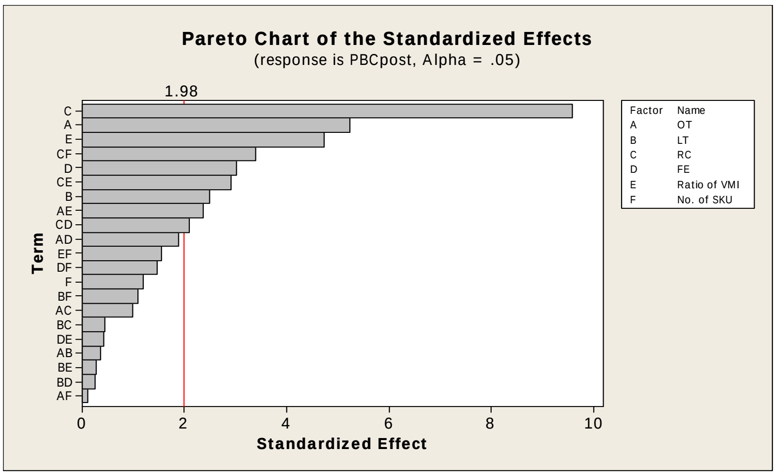


Figure 7-7: Pareto Chart for PBC_{post}

Table 7-8: p Values of Two-Way Interactions for PBC_{post}

Factor	p value
RC*No. of SKU	0.001
RC*Ratio of VMI	0.004
OT*Ratio of VMI	0.020
RC*FE	0.039
OT*FE	0.061
Ratio of VMI*No. of SKU	0.122
FE*No. of SKU	0.144
LT*No. of SKU	0.282
OT*RC	0.331
LT*RC	0.659
FE*Ratio of VMI	0.678
LT*Ratio of VMI	0.786
OT*LT	0.727
LT*FE	0.797
OT*NO. of SKU	0.910

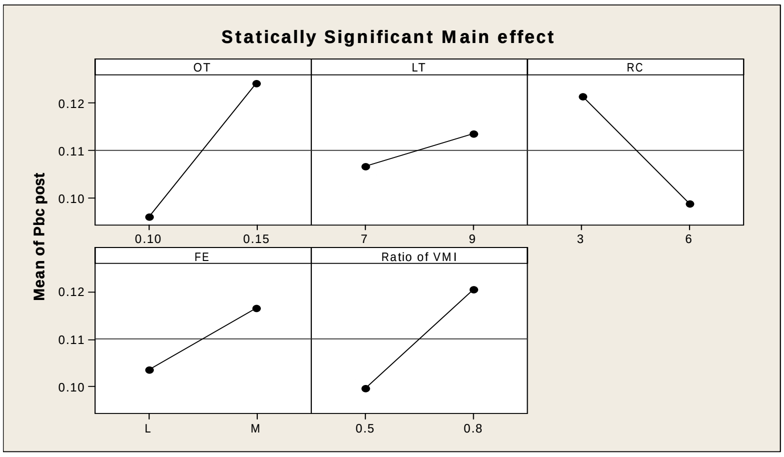


Figure 7-8: Statistically Significant Main Effects for PBC_{post}

Comparing the Pareto chart of PBC_{post} in Figure 7-7 with that of PBC_{pre} in Figure 7-1, it is not surprising that the factor of OT is statistically significant to the performance of PBC_{post}. The effect of OT can also be observed from Figure 7-8 that higher tolerance of OT will cause more fluctuation in production capacity. For other significant factors, the effects on the performance of PBC_{post} are identical to those on performance of PBC_{pre}.

Considering the effect of factor RC, more frequent use of replenishment strategy may cause higher imbalance of production. Another reason for this phenomenon may be that in the proposed optimization model, the optimization strategy is to adjust the replenishment among three contiguous RCs. For the RC which is equal to 6 weeks, each adjustment of the replenishment will cover 18 weeks. In contrast, when RC is equal to 3 weeks, this adjustment period will be equal to 9 weeks. Since the former covers more weeks of imbalance replenishment goods in one adjustment, the more imbalance of production before optimization is adjusted under this situation, resulting in more stable production after the optimization. As far as interactions are concerned, it is clear that the interactions between the RC and $No. of\ SKU$, RC and $Ratio\ of\ VMI$ are the two most significant ones on the performance of PBC_{post}.

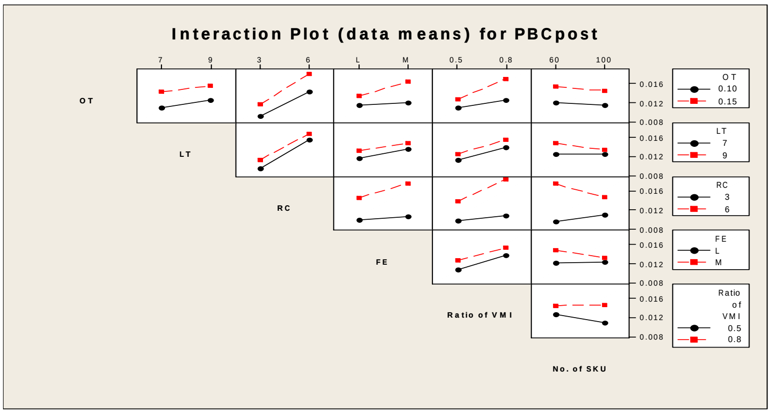


Figure 7-9: Interaction Plot for PBC_{post}

2) Customer Service Level after optimization (CSL_{post})

ANOVA was performed on the performance measurement of Customer Service Level (CSL_{post}). Table 7-9 shows the result of main effect while Table 7-10 illustrates the result of two-way interactions for CSL_{post}. All 6 main effects and 5 out of 15 two-way interactions are statistically significant in determining CSL_{post}. This result of significance is consistent with that in Pareto chart shown in Figure 7-0.

Table 7-9: p Values of Main Effect for CSL_{post}

Factor	p value
OT	0.000
LT	0.000
RC	0.000
FE	0.000
Ratio of VMI	0.000
No. of SKU	0.013

Table 7-10: p Values of Two-Way Interactions for CSL_{post}

Factor	p value
LT*RC	0.000
RC*FE	0.000
FE*Ratio of VMI	0.015
LT*FE	0.021
RC*Ratio of VMI	0.043
LT*Ratio of VMI	0.061
FE*No. of SKU	0.095
RC*No. of SKU	0.122
OT*FE	0.123
LT*No. of SKU	0.484
OT*RC	0.570
OT*LT	0.618
OT*Ratio of VMI	0.624
OT*No. of SKU	0.808
Ratio of VMI*No. of SKU	0.915

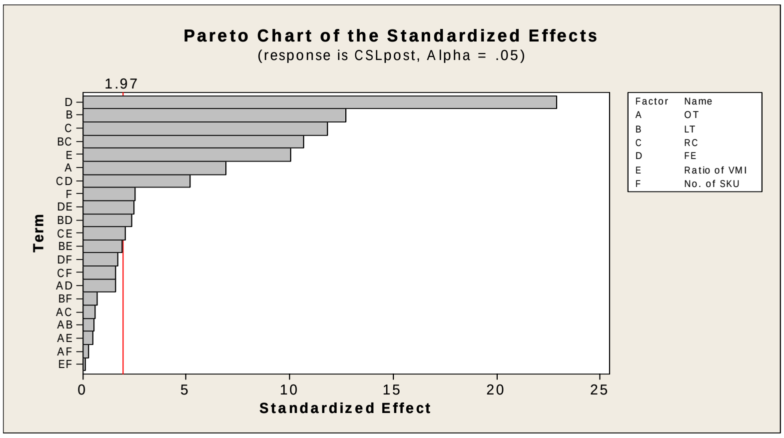


Figure 7-10: Pareto Chart for CSL_{post}

From the main effect plot of CSL_{post} in Figure 7-11, the impacts of OT, LT, FE, $Ratio\ of\ VMI$ and $No.\ of\ SKU$ on performance of CSL_{post} could be reflected. In general, with more OT, shorter LT, less FE, fewer $No.\ of\ SKU$ and lower $Ratio\ of\ VMI$, higher CSL_{post} is obtained. For the factor of RC, it was found that more frequent RC will lead to lower CSL_{post}. The reason for the phenomena may largely be due to the proposed optimization strategy in the model. In the proposed model, it is supposed that the replenishment goods could be shifted to its contiguous RCs. When the RC is equal to 6 weeks, each adjustment of the replenishment covers 18 weeks. In contrast, when RC is equal to 3 weeks, this adjustment period is 9 weeks. Therefore, it is reasonable that more garments are ready for the customer at the retailer when RC is higher which ultimately increases the corresponding CSL_{post}.

From Figure 7-12, it is seen that the interactions between RC and LT, RC and FE are significant to the performance of CSL_{post}.

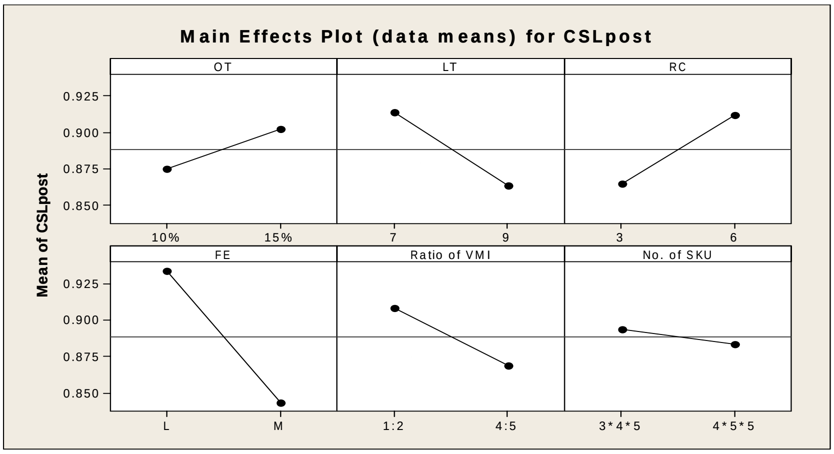


Figure 7-11: Statistically Significant Main Effects for CSL_{post}

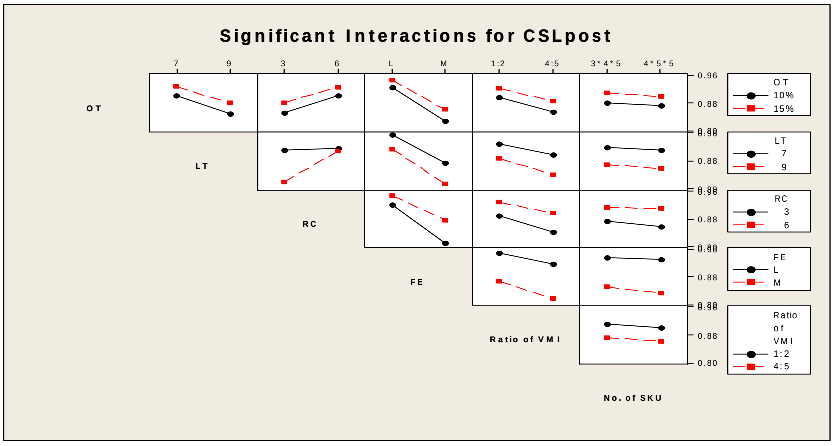


Figure 7-12: Interaction Plot for CSL_{post}

4) Inventory Turnover after optimization (IT_{post})

ANOVA was performed on the performance measure of IT_{post}. The ANOVA table presented in Tables 7-11 and 7-12 includes factors up to two-way interactions. It was found that all the main effects of the six factors and 3 out of 15 two-way interactions whose p values are less than 0.05 are statistically significant in determining IT_{post}. This result of significance is consistent with that in Pareto chart shown in Figure 7-13.

Table 7-11: p Values of Main Effect for IT_{post}

Factor	p value
LT	0.000
RC	0.000
FE	0.000
Ratio of VMI	0.000
No. of SKU	0.000
OT	0.038

Table 7-12: p Values of Two-Way Interactions for IT_{post}

Factor	p value
FE*No. of SKU	0.000
LT*RC	0.001
RC*FE	0.001
RC*No. of SKU	0.060
LT*No. of SKU	0.228
RC*Ratio of VMI	0.307
OT*Ratio of VMI	0.421
OT*No. of SKU	0.716
OT*FE	0.745
Ratio of VMI*No. of SKU	0.774
OT*LT	0.825
FE*Ratio of VMI	0.857
LT*FE	0.935
LT*Ratio of VMI	0.945
OT*RC	0.976

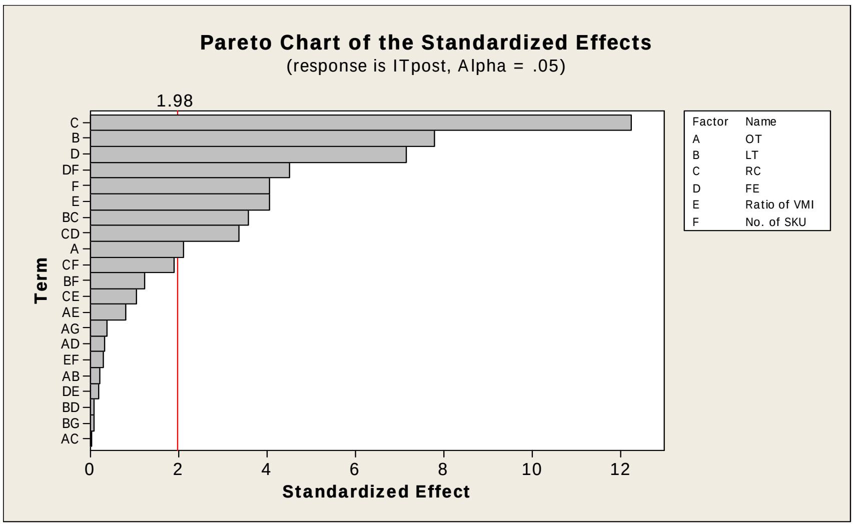


Figure 7-13: Pareto Chart for IT_{post}

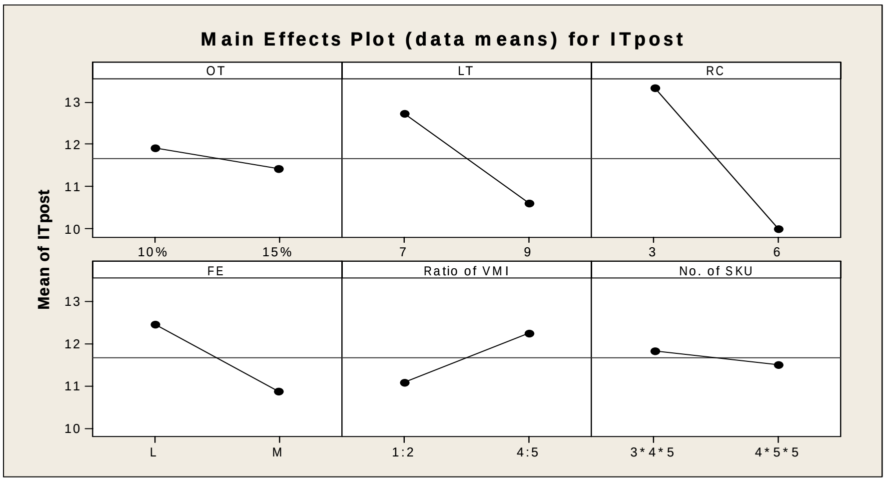


Figure 7-14: Statistically Significant Main Effects for IT_{post}

Comparing the performance of IT_{post} with IT_{pre}, all the effects of factors are comparable to those for the effect of IT_{pre} except the factor of $Ratio\, of\, VMI$. This factor is statistically significant to the performance of IT_{post}. The higher the $Ratio\, of\, VMI$, the higher the IT_{post}. However, in the overall performance of the supply chain, we should consider not only the IT_{post} but also the CSL_{post}. In other words, IT_{post} is not the only factor determining the supply chain performance. With low inventory held by the retailer, although the IT_{post} is high, it also results in lower CSL_{post}. Therefore, it could be concluded that when the $Ratio\, of\, VMI$ increases, the corresponding increase of IT_{post} could be attributed to the decrease of CSL_{post}, which is shown in Figure 7-11.

Figure 7-15 shows that the interactions between RC and LT, RC and FE as well as FE and $No.\, of\, SKU$ are significant to the performance of IT_{post}.

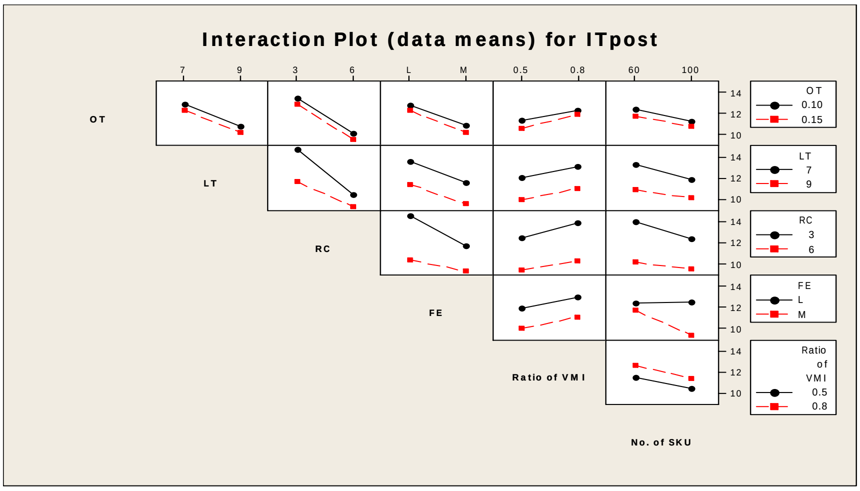


Figure 7-15: Interaction Plot for IT_{post}

7.3.3 Summary of the Main Effects

Based on the analysis in subsections 7.3.1 and 7.3.2, the main effects of the six factors on the performance in the replenishment model (for both before optimization and after optimization) were summarized. Table 7-13 shows the summary of the main effects. In this table, the sign "+" means the factor has positive effect on the performance; the symbol "-" represents that the factor has negative effect on the performance and the mark "/" indicates that the factor has no effect on the performance.

Take the column of PBC_{pre} as an example. Factors of FE, LT and $No.\ of\ SKU$ have positive effect on the performance of PBC_{pre}; factors of OT and $Ratio\ of\ VMI$ have no effect on the performance of PBC_{pre} and factors of RC has negative effect on the performance of PBC_{pre}. This result shows that higher FE, longer LT and more $No.\ of\ SKU$ lead to higher production imbalance. In contrast, longer RC may balance the production limitation. For the factors of OT and $Ratio\ of\ VMI$, the performance of PBC_{pre} are not influenced by these two factors. Other results of the main effects can be explained in the same methods.

Table 7-13: Summary of Main Effects

	Performance before Optimization		Performance after Optimization		
Factor	PBC_{pre}	IT_{pre}	CSL_{post}	PBC_{post}	IT_{post}
FE	+	-	-	+	-
OT	/	/	+	+	-
LT	+	-	-	+	-
RC	-	-	-	-	-
Ratio of VMI	/	/	-	+	-
No. of SKU	+	-	-	+	-

7.4 Implications

In this section, the implications on the performance of the replenishment model adopting the VMI strategy is discussed in detail by classifying the factors into policy of the manufacturer, policy of the retailer, agreements between manufacturers and retailers, and uncontrollable parameters.

7.4.1 Policy of the Manufacturer

Policy of the manufacturer includes the factors of LT, OT and $Ratio\,of\,VMI$.

1) Lead time (LT)

LT represents the time gap between the order released from the manufacturer and the garments arrived at the retailer. This factor is mainly determined by the production efficiency of the manufacturer. The conclusions drawn from the above sections for this factor are:

- For the retailer, the shorter the LT, the faster the replenishment getting ready at the retailer. This will bring higher IT. For the retailer's concern of performance CSL, shorter LT may lead to higher CSL.

- From the view of the manufacturer, PBC decreases with the shortening of LT before and after optimization.

- Shorter LT benefits both manufacturers and retailers in the VMI-based apparel supply chain before and after optimization. Therefore, the suggestion to the industry is to shrink the LT of the manufacturer as much as possible so as to improve the performance of the whole supply chain.

2) Overtime production (OT)

OT is the tolerance to cover the surplus production caused by fluctuating customers' demand. The following observations on this factor are made based on the discussions described in section 7.3:

- OT has no effect on the performance before optimization since it is supposed that no limitation is set in such a situation.

- After the optimization of the replenishment strategy, OT has certain effects on the performance of the supply chain. Extending the OT will increase the PBC, CSL and decrease the IT.

3) Ratio of VMI orders occupying total production capacity ($Ratio\,of\,VMI$)

For the factor of $Ratio\,of\,VMI$, the following observations are made based on the results given in the above sections:

- Changing the $Ratio\,of\,VMI$ has no effect on CSL before optimization. However, it has some effects on the same performance after optimization.

- For the performance of PBC, the more orders for the VMI strategy, the more unstable the production is, no matter whether the optimization strategy is employed or not. This conclusion is not consistent with that in Waller et al (1999) as the author concluded that with the increase of the proportion of the VMI orders in the total number of production orders of a manufacturer, the production capacity utilization could be improved which contributed to the stable manufacturing in the VMI strategy. Their conclusion was based on the scenario that the replenishment cycle in the VMI strategy was much shorter than that in the traditional OB manner. However, the forecasting error on customers' demand was not considered in their study. Therefore, the production imbalance caused by the forecasting error was not investigated under the VMI replenishment strategy in their study.

7.4.2 Policy of the Retailer

Among the six factors, $No.\ of\ SKU$ is determined by the retailer. In the proposed model, different $No.\ of\ SKU$ cases are supposed under the same quantity of total volume. The following observations are made based on the results given in section 7.3:

- The factor of $No.\ of\ SKU$ does not have an impact on the performance of PBC before and after optimization. This is due in part to the fact that the shift time of production from one SKU to another SKU is not considered in the proposed model. If the shift time is considered, this might not be the case.

- The IT drops as the $No.\ of\ SKU$ increases before and after optimization. This is mainly due to the fact that the quantities of garments kept at the retailer are proportional to the $No.\ of\ SKU$ for ensuring that the customers receive their demands for a certain SKU. Therefore, with more SKUs, the retailer should keep more inventories which leads to lower IT.

- CSL after optimization decreases when adding the $No.\ of\ SKU$. The possible reason is that when certain quantity of garments is replenished to the retailer, the more SKU number means that replenished garments distributed to each SKU will be reduced. Therefore, when customers go into a shop for a certain item, the possibility of lost sale increases.

- Although the increase of the *No. of SKU* may lead to the decline of the supply chain performance in terms of *PBC*, *CSL* and *IT*, retailers are not advised to cut down the *No. of SKU*. In the fashion market, customers nowadays desire for more styles in their fashion and retailers are under great pressure to cater for the ever-changing needs of the customers. The industry should explore other solutions to compensate the sacrifice of the supply chain performance caused by the increase in the *No. of SKU*, for instance, shrinking the *LT* or spending more resources on maximizing the forecasting accuracy.

7.4.3 Agreements between the Manufacturer and the Retailer

RC represents the frequency that the manufacturer ships garments to the retailer. It is determined by the retailer and the manufacturer before the sales season. From the previous discussion in section 7.3, the following observations on *RC* in the apparel supply chain adopting the VMI replenishment strategy are made:

- *PBC* decreases with the increase of *RC* no matter whether the optimization of the replenishment strategy is employed or not.

- *CSL* increases with the increase of *RC* with replenishment models after optimization. For models before optimization, the performance of CSL is not considered in this chapter since 95% of CSL is set as a constraint of the models.

- IT decreases with the increase of RC for replenishment models before and after optimization.

- Since the manufacturer is concerned more about PBC while the retailer emphasizes CSL and IT in the supply chain, it can be concluded that for the factor of RC, the opinions of the manufacturer and the retailer may be different and even conflict with each other. In order to acquire higher customers' satisfaction, the retailer would prefer a more frequent RC policy; however, this higher frequency may be a burden to the manufacturer. The fares of frequent shipping are not considered in the proposed model and the imbalance of production caused by the frequency is critical to the manufacturer.

7.4.4 Uncontrollable Parameter for Manufacturers

FE defines the difference between the initial plan and the actual demand from the customer. This factor is caused by fluctuating customers' demand. Form the view of the manufacturer, FE is usually uncontrollable. From the discussions in the previous sections, it is concluded that:

- There is no doubt that FE has a negative effect on the entire performance index in the supply chain adopting the VMI replenishment strategy. This finding is consistent with the conclusions stated in Toni et al (2004) and Cochen (2002) that "the VMI performance turns out to be deeply affected by the predictability and accuracy level of demand. Indeed with a highly unpredictable demand and most of all with low reliability and information accuracy transmitted between customer and supplier."

- The suggestion to the industry is to put more resources on maximizing forecasting accuracy. With the improvement on forecasting customers' demand, the performance of the supply chain adopting the VMI replenishment strategy will be improved.

7.5 Summary

In this chapter, in-depth simulation experiments were conducted on the VMI-based apparel supply chain using the simulation-based optimization model proposed in Chapter 6. As a comprehensive study of the current practice in the apparel supply chain adopting the VMI-based replenishment strategy, the findings from this chapter provide insights into how the VMI-based apparel supply chain strategy (in terms of replenishment cycle, lead time as well as other relevant factors in the VMI-based replenishment model such as forecasting error, ratio of VMI orders occupying total production capacity and tolerance of overtime and the interactions of them) affects the performance of the apparel supply chain (CSL, IT and PBC). With the discussion on the simulation experimentation results, the implications on the VMI-based replenishment strategy were also given. Finally, suggestions on how to improve the performance of the whole supply chain were made for the manufacturers and retailers in the VMI-based apparel supply chain based on the implications.

CHAPTER 8

CONCLUSION AND FUTURE RESEARCH

This chapter starts with a summary which concludes the study. It also states some limitations of the study and suggestions for future research based on these limitations.

8.1 Conclusion

With the forthcoming of economic globalization, the apparel manufacturers are under the pressure to establish close coordination with their retailers. Vendor Managed Inventory (VMI) strategy has received considerable attention in apparel supply chain management and many apparel manufacturers have implemented VMI-based replenishment strategy with their retailers. While research has been increasing in the area of VMI, current research in apparel supply chain are mainly reported on how the benefits brought to the retailer. Some of the benefits are reducing costs and increasing *CSL* of the retailer. Study on apparel manufacturers who provide garments to their retailers under VMI strategy is limited.

In the supply chain adopting the VMI replenishment strategy, the manufacturers make replenishment decisions about how many products to ship to the retailers in every replenishment cycle. The effect of the manufacturers' decisions on different replenishment strategies with their retailers (lead time, replenishment cycle and replenishment quantities) to satisfy the retailers' demand is significant to the performance of the whole supply chain. The questions of how to implement the replenishment strategies and what will be the benefits to the participating firms within the supply chain are the key issues for manufacturers to make replenishment decision. Owing to the fluctuating demand of the customers, the replenishment quantity varies in each replenishment cycle which will directly influence the balance of production capacity of the manufacturers. How does VMI replenishment strategy influence the manufacturers' *PCB* under the supply chain dynamics has received little work.

This research optimizes the performance of the two-echelon supply chain using the optimization replenishment model. It investigates the replenishment problem in the VMI-based apparel supply chain. Specifically, a replenishment simulation model and a simulation-based optimization replenishment model for VMI-based apparel supply chain were developed. The replenishment simulation model enables the retailers and manufacturers adopting the VMI replenishment strategy to understand how the various factors affecting the performance of the apparel supply chain. The simulation-based optimization replenishment model optimizes the *PCB* of the manufacturer while maintaining the *CSL* of the retailer at a certain level.

Specifically, the VMI-based replenishment simulation model integrated customer, retailer and manufacturer in the dynamic supply chain for the apparel industry. The simulation model provided a tool to generate a set of replenishment strategies under different forecasting error to satisfy *CSL* required by the retailer. Firstly, the desired

CSL was determined by the retailer. Other pre-defined parameters, such as length of the sales season, forecasted sales and pre-defined forecasting error were input into the simulation model. After simulating the operation of the apparel supply chain and applying the replenishment algorithms, the simulation model generated a set of outputs in terms of the replenishment strategy and the performance index. The replenishment simulation model also provided a fundamental platform for the proposed simulation-based optimization replenishment model. Actual data from the industry was employed to validate the proposed model.

In order to investigate the uncertainty forecasting error which significantly affects the performance of the apparel supply chain, fuzzy set theory was proposed to represent the uncertainty of forecasting error. After determining the expected value of the fuzzy estimation of the forecasting error, the fuzzified forecasting error was then integrated into a replenishment simulation model developed for the VMI-based apparel supply chain. The fuzzy set theory employed in this study contributed to the scientific approach of the supply chain practitioners to deal with uncertainties in dynamic market environment.

With the development of simulation program and genetic algorithm (GA), a simulation-based optimization replenishment model was developed in a dynamic rolling horizon. This model considers the interests of manufacturers and retailers in terms of *PCB* of manufacturers and the *CSL* of the retailer. The optimization of the replenishment strategy was implemented with the utilization of GA. Two situations were considered in the simulation-based optimization model. One was for single VMI-based order and the other was for multiple VMI-based orders with different targeted CSL_t requirements. Experiments using the simulation-based optimization model to validate the feasibility of the optimization model were conducted. The experimental results indicated that the proposed simulation-based optimization model could maintain the retailers' CSL while improving the PCB of the manufacturers significantly. The performance of the VMI-based apparel supply chain was better than that of the industrial experience.

The development of the optimization model provides a novel optimization method to solve the replenishment problem. With considering the two-echelon apparel supply chain as a whole unit and optimization of the performance index belongs to different participants in the supply chain simultaneously, the knowledge of the VMI-based apparel supply chain was enriched.

To understand thoroughly about the current practice of the apparel supply chain adopting VMI-based strategy, in-depth experiments were conducted. Full factorial simulation experimentation on the VMI-based apparel supply chain was conducted using the proposed simulation-based optimization model. ANOVA was performed on the significant analysis using the result of this simulation experimentation so as to provides insights on how the VMI-based apparel supply chain strategy (in terms of replenishment cycle, lead time as well as other relevant factor in the VMI-based replenishment model such as forecasting error, ratio of VMI orders occupying total production capacity and tolerance of over time and the interactions of them) affects the performance (CSL, IT and PBC) of the apparel supply chain. With reference to the simulation experimentation results, the implications on the VMI-based replenishment strategy were concluded by classifying the factors into policy of the manufacturers, policy of the retailers, agreements between manufacturers and retailers, and uncontrollable parameters. Suggestions on how to improve the performance of the whole supply chain were given to the manufacturers and retailers in the VMI-based apparel supply chain based on the implications.

8.2 Limitations and Suggestion for Future Research

There are three major limitations in this research work and it can be extended in various ways. Directions for future work are organized under three categories.

1. Improving the accuracy of forecasting in the VMI-based apparel supply chain

Based on the full factorial experimentations, it was found that forecasting error between the predicted customers' demand and actual one was a significant factor affecting the performance of the VMI-based apparel supply chain. The industry could benefit from using the proposed simulation-based optimization model to improve the performance of the supply chain with less forecasting error on the customers' demand. It was concluded that maximizing the forecasting accuracy would definitely benefit the VMI-based apparel supply chain.

However, the investigation on the forecasting error in this research was limited. Fuzzy set theory was employed to represent the retailer-defined forecasting error. Fuzzy number generated using the fuzzy set theory was set as an input to the simulation model. Further analysis on the forecasting error is required so that the performance index of the VMI-based apparel supply chain can be improved.

2. Fine tuning the replenishment algorithm in the simulation model

In this study, the replenishment algorithm developed in the simulation model was based on the industrial practice. Firstly, in the replenishment algorithm, the inventory strategy for the retailer was to stock safety stock week's (SSW 's) demand on hand in the retailer's store. Secondly, the SSW generated in the simulation program was the aggregate for all SKUs, i.e. SSW for all SKUs were identical to each other. The reason for adopting these two assumptions was to maintain the consistence of the simulation model with that of the industrial practice.

To improve the flexibility of the simulation model, these assumptions should be released. Other feasible inventory strategies including News boy, (s, S) periodic review and Quick response (QR) can be investigated and integrated into the replenishment algorithm in the simulation model.

The assumption on calculating the SSW could be released so that the safety stock for individual SKU is independent to each other. The SSW generated in the independent algorithm will be more precise for individual SKUs. With the improvement of the replenishment algorithm on designing independent SSW, it is expected that the retailer can keep less inventory as safety stock. The performance of the VMI-based apparel supply chain in terms of IT may be enhanced under the same CSL.

3. Improvement of optimization algorithm

In this research, the optimization algorithm designed in the simulation-based optimization model was flexible so that two different objectives (balancing the production capacity and minimizing the lost sales) could be selectively chosen for optimization. (Simulation experiments in Chapter 6 showed the examples in which different objectives were set for optimization.) However, these two objectives in terms of PCB and Customer Service Level (CSL) could be combined into one global optimization objective by defining a global optimization objective.

One possible solution to obtain the global objective is to use linearization of the two different objectives. More industrial data and practices should be collected and analyzed to determine the weights of the two objectives occupying the combined one. Another possible solution is to design a multi-objective optimization algorithm. The multi-objective optimization algorithm will generate optimal frontier for the decision-makers to select their most appreciated replenishment strategy among a set of solutions.

8.3 Related Publications

The author demonstrates the originality of this research through the following publications.

<u>Refereed Journal</u>

1. Dong, A.H., Wong, W.K., Yeung, K.W.P. and Chan, S.F., Development of a Portfolio Simulation System for Apparel Supply Chain, to be published in Journal of Dong Hua University 2006, 23(3).

2. Dong, A.H., Wong, W.K., Chan, S.F. and Yeung, K.W.P., Supply Chain Replenishment Strategy Using Simulation and Fuzzy Logic, submitted to International Journal of Production Economics (Under review).

3. Dong, A.H., Wong, W.K., Chan, S.F. and Yeung, K.W.P., A Replenishment Optimization Model for VMI-Based Apparel Supply Chain, submitted to International Journal of Production Economics (Under review)

<u>Book Chapter</u>

4. Dong, A.H., Wong, W.K., Chan, S.F. and Yeung, K.W.P., Developing an Apparel Supply Chain Simulation System with the Application of Fuzzy Logic, Part

V: Computerized Textile Management and Textile Supply Chain, Chapter 17, in Computational Textile, to be published by Springer Publisher

Conference Paper

5. Dong, A.H., Wong, W.K., Chan, S.F. and Yeung, K.W.P., Developing an Apparel Supply Chain Simulation System with the Application of Fuzzy Logic, Proceedings of the 17th IMACS World Congress, Paris, France, July 2005, 78.

6. Dong, A.H., Wong, W.K., Chan, S.F. and Yeung, K.W.P., Improve Production Balance for Apparel Supply Chain Adopting VMI Replenishment Strategy, Proceedings of the 3rd IEEE International Conference on Management of Innovation and Technology, Singapore, June 2006, 848-852.

Bibliography

Abernathy, F.H., Dunlop, J.T., Hammond, J.H. and Weil, D., 1999, A Stitch in Time: Lean Retailing and the Transformation of Manufacturing - Lessons from the Apparel and Textile Industries, Oxford University Press, New York.

Abernathy, F.H., Dunlop, J.T., Hammond, J.H. and Weil, D., 2000, Retailing and supply chains in the information age, Technology in Society 22(1), 5-31.

Achabal, D.D., Mcintyre, S.H., Smith, S.A. and Kalyanam, K., 2000, A decision support system for vendor managed inventory, Journal of Retailing 76(4), 430-453.

Agrawal, N., Smith, S.A. and Tsay, A.A., 2002, Multi-vendor sourcing in a retail supply chain, Production and Operations Management 11(2), 157-182.

Andradottir, S., 1998, A review of simulation optimization techniques, Proceedings of the 1998 Winter Simulation Conference, Washington, D.C., 151-158.

Andradottir, S., 1998, Simulation optimization, In: Handbook of Simulation, New York, Wiley, 307-334.

Aron, L.J., 1998, From push to pull: the supply chain management shift, Apparel Industry Magazine 59(6), 58-59.

Azadivar, F. and Tompkins, G., 1999, Simulation optimization with qualitative variables and structural model changes: a Genetic Algorithm approach, European Journal of Operational Research 113, 169-182.

Bagchi, S.J., Ettl, M. and Lin, G.Y., 1998, Experience using the IBM supply chain simulator, Proceedings of the 1998 Winter Simulation Conference, Washington, D.C., 1387-1397.

Baker, K.R., 1977, An experimental study of the effectiveness of rolling schedules in production planning, Decision Science 8, 19-27.

Banks, J., Carson, J.S., Nelson, B.L. and Nicol, D.M., 2001, Discrete-Event System Simulation, 3rd Eds., Prentice Hall, Upper Saddle River, NJ.

Behling, R.L., 1982, Supply chain management with capacity constraints, American Production and Inventory Control Society 25th Annual Conference Proceedings, Falls Church, 379-383.

Belpaire, B., Van Landeqhem, R. and Petuhova, J., 2000, Implementing a cost model in a textile supply chain using simulation, 14th European Simulation Multiconference, SCS, Ghent, Belgium, 454-460.

Biswas, S. and Narahari, Y., 2004, Object oriented modeling and decision support for supply chain, European Journal of Operational Research 153, 704-726.

Bouhia, S., 2004, A Risk-based Approach to Scheduling and Ordering Production in Manufacturing System: Real Options on Production Capacity, Harvard University.

Brooks, R. and Robinson, S., 2001, Simulation, Palgrave, Basingstoke.

Cachon, G. and Fisher, M.L., 1997, Campbell Soup's continuous replenishment program: Evaluation and enhanced inventory decision rules, Production and Productions Management 6(3), 266-276.

Carson, Y. and Kumar, S., 1997, Simulation optimization: methods and applications, Proceeding of the 1997 Winter Simulation Conference, Piscataway, 118-143.

Cetinkaya, S. and Lee, C.Y., 2000, Stock replenishment and shipment scheduling for vendor-management inventory systems, Management Science 46, 217-232.

Chan, F.T.S., Humphreys, P. and Lu, T.H., 2001, Order release mechanisms in supply chain management: a simulation approach, International Journal of Physical Distribution and Logistics Management 31, 124-133.

Chan, F.T.S. and Chan, H.K., 2005, Simulation modeling for comparative evaluation of supply chain management strategies, International Journal of Advanced Manufacturing Technology 25, 998-1006.

Chandra, C. and Kumar, S., 2001a, Enterprise architectural framework for supply-chain integration, Industrial Management and Data System 101(5/6), 290-303.

Chandra, C. and Kumar, S., 2001b, Taxonomy of inventory policies for supply-chain effectiveness, International Journal of Retail and Distribution Management 29(4), 161-184.

Chandra, C. and Grabis, J., 2001c, A coordinated supply chain dynamic production planning model, Proceedings of SPIE, San Jose, 91-101.

Christopher, M., 1992, Logistics and Supply Chain Management, Pitman Publishing, London.

Clark, T.H. and Hammond, J.H., 1997, Reengineering channel reordering processes to improve total supply-chain performance, Production and Operations Management 6(3), 248-265.

Cochen, K.S., 2002, The effect of information precision and information reliability on manufacturer-retailer relationship, The Accounting Review 77(3), 653-677.

Committee on the Next Decade of Operations Research (CONDOR), 1988, Operations research: the next decade, Operations Research 36.

Connor, D., An, C., Buckley, S., Feigin, G., Levas, A., Nayak, N., Petrakian, R., Srinivasan, R. and Jayraman, R., 1995, Dynamic modeling for re-engineering supply chains, IBM Research Division.

Cooper, M.C. and Ellram, L.M., 1993, Characteristics of supply chain management and the implications for purchasing and logistics strategy, International Journal of Logistics Management 4(2), 13-24.

Cooper, M.C. and Lambert, D.M., 1997, Supply chain management: more than a new name for logistics, International Journal of Logistics Management 8(1), 1-12.

Croom, S., Romano, P. and Giannakis, M., 2000, Supply chain management: an analytical framework for critical literature review, European Journal of Purchasing and Supply Management 6(1), 67-83.

Dandeo, L.M., Fiorito, S.S., Giunipero, L. and Pearcy, D.H., 2004, Determining retail buyers' negotiation willingness for automatic replenishment programs, Journal of Fashion Marketing and Management 8(1), 27-40.

Daugherty, P.J., Myers, M.B. and Autry, C.W., 1999, Automatic replenishment programs: an empirical examination, Journal of Business Logistics 20(2), 63-81.

Davis, L., 1991, Handbook of Genetic Algorithms Eds., Van Nostrand Reinhold, New York.

Deb, K. and Agrawal, R.B., 1995, Simulated binary crossover for continuous search space, Complex Systems 9, 115-148.

Deb, K., 2001, Multi-Objective Optimization Using Evolutionary Algorithms, Wiley, New York.

Dengiz, B., Sen, F. and Bulgak, A., 1997, Optimization of stochastic systems using genetic algorithms, Transactions on Operational Research 9, 43-62.

Dickerson, K.G., 1999, Textiles and Apparel in the Global Economy, 3rd Eds., Prentice-Hall, Englewood Cliffe, NJ.

Dickerson, K.G., 2003, Inside the Fashion Business, 7th Eds., Pentice Hall, Upper Saddle River, NJ.

Ding, H.W., Benyoucef, L. and Xie, X.L., 2004, A multiobjective optimization method for strategic sourcing and inventory replenishment, Proceedings of the IEEE International Conference on Robotics & Automation, New Orleans, LA, 2711-2716.

Disney, S.M., Naim, M.M. and Towill, D.R., 2000, Genetic algorithm optimisation of a class of inventory control systems, International Journal of Production Economics 68, 259-278.

Disney, S.M. and Towill, D.R., 2003, The effect of vendor managed inventory (VMI) dynamics on the Bullwhip Effect in supply chains, International Journal of Production Economics 85(2), 199-215.

Dunn, B., 2003, Replenishment program sets up a win-win scenario, Canadian Apparel 27(3), 14-15.

Fang, S.-C., Nuttle, H., King, R.E. and Wilson, J.R., 2003, Soft computing for softgoods supply chain analysis and decision support, In: Soft Computing in Textile Sciences, New York, Physica-Verlag, 1-15.

Federgruen, A., 1993, Centralized planning models for multi-echelon inventory systems under uncertainty, In: Logistics of Production and Inventory, Amsterdam, New York, North-Holland, 133-174.

Feitelberg, R., 1995, Makers see special sizes as growth channel, Women's Wear Daily 169(45), 17.

Fisher, M.L., Hammond, J., Obermeyer, W.R. and Raman, A., 1994, Making supply meet demand in an uncertain world, Harvard Business Review 72, 83-93.

Fisher, M.L. and Raman, A., 1996, Reducing the cost of demand uncertainty through accurate response to early sales, Operations Research 44(1), 87-99.

Fisher, M.L., 1997, What is the right supply chain for your product? Harvard Business Review 75 (March-April), 105-116.

Fisher, M.L., Hammond, J.H., Obermeyer, W.R. and Raman, A., 1997, Configuring a supply chain model to reduce the cost of demand uncertainty, Production and Operations Management 6(3), 211-225.

Forrester, J., 1961, Industrial Dynamics, MIT Press, Boston, MA.

Fox, M.L., 1996, Integrating Vendor-Managed Inventory into supply chain decision-making, APICS 39th International Conference Proceedings, New Orleans, LA, 126-128.

Fu, M.C., 2002, Optimization for simulation: theory vs. practice, INFORMS Journal on Computing 14(3), 192.

Giannoccaro, H., Pontrandolfo, P. and Scozzi, B., 2003, A fuzzy echelon approach for inventory management in supply chains, European Journal of Operational Research 149, 185-196.

Gokce, M.A., 1999, Optimal Production and Inventory Control to Meet Peak Season Demand, Department of Industrial Engineering, North Carolina State University.

Gokce, M.A., 2002, Optimization of sourcing decision in supply chains, Industrial Engineering Department, North Carolina State University.

Goldberg, D.E., 1989, Genetic algorithms in search, optimization, and machine learning, Addison-Wesley, Reading, Mass.

Haddock, J. and Bengu, G., 1987, Application of a simulation optimization system for a continuous review inventory model, Proceedings of the 1987 Winter Simulation Conference, Arlington, VA, 382-390.

Hammond, J. and Kellly, M.G., 1990, Quick response in the apparel industry, Harvard Business School.

Hammond, J.H., 1992, Coordination as the basis for Quick Response: a case for "Virtual" integration in supply networks, Harvard Business School Working Paper.

Hammond, J.H., 1993, Quick Response in Retail Manufacturing Channels, In: Globalization, Technology, and Competition: the Fusion of Computers and Telecommunications in the 1990s, Boston, Mass, Harvard Business School Press.

Hamnant, J., Disney, S.M., Childerhouse, P. and Naim, M.M., 1999, Modeling the consequences of a strategic supply chain initiative of an automotive aftermarket operation, International Journal of Physical Distribution and Logistics Management 29, 535-550.

Hanselman, D.C., 2001, Mastering Matlab 6: A Comprehensive Tutorial and Reference, Prentice hall, Upper Saddle River, NJ.

Harland, C.M., 1996, Supply chain management: relationships, chains and network, British Journal of Management 7(1), 63-80.

Harland, C.M., 1997, Supply chain operational performance roles, Integrated Manufacturing System 8(2), 70-78.

Heilpern, S., 1992, The expected value of a fuzzy number, Fuzzy Sets and Systems 47, 81-86.

Heita, S., 1998, Supply chain simulation with LOGSIM-simulator, Proceedings of the 1998 Winter Simulation Conference, Washington, D.C., 323-326.

Hewitt, W.C., Hunter, N.A. and King, R.E., 1991, Analysis of the benefits of quick response implementation for the domestic retail, Apparel and Textile Industries.

Holland, J.H., 1975, Adaptation in Natural and Artificial Systems, University of Michigan Press, Michigan.

Houlihan, J., 1985, International supply chain management, International Journal of Physical Distribution and Logistics Management 15(1), 22-38.

Hung, W.Y., Kucherenko, S. and Samsatli, N.H., 2004, A flexible and generic approach to dynamic modelling of supply chains, Journal of Operational Research Society 55, 801-813.

Hunter, N.A., King, R.E. and Nuttle, H.L.W., 1992, An apparel-supply system for QR Retailing, Journal of Textile Institute 83(3), 462-471.

Hunter, N.A., King, R.E., Nuttle, H.L.W. and Wilson, J.R., 1993, North Carolina apparel pipeline modeling project, International Journal of Clothing Science and Technology 5, 19-24.

Hunter, N.A., King, R.E. and Nuttle, H.L.W., 1996a, Evaluation of traditional and quick-response retailing procedures by using a stochastic simulation model, Journal of Textile Institute 87(2(1)), 42-55.

Hunter, N.A. and King, R.E., 1996b, The impact of size distribution forecast error on retail performance, North Carolina State University Annual Report, 1-4.

Hunter, N.A., King, R.E. and Lowson, R.H., 2002, The Textile/Clothing Pipeline and Quick Response Management, Textile Institute, Manchester.

Ingalls, R.G. and Kasales, S., 1999, CSSAT: the Compaq supply chain analysis, Proceedings of the 1999 Winter Simulation Conference, Phoenix, AZ, 1201-1206.

James, R., Rich, N. and Francis, M., 1997, Vendor Managed Inventory: a processual approach, Proceedings of the 6th International IPSERA Conference, Ischia, Italy.

James, R., Francis, M. and Rich, N., 2000, Vendor-Managed Inventory (VMI): A Systemic Approach, In: Value Stream Management: Strategy and Excellence in the Supply Chain, Harlow, Financial Times/Prentice Hall, 335-357.

Jin, S., 2004, Strategic Sourcing and Supplier Selection in the Unite States textile-apparel-retailer supply network, the Faculty of the Graduate School, The University of North Carolina at Greensboro.

Joines, J.A., Gupta, D., Gokee, M.A., King, R.E. and Kay, M.G., 2002, Supply chain multi-objective simulation optimization, Proceedings of the 2002 Winter Simulation

Conference, San Diego, California, 1306-1314.

Jones, T.C. and Riley, D.W., 1985, Using inventory for competitive advantage through supply chain management, International Journal of Physical Distribution and Logistics Management 15(5), 16-26.

Jung, J.Y., Blau, G., Pekny, J.F., Reklaitis, G.V. and Eversdyk, D., 2004, A simulation based optimization approach to supply chain management under demand uncertainty, Computers and Chemical Engineering 28, 2087-2106.

Katagiri, H. and Ishii, H., 2000, Some inventory problems with fuzzy shortage costs, Fuzzy Sets and Systems 111, 87-97.

Kincade, D.H. and Cassill, N.L., 1993, Company demographics as an influence on adoption of Quick Response by North Carolina apparel manufacturers, Clothing and Textiles Research Journal 11(3), 23-30.

Kincade, D.H., Vass, D. and Cassill, N.L., 2001, Implementation of technology and relationships to supply chain performance: apparel manufacturer's perspective, International Reviews of Retail, Distribution and Consumer Research 11, 301-327.

King, R.E. and Hunter, N.A., 1996, Demand re-estimation and inventory replenishment of basic apparel in a specialty retail chain, Journal of the Textile Institute 87(2(1)), 31-41.

King, R.E., Hodgson, T.J., Little, T., Carrere, C., Benjamin, M. and Curran, T., 1999, Analysis of apparel production systems to support quick response replenishment, National Textile Center Annual Report, 1-10.

Klir, G.J. and Folger, T.A., 1988, Fuzzy Sets, Uncertainty, and Information, Prentice

Hall, Englewood Cliffs, NJ.

Ko, E. and Kincade, D.H., 1998, Product line characteristics as determinants of Quick Response implementation for U. S. apparel manufacturers, Clothing and Textiles Research Journal 16(1), 11-18.

Koks, T. and Nordqvist, A.R., 2003, Using discrete event simulation to analyze product utilization, International Conference on Mechatronics, Loughborough University, 117-122.

Kulp, S.C., Lee, H.L. and Ofek, E., 2004, Manufacturer benefits from information integration with retail customers, Management Science 50(4), 431-444.

Law, A.M. and Kelton, W.D., 2002, Simulation based optimization, Proceedings of the 2002 Winter Simulation Conference, San Diego, LA, 41-44.

Lee, E.S. and Li, R.J., 1998, Comparison of fuzzy numbers based on the probability measurement of fuzzy events, Computers and Mathematics with Applications 15, 887-896.

Lee, Y., 2000, Study of Relationships between Apparel Manufacturer's Supply Chain Management, Company Characteristics, and Inventory Performance, Virginia Polytechnic Institute and State University.

Lee, Y. and Kincade, D.H., 2003, US apparel manufacturers' company characteristic differences based on SCM activities, Journal of Fashion Marketing and Management 7, 31-48.

Lee, Y.H. and Kim, S.H., 2000, Optimal production-distribution planning in supply chain management using hybrid simulation-analytic approach, Proceedings of the

2000 Winter Simulation Conference, Orlando, FL, 1252-1259.

Lendermann, P., Gan, B.P. and Mcginnis, L.F., 2001, Distributed simulation with incorporated AS procedures for high-fidelity supply chain optimization, Proceedings of the 2001 Winter Simulation Conference, Arlington, VA, 1138-1145.

Lowson, B., King, R.E. and Hunter, N.A., 1999, Quick Response: Managing the Supply Chain to Meet Consumer Demand, John Wiley & Sons, New York.

Magee, J.F., 1958, Production Planning and Inventory Control, McGraw-Hill, New York.

Mason-Jones, R., Naim, M.M. and Towill, D.R., 1997, The impact of pipeline control on supply chain dynamics, International Journal of Logistics Management 8, 47-62.

Mathews, P.G., 2005, Design of Experiments with Minitab, ASQ Quality Press, Milwaukee.

Michalewicz, Z., 1996, Genetic algorithms+Data structures=Evolution Programs, 3rd Eds., Springer-Verlag, New York.

Midler, J.L., 1969, A stochastic multiperiod multimode transportation model, Transportation Science 3, 8-29.

Mohafiqul, K.M., MNarita, H., chen, L.Y. and Fujimoto, H., 2005, Capacity planning to optimize the profit of an apparel manufacturer in developing country, JSME International Journal (Japan Society of Mechanical Engineers), Series C: Mechanical Systems, Machine Elements and Manufacturing 48(1), 31-36.

Morton, T.E., 1971, The Near-myopic nature of the Lagged-Proportional-Cost inventory problem with lost sales, Operations Research 19(7), 1708-1716.

Nuttle, H., King, R.E. and Hunter, N.A., 1991, A stochastic model of the apparel retailing process for seasonal apparel, Journal of the Textile Institute 82, 247-259.

Nuttle, H.L.W., King, R.E., Fang, S.-C., Wilson, J.R. and Hunter, N.A., 2001a, Simulation modeling of the textile supply chain, Part II - Results and research directions, Journal of the Textile Institute 91(1), 51-64.

Nuttle, H.L.W., King, R.E., Hunter, N.A., Wilson, J.R. and Fang, S.-C., 2001b, Simulation modeling of the textile supply chain, Part I - The textile plant model, Journal of the Textile Institute 91(1), 31-50.

Oliver, R.K. and Webber, M.D., 1982, Supply Chain Management: Logistics Catches Up With Strategy, In: Logistics: The Strategic Issues, London, Chapman and Hall, 63-75.

Onoyoma, T., Maekawa, T., Kubota, S., Taniguchi, Y. and Tsuruta, S., 2002, Intelligent evolutional algorithm for distribution network optimization, IEEE Conference on Control Applications, Glasgow, Scotland, 802-807.

Peck, J., Kernodle, B., Davis, S. and Pargas, R., 1998, Decision support for balanced inventory flow replenishment system, International Journal of Clothing Science and Technology 10(6), 77-80.

Pegden, C.D., Shannon, R.E. and Sadowski, R.P., 1995, Introduction to Simulation Using Siman, 2nd Eds., McGraw-Hill, New York.

Persson, F. and Olhager, J., 2002, Performance simulation of supply chain designs, International Journal of Production Economics 77, 231-245.

Petrovic, D., Petrovic, R. and Vujosevic, M., 1996, Fuzzy models for the newsboy problem, International Journal of Production Economics 45, 435-441.

Petrovic, D., Roy, R. and Petrovic, R., 1998, Modelling and simulation of a supply chain in an uncertain environment, European Journal of Operational Research 109, 299-309.

Petrovic, D., Roy, R. and Petrovic, R., 1999, Supply chain modeling using fuzzy sets, International Journal of Production Economics 59, 443-453.

Petrovic, D., 2001, Simulation of supply chain behavior and performance in the uncertain enviroment, International Journal of Production Economics 71, 429-438.

Petrovic, R. and Petrovic, D., 2001, Multicriteria ranking of inventory replenishment policies in the presence of uncertainty in customer demand, International Journal of Production Economics 71, 439-446.

Philip, W. and Wendell, J.V., 1996, Supply chain management: a time-based strategy, Industrial Management and Data System 38(5), 24-27.

Pidd, M., 1998, Computer Simulation in Management Science, 4th Eds., Wiley, Chichester.

Porteus, E.L., 1990, Stochastic Inventory Theory, In: Handbook of Operations Research and Management Science, Amsterdam, Elsevier Science Publishers, 605-652.

Porteus, E.L., 2002, Foundations of Stochastic Inventory Theory, Stanford Business Books, Stanford, Calif.

Rajamanizkam, R. and Jayaraman, S., 1998, U.S. apparel distribution: Where we stand and where we're going, Bobbin Dec, 51-53.

Raman, A., 1999, Managing Inventory for Fashion Products, In: Quantitative Models for Supply Chain Management, Norwell, Massachusetts, Kuluwer Academic Publisher, 789-806.

Raman, A. and Kim, B., 2002, Quantifying the impact of inventory holding cost and reactive capacity on an apparel manufacturer's profitability, Production and Operations Management 11(3), 358-373.

Rollins, R.P., Porter, K. and Little, D., 2003, Modelling the changing apparel supply chain, International Journal of Clothing Science and Technology 15(2), 140-156.

Romano, P. and Vinelli, A., 2001, Quality management in a supply chain perspective, Strategic and operative choices in a textile-apparel network, International Journal of Operations and Production Management 21, 446-460.

Sabel, C., Herrigel, G., Kazis, R. and Deeg, R., 1987, How to keep mature industries innovative, Technology Review 90(3), 26-35.

Sangmoo, S., 2004, The effects of supply chain management factors on the performance of SCM adoption in textile/apparel firms, 2004 Proceedings of the Annual Meeting of the International Textile and Apparel Association, Portland.

Schunk, D. and Plott, B., 2000, Using simulation to analyze supply chains, Proceedings of the 2000 Winter Simulation Conference, Piscataway, NJ, 1211-1216.

Sender, I., 1998, Microplanning jeanswear for the masses, Chain Store Age Executive with Shopping Center Age 74(1), 60-64.

Shapiro, J.F., 2001, Modeling the Supply Chain, Duxbury/Thomson Learning, Pacific Grove, Calif.

Simchi-Levi, D., Kaminsky, P. and Simchi-Levi, E., 2003, Designing and Managing the Supply Chain: Concepts, Strategies, and Case Studies, 2nd Eds. McGraw-Hill/Irwin, Boston.

Slack, N., 1991, The Manufacturing Advantage, Business Books, London.

Southall, J.T., Mirbagheri, S. and Wyatt, M.D., 1998, Investigation using distribution chain relationship simulation models into manufacturing/distribution chain relationships, BPICS Control, 29-34.

Stevens, G.S., 1989, Integrating the supply chain, International Journal of Physical Distribution and Logistics Management 19, 3-8.

Stratton, R. and Warburton, R.D.H., 2003, The strategic integration of agile and lean supply, International Journal of Production Economics 85, 183-198.

Taerno, T., Asai, K. and Sugeno, M., 1992, Fuzzy Systems Theory and Its Application, Academic Press, San Diego.

Tekin, E. and Sabuncuoglu, I., 2004, Simulation optimization: a comprehensive review on theory and application, IIE Transactions 36, 1067-1081.

Terzi, S. and Cavalieri, S., 2004, Simulation in the supply chain contest: a survey, Computers in Industry 53, 3-16.

Tocher, K.D. and Owen, D.G., 1960, The automatic programming of simulation, Proceedings of the 2nd Conference of IFOR, Aix en Providence, 50-68.

Tompkin, S. and Aadivar, F., 1995, Genetic algorithms in optimizing simulated systems, Proceedings of 1995 Winter Simulation Conference, Arlington, VA, 757-762.

Toni, A.D. and Meneghetti, A., 2000, The production planning process for a network of firms in the textile-apparel industry, International Journal of Production Economics 65, 17-32.

Toni, A.F.D. and Zamolo, E., 2004, From a traditional replenishment system to vendor-managed inventory: a case study from the household electrical appliances sector, International Journal of Production Economics 96, 63-79.

Towill, D.R., 1991, Supply chain dynamics, International Journal of Computer Integrated Manufacturing 4(4), 197-208.

Towill, D.R., Naim, M.M. and Wikner, J., 1992, Industrial dynamics simulation models in the design of supply chain, International Journal of Physical Distribution and Logistics Management 22, 3-13.

Towill, D.R., 1996, Industrial dynamics modelling of supply chain, Logistics Information Management 9(4), 43-56.

Truong, T.H., 2002, Simulation Based Optimization for Supply Chain Configuration Design, Department of Industrial and Manufacturing Systems Engineering, College of Engineering, Kansas State University.

Tyler, D., 1989, Managing for production flexibility in the clothing industry, Textile Outlook International (September), 63-84.

Umeda, S. and Zhang, F., 2006, Supply chain simulation: generic models and application examples, Production Planning and Control 17(2), 155-166.

Vlachos, D. and Tagaras, G., 2001, An inventory system with two supply modes and capacity constraints, International Journal of Production Economics 72, 41-58.

Vorst, J.G.A.J.V.D., Beulens, A.J.M. and Beek, P.V., 2000, Modeling and simulating multi-echelon food systems, European Journal of Operational Research 122, 354-366.

Vujosevic, M., Petrovic, D. and Petrovic, R., 1996, EOQ formula when inventory cost is fuzzy, International Journal of Production Economics 45, 499-504.

Waller, B., 2005, Balancing demand management and capacity flexibility: challenges faced by automotives supply chains, International Journal of Agile Manufacturing 8(2), 235-243.

Waller, M., Johnson, M.E. and Davis, T., 1999, Vendor-managed inventory in the retail supply chain, Journal of Business Logistics 20(1), 183-203.

Wang, J., Schroer, B.J. and Ziemke, M.C., 1991, Understanding modular manufacturing in the apparel industry using simulation, Proceedings of the 1991 Winter Simulation Conference, Phoenix, Arizona, 441-447.

Wang, J. and Shu, Y.F., 2005, Fuzzy decision modeling for supply chain management, Fuzzy Sets and Systems 150(1), 107-127.

Weng, Z.K. and McClurg, T., 2003, Coordinated ordering decisions for short life cycle products with uncertainty in delivery time and demand, European Journal of Operational Research 151, 12-24.

Whitaker, D., 1973, A study of a production line in the garment industry, Clothing Institute Journal 21, 113-120.

Wu, P., Wei, N.C., Lin, Z.P. and Hung, Y.Y., 2004, The study of retail inventory strategies under uncertainties, International Journal of Electronic Business Management 2(2), 131-139.

Wyland, B., Buxton, K. and Fuqua, B., 2000, Simulating the supply chain, IIE Transactions 32, 37-41.

Yao, L., Feng, Y. and Ju, Y., 2002, A survey of supply chain simulation, Proceedings of Asian Simulation Conference on System Simulation and Scientific Computing, Shanghai, 51-57.

Zadeh, L.A., 1965, Fuzzy sets, Information and Control 8, 338-353.

Zimmermann, H.J., 2001, Fuzzy Set Theory and Its Applications, 4th Eds. Kluwer Academic Publishers, Boston/Dordrecht/London.