RESOURCE MODELLING AND ALLOCATION FOR STOCHASTIC RETAILER DEMAND

BY

NING ANDREW

Ph.D

THE HONG KONG POLYTECHNIC UNIVERSITY

2013

THE HONG KONG POLYTECHNIC UNIVERSITY

DEPARTMENT OF INDUSTRIAL AND SYSTEMS ENGINEERING

Resource Modelling and Allocation for Stochastic Retailer Demand

By

NING Andrew

A thesis submitted in partial fulfillment of the requirements for

the Degree of Doctor of Philosophy

November, 2012

Certificate of Originality

I hereby declare that this thesis is my own work and that, to the best of my knowledge and belief, it reproduces no material previously published or written, nor material which has been accepted for the award of any other degree or diploma, except where due acknowledgment has been made in the text.

________________________________(Signed)

NING Andrew (Name of student)

Abstract

In this study the supply chain of an enterprise with a wholesaler and retailer section is considered whereby retailers make demand requests to wholesalers. Each wholesaler is serviced by a number of suppliers of goods that have varying purchase prices and varying delivery lead times. In addition to their suppliers, wholesalers are also allowed to replenish their supplies from other wholesalers (which belong to the same cost centre) at mutually agreed fixed prices. These kinds of shipment are called trans-shipments and are assumed to be immediately available.

When a demand for goods arrives at a wholesaler, one important decision that must be taken is whether or not a trans-shipment should be used to meet the demand. The scope for this study is to minimize the total operational cost of a wholesaler (i.e. the sum of product cost, total backorder, and holding cost related to lead time) by selection of a combination of suppliers, possible trans-shipment and minimizing shortage cost related to unfulfilled retailer demand. In order to assist calculation in minimizing total operation cost (of a wholesaler), an Intelligent Supply Chain System (ISCS) that aims to understand the underlying pattern and prediction of future retailer demand has been developed.

The ISCS consists of three modules; these comprise of a Predictability Module (PM), an Optimized Forecast Module (OFM) and a Decision Rule Module (DRM). The PM is responsible for collecting the historical demand from each retailer at the end of the supply chain, and to evaluate the predictability of these demands. The OFM module is responsible for providing an optimized forecast by using a hybrid of artificial intelligence technologies. The DRM module is responsible for providing advisory options under different inventory replenishment policies.

To validate the feasibility of the ISCS, a case study has been conducted in a local company using the approach explained above. The optimal prediction policy exhibits a significant advantage of reducing the wholesaler's inventory cost in comparison with the normal cost without any analysis of the predicted demand.

The significance of this research study includes an innovative approach that formulates decision rules which can be used for trans-shipment decision-making in supply chains made up of suppliers, wholesalers, and retailers, in any local region. One advantage of the model presented includes the inclusion of multiple suppliers for wholesalers as well as variable goods delivery lead times, both of which are important issues of the properties of previous models that neglect the main features of real operations in inventory systems. Another advantage is that its implementation is straight-forward and only requires direct calculations and a comparison of total costs.

Publication Arising from the Thesis

(**4** international journal papers are published and **1** book chapter is under review)

List of International Journal Paper

1. Ning, A; Lau, HCW; Zhao, Y & Wong, TT (2009) "Fulfillment of Retailer Demand by Using the MDL-Optimal Neural Network Prediction and Decision Policy", *IEEE Transactions on Industrial Informatics*, Vol. 5, No. 4, PP: 495-506.

2. Ning, A; Lau, HCW; Cheng, ENM & Wong, TT (2009) "A fuzzy rule-based system for evaluating logistics partners in the supply chain network", *International Journal of Value Chain Management*, Vol. 3, No. 1, PP. 64-86.

3. Lau, HCW; Ning, A; Pun, KF; Chin KS & Ip, WH (2005) "A Knowledge Based System to Support Procurement Decision", Journal of Knowledge Management, Vol. 9, No.1, PP: 87-100.

4. Lau, HCW; Ning, A; Ip, WH & Choy, KL (2004) "A Decision Support System to Facilitate Resources Allocation: An OLAP-based Neural Network Approach", International Journal of Manufacturing Technology and Management (IJMTM), Vol. 15, No. 8, PP: 771-778.

List of Book Chapter

1. Ning, A; Wong, TT & Lau, HCW, "Method In Optimizing Resource Allocation for Supply Chain Network By Using Hybrid Genetic Algorithms", *Encyclopedia of Information Science and Technology* (Second Review)

Acknowledgement

First of all, I would like to express my sincere appreciation and gratitude to my dissertation supervisor, Dr Henry Lau for his considerable help, continual guidance and encouragement throughout the research period. Sincere thanks also to my dissertation co-supervisor, Dr Eric Wong. He has always been supportive and has provided direction for this research.

Secondly, I would like to thank all the staff of the case company for providing the practical cases for this research. Appreciation then goes to my colleagues and friends for their generous help in providing valuable technical information and support for my research.

Furthermore, without mentioning any names, I would like to express my thanks to my colleagues in the Department of Industrial and Systems Engineering for their thoughtful discussion and assistance.

Last but not least, I would like to thank my families who have whole heartedly supported my study over the past many years.

Table of Contents

List of Figures

List of Tables

List of Glossary

AI, Artificial Intelligence

AIC, Akaike Information Criterion

ARIMA, Autoregressive Integrated Moving Average

ARMA, Autoregressive Moving Average

BIC, Bayesian Information Criterion

DRM, Decision Rule Module (DRM)

ISCS, Intelligent Supply Chain System

MAPE, Mean Absolute Percentage Error

MDL, Minimum Description Length

NMSE, Normalized Mean Square Error

NN, Neural Network

OFM, Optimized Forecast Module (OFM)

PM, Predictability Module (PM)

Chapter 1 Introduction

1.1 Background to the Study

During the last three decades, the importance of supply chain management has been gradually recognized in the world business environment, and as the 21st century unfolds supply chain management becomes both a prominent strategy and a productive aim of corporations. In particular, the increasing competition in the business sectors has accelerated the significant growth by using supply chain management concepts to streamline the flow of goods. It is well known that with the supply chain concept, many enterprises (especially the wholesaler section) are under pressure to reduce inventories at all levels to reduce the related costs (Master, 1993; Hollier et al, 2002). This strategy is considered as one of the critical elements of success for an enterprise. Therefore, this research aims to develop an Intelligent Supply Chain System (ISCS), with a combination of existing technologies, in order to assist wholesalers to allocate their resources more effectively.

1.2 Statement of Problem

The logistics industry has undergone significant changes over the past decade with the introduction and development of supply chain management. The ever-changing economic situation and the fierce competition environment require the wholesaler section to be very cautious about cost, speed of delivery and inventory policies in order to remain competitive (Wadhwa, 2008). However, retailer demands are making it difficult for wholesalers to maintain efficiency and flexibility in their operations, and wholesalers are being forced to increase the number of their stock keeping units. Thus, the challenging task for this sector is to determine the time when they need to order goods and the quantity it is appropriate for them to order from their suppliers. There are a number of approaches and systems that have been designed and implemented to improve supply chain network efficiency. However, an integrated intelligent system, which is able to practically assist wholesalers to allocate resources more efficiently, is still an area that requires more in-depth study and investigation. There are still major issues to be resolved, and they are summarized as follows:

(i) How to differentiate the predictable demand and the stochastic demand?

(ii) How to develop decision rule models that are suitable to be implemented for supply chain network?

(iii) How to achieve proactive resource allocation to cope with predicted retailer demand?

(iv) How to design an intelligent system framework to incorporate the above requirements, yet it is still easy for practitioners to follow and implement?

1.3 Research Objectives

The specific objectives of this research are:

(i) To investigate the derivation of the decision rule models that explain the achievement in minimizing the total expected future costs of the wholesaler when considering replenishment from one supplier and trans-shipment from one wholesaler;

(ii) To identify the dynamics of retailer demand, so as to exclude the completely stochastic demands from the following predictability evaluation;

(iii) To develop MDL-optimal neural network that aims to achieve accurate prediction of retailer demand;

(iv) To design and validate an ISCS framework, which incorporates the decision rule models, embraces MDL-optimal neural network and surrogate data method to achieve accurate prediction of retailer demand and optimized resource allocation.

1.4 Significance of the Research

In this study, a practical three-echelon supply chain network with focus on the operation of the wholesaler has been investigated. We explain the theories and corollaries behind the derivation of the decision rule models that help to explain the achievement in minimizing the total expected future costs of the wholesaler, when considering replenishment from one supplier and trans-shipment from one wholesaler. Prediction of demand and subsequent resource allocation plays a critical role in supply chain management. Accurate prediction of demand is a fundamental requirement and is also a great challenge to demand prediction models. This research is concerned with the introduction of ISCS, aiming to assist wholesalers in minimizing the total expected future costs while considering resources allocation. The use of the developed Minimum Description Length (MDL)-optimal neural network can accurately predict retailer demands with various time lags. Moreover, a surrogate data method is proposed prior to the prediction to investigate the dynamical property (i.e. predictability) of various demand time series, so as to avoid predicting random demands. In this study, we validate the proposed ideas by a full factorial study combining its own decision rules. We also describe improvements on prediction accuracy and propose a replenishment policy for a Hong Kong food wholesaler. This leads to a significant reduction in its operation costs and to an improvement in the level of retailer satisfaction. Most work in this aspect is original and makes a contribution to the development of an intelligent system for wholesales to make use of the ISCS framework to integrate practical inventory decision rules of the company.

1.5 Thesis Outline

The dissertation is divided into eight chapters. The outline of the dissertation is as follows:

(i) Chapter one states the problems that occur in existing supply chain network and describes the background and motivation for this research.

(ii) Chapter two is an academic review on supply chain management. This chapter describes the development of a classification scheme that follows the sequence from the general area to the specific area; a historical review of each area that provides a guide to the development on the corresponding subjects; and identification of the promising research topics as well as an investigation into future trends in supply chain management.

(iii) Chapter three depicts an investigation of the inventory system that we are focusing in this study. This chapter describes the derivation of the mathematical model, the concept of the proposed decision rule models and the application of the proposed methodology with numerical examples.

(iv) Chapter four depicts an investigation of a supply chain network comprising suppliers, wholesalers, and retailers (an extended scope).

Again this chapter describes the derivation of the mathematical model, the concept of the proposed decision rule models and the application of the proposed methodology with numerical examples.

(v) Chapter five presents an Intelligent Supply Chain System (ISCS), which is based on the Minimum Description Length-optimal (MDL-optimal) neural network combined with the surrogate data method for “learning” the underlying pattern and predicting future demands. The ISCS will act as a guide to forecast the coming retailer demands and thus improve supply chain network.

(vi) Chapter six is about operating the system in a case company which is a food distributor based in Hong Kong. Parts of the processes within the companies’ workflow are chosen to demonstrate the feasibility of the proposed methodology. An ISCS software prototype has been developed and system verification of the proposed design methodology is also shown in this chapter.

(vii) Chapter seven comprises two sections. The first section is general discussion of the decision rule models stated in this study, while the other section is a general discussion on the different modules of ISCS.

(viii) Chapter eight draws conclusions from the work undertaken. In this chapter the contribution made by this research is presented, and areas for future research are identified.

Chapter 2 Survey on Supply Chain Modeling and Decision Rules

2.1 Introduction

During the last three decades, supply chain management has become much studied topic and its importance has also been gradually recognized in the world business environment, and as the 21st century unfolds better supply chain management has become both a prominent strategy and a productive aim of corporations. Deloitte's survey in 1999 reveals that more than 90 percent of North American manufacturers classify the supply chain network as an element which is critical to their business (Thomas, 1999). Individual firms operate as supply chains in this era of network competition (Christopher, 2000), and achieve better performance (i.e. greater customer satisfaction) and profit from more efficient supply chain management (Chopra and Meindl, 2001; Lambert and Cooper, 2000). Supply chain management is an important issue in today global business market (Prasad and Babbar, 2000).

2.2 Brief History of Supply Chain Management

A supply chain is defined as a network of manufacturing and distribution sites (i.e. suppliers and customers), where a site in the upstream is in turn a supplier to the downstream entities, through processes of supplying raw material for production, producing products, and moving goods to meet customer demands (Lee and Billington, 1992; Handfield and Nichols, 1999). An example of a typical architecture of a supply chain is shown in Figure 1.

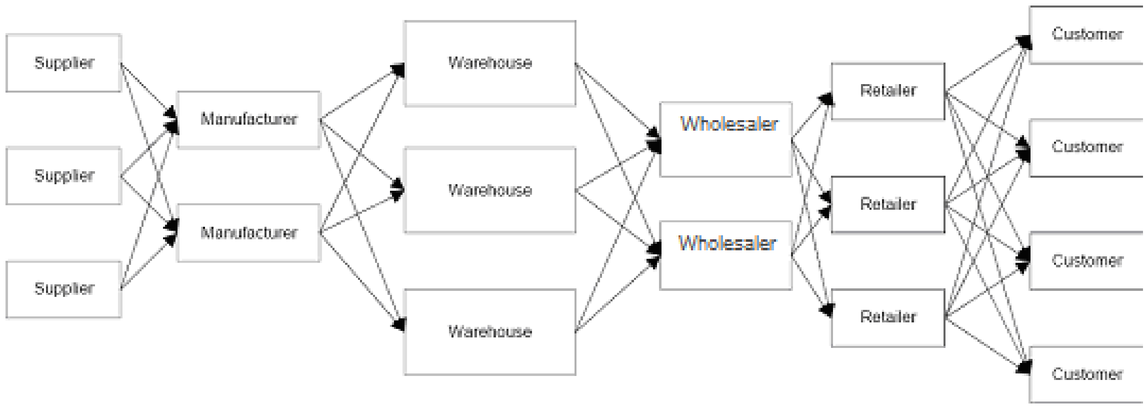


Figure 2.1 A typical supply chain from suppliers, manufacturers, warehouses, wholesalers, and retailers to the end users. (Source: Chang and Makatsoris, 2001)

Effective supply chain networks need a smooth coordination in all these activities from the stage of ordering the raw materials to moving the final products to the end customers, so as to reduce the total operation costs as well as the risks (Elmuti, 2002). Supply chain management refers to managing the supply chain processes as efficiently as possible. Supply chain management integrates supply and demand management within and across individual corporations. Supply chain management is not just a new label for the management of a supply chain across organizations (Cooper et al. 1997) but it represents a new model of managing the business and its relationships (Lambert and Cooper 2000).

Here we briefly review the history of supply chain management. We should note that there is no universal agreement on the definition and content of supply chain management (Croom et al 2000). The importance of what we would now call an efficient supply chain was recognized several centuries ago (Hugos, 2003) but the concept of supply chain management was originally introduced by consultants in the early 1980s (Oliver and Webber, 1982; Houlihan, 1985; Jones et al, 1985) and then introduced to the academic community (Harland, 1996; Cooper et al, 1997). Some articles in the literature described supply chain management as a system governed by strategic decision rules (Oliver and Webber, 1982; Cooper and Ellram, 1993; Chandra and Kumar, 2001). Supply chain management was also considered to deal with a series of processes of planning, coordinating and producing goods from source to the end customers (Stevens, 1989; Thomas and Griffin, 1996; Copacino 1997). It was concerned with both material and information flows throughout, and focused on the interfaces in between these. In practice, a few practitioners regarded supply chain management as strategic management of the organization through upstream and downstream linkages (e.g. Christopher, 1992). In Tables 2.1 and 2.2, we summarize the characteristics of the definitions of supply chain management.

Table 2.1 Review of the definition of supply chain management by year.

Names	Comments
Oliver and Webber (1982)	They first introduced the concept, supply chain management.
Houlihan (1985) Jones et al. (1985)	They enhanced the contents of supply chain management and discussed its advantages.
Stevens (1989)	Supply chain management manages the feed-forward flow of materials and feedback flow of information in the supply chain.
Berry et al. (1994)	He defined supply chain management from the perspective of trust, information exchange and relationships in the market.
Harland (1996) Cooper et al (1997)	They developed supply chain management in the academic area. Copper et al. also summarized the characteristics of supply chain management in the past years
Lummus and Vokurka (1999)	They considered that supply chain management coordinates and integrates all activities and facilities involved in the supply chain into a seamless process.
Mentzer (2001)	Supply chain management was defined as the systemic, strategic coordination of the traditional business functions.
Chopra and Meindl (2003)	Their supply chain management involving information, product, and funds flows, significantly targeted the maximization of the profitability of the total supply chain.
Supply Chain Council (2004)	The Supply Chain Council formally gave the definition of supply chain management.

Table 2.2 Review of the definition of supply chain management classified by its characteristics

References	Category of Supply Chain Management
Oliver and Webber,1982 Cooper and Ellram, 1993 Tan et al., 1998 Lummus and Vokurka, 1999 Narasimhan and Das, 1999 Chandra and Kumar, 2001 Mentzer, 2001	A set of decisions or activities of business functions from the perspective of purchasing and supply management.
Stevens, 1989 Thomas and Griffin, 1996 Copacino 1997 Handfield and Nichols, 1999 Chopra and Meindl, 2003	Management of materials, products and information flows from source to the end customers from the perspective of logistics and delivery functions

Hence, as Tan (2001) concludes, some researchers investigated supply chain networks by looking at business functions and defining its management as a set of decisions or activities of purchasing, and supplier management, while others considered it from the perspective of logistics and delivery functions and defined it as the management of materials, products and information flows (Salvador et al., 2001) from source to user. It appears that more scholars have adopted the purchasing and supply management perspective when referring to supply chain management, as indicated in Table 2. But describing supply chain networks merely in terms of purchasing and supplier management is not adequate since firms collaborate with other important members (such as customers) in the supply chain network. Nowadays, more new terms addressing certain phenomena of this management philosophy, have appeared and have enriched its contents, as indicated by Tan et al. (1998).

Regarding various researches into supply chain management, Chen and Paulraj (2004) did wonderful work, which summarized the supply chain management research, as shown in Figure 2. An earlier summary can be found in Ganeshan et al. (1999). They also discussed the solution methodologies corresponding to the researches they classified.

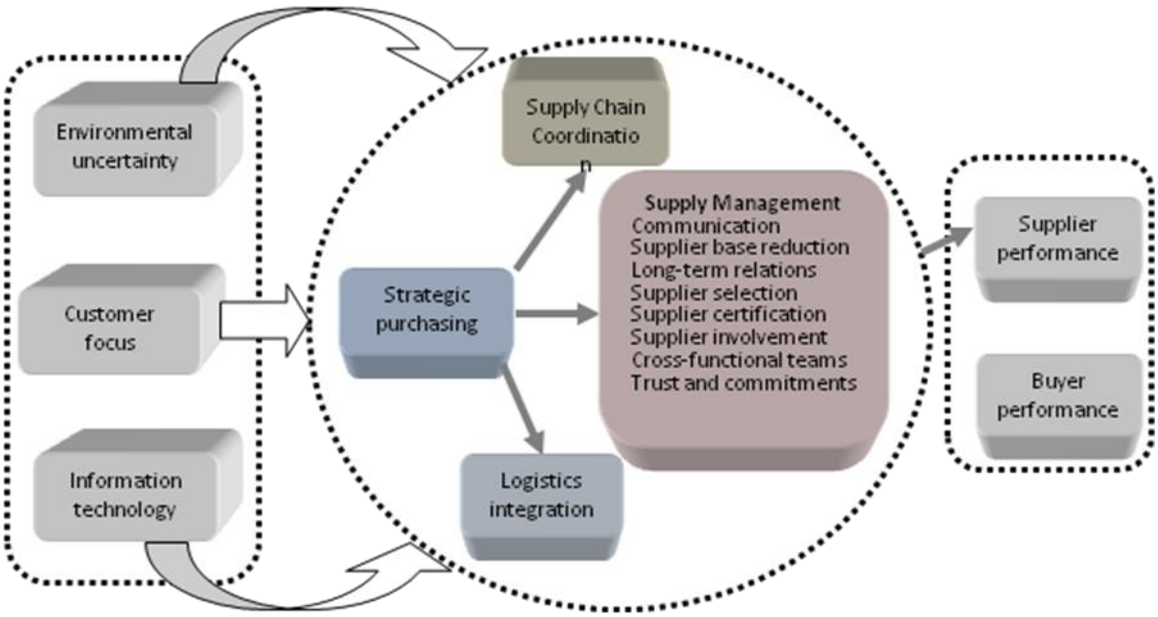


Figure 2.2 Schematic diagram for supply chain management research (Source: Chen and Paulraj, 2004)

Advantages through supply chain management have been appreciated by manufacturers since it appeared (Sabel et al, 1987; Slack, 1991), and much more research has tried to gain greater insight into supply chain management and put such insights to practical use. Supply chain management has become such a hot topic that it appears in all periodicals related to manufacturing, marketing, customer management and logistics (Ross, 1998). However, although there is growing interest in studying supply chain management, studies on this subject are primarily empirical-descriptive, lacking theoretical guidance. Application of a multidisciplinary approach to the advancement of supply chain management in theory is imperative (Das and Handfield, 1997; Croom et al., 2000). Therefore, theoretical studies have been stressed by researchers as an important way to advance supply chain management and its sub-fields (Amundson 1998, Handfield and Melnyk 1998).

2.3 Supply Chain Modeling

A supply chain model needs to take as many realistic factors as possible into consideration but if all the possible factors are included the model would become so complex that it would be extremely difficult to find a solution. Hence, there is always some compromise in a supply chain model between practice and theory. A supply chain could be modeled and analyzed in many distinct ways due to the definition of supply chain management being so flexible, as we mentioned before. Furthermore, different members in the supply chain have different and conflicting interests (Simchi-Levi et al., 2003). Researchers are inclined to model the supply chain according to their own interests, requirements and conditions.

The earliest well-known supply chain practices were at Ford's River Rouge factory in the early 20th century and then Toyota's novel supply chain standards after World War II. Wal-Mart's stimulated another evolution in the supply chain management, when it developed cross-docking and vendor-managed inventory. Also, Dell is also famous for its direct linking to consumers (Boyer et al., 2004).

On the theoretical side, the early efforts in modeling the supply chain were guided by the application of servomechanism theory to study the production control (Simon, 1952). Forrester (1958, 1961) introduced a theory of industrial dynamics that revealed the integrated nature of organizational relationships in distribution channels. Forrest investigated key management issues and the dynamics of factors associated with the supply chain. After that, numerous mathematical modeling and simulation techniques were developed to analyze the supply chain systems. Baumol and Vinod (1970) developed both deterministic and stochastic models to investigate the shipment mode of transportation. Azoury (1985) formularized two types of dynamic models: the depletive and non-depletive models. Braford and Sugrue (1990) modeled a two-period multi-location inventory problem with stochastic demand and trans-shipment. Christy and Grout (1994) employed game theory to provide a relationship matrix for customers and suppliers in the supply chain. Melachrinoudis and Min (2002) provided a multi-objective model to find the relocation and phase-out of warehousing facilities in a multi-period planning horizon. Biswas et al (2004) summarized the supply chain modeling methodology from the perspective of optimization models, analytical performance models, and simulation models. During this time, the stability of the supply chain model was definitely an important issue in the development of supply chain modeling. In the 1990s, researchers started to investigate the stability and robustness properties for different models of the supply chain (Marshall et al., 1992; Toffner-Clausen, 1996; Niculescu et al., 1997).

In particular, inventory management is one of the most promising areas and fundamental elements in supply chain management. We classify the inventory models according to their mathematical techniques, as shown in Table 2.3.

Table 2.3 Classification of inventory models by their modeling techniques

Mathematical Approaches		
Bayesian Technique	Markov Chain Modeling	Time Series Analysis
Scarf, 1959 and 1960 Harpaz et al., 1982 Azoury and Millerl, 1984 Azoury, 1985 Bradford and Sugrue , 1990 Hill, 1999 Kamath and Pakkala, 2002 Choi et al., 2003 Sethi et al., 2003	Pegels and Jelmert, 1970 Song and Zipkin, 1993 Sethi and Cheng, 1997 Chen and Song, 2001 Trecharne and Sox, 2002 Mohebbi, 2006	Johnson and Thompson, 1975 Graves, 1999 Dong and Lee, 2003 Aviv, 2003 Zhang, 2004 Lu et al, 2006 Aburto and Weber, 2007

2.4 Decision Rules for Lateral Trans-shipment

Among the research in supply chain modeling, inventory modeling usually deals with various direct demands of retailers and then the end customers of the whole supply chain, as shown in Figure 3. By meeting customers' requirements, the enterprises get their investment back and make a profit. Effective inventory control should efficiently respond to customers' demands, fulfill their demands, and avoid shortage. Back in 1960s and 70s, lateral trans-shipment was studied in order to improve inventory control. Relatively little benefit was gained from this in 1980s and 90s although Lee (1987) and Axsäter (1990) validated the feasibility and utility of lateral trans-shipment. It was not until the 2000s that lateral trans-shipment became a hot topic in supply chain management and its value was appreciated by more and more researchers. Fruitful new developments of lateral trans-shipments emerged at that time, which brought about substantial cost reductions and significant improvements in customer satisfaction levels.

Inventory control can be defined as a process of managing the timing and the quantities of goods to be ordered, stocked, and delivered. It aims to meet retailer demands satisfactorily and keep its operation cost at an economic level. Inventory control policies are decision rules that make the best balance between the costs and benefits of alternative solutions. The benefits of carrying inventory have to be compared with the costs of holding it while the benefits of dropping inventory have to be compared with the costs of back ordering it. So decision rules need to compute expected total costs and identify the optimum arrangement between the quantity to be ordered from the suppliers directly and the quantity required in order to replenish the goods through lateral trans-shipment. Therefore, we need multi-objective functions in the decision-making process to arrive at the best balance among such conflicting goals (Axsäter, 2006). The typical process for decision-making is simulation, where many realistic features can be represented. The development of simulation models to understand supply chain decision-making has been the focus in recent years (Yao et al., 2002; Simchi-Levi et al., 2003; Umeda et al., 2006).

There has been a significant growth in using supply chain management concepts to streamline the flow of goods. It is well known that many enterprises will always want to keep a low inventory for buffering, in order to save the cost of storage. This strategy is considered as one of the critical elements for the success of an enterprise, especially in today's globalized business environment. On the other hand, the ever changing economic situation and the fierce (retail) business competition requires that the enterprise holds enough stock to fulfill user's regular demands as well as sudden demands that are needed quickly. In general, they are facing a dilemma regarding this, in their daily operations. As a result, the concept of lateral trans-shipment is used to address this problem. Nowadays, it is a hot topic in supply chain modeling. Figure 2.3 presents a schematic diagram of the supply chain of wholesalers, retailers and suppliers for reference.

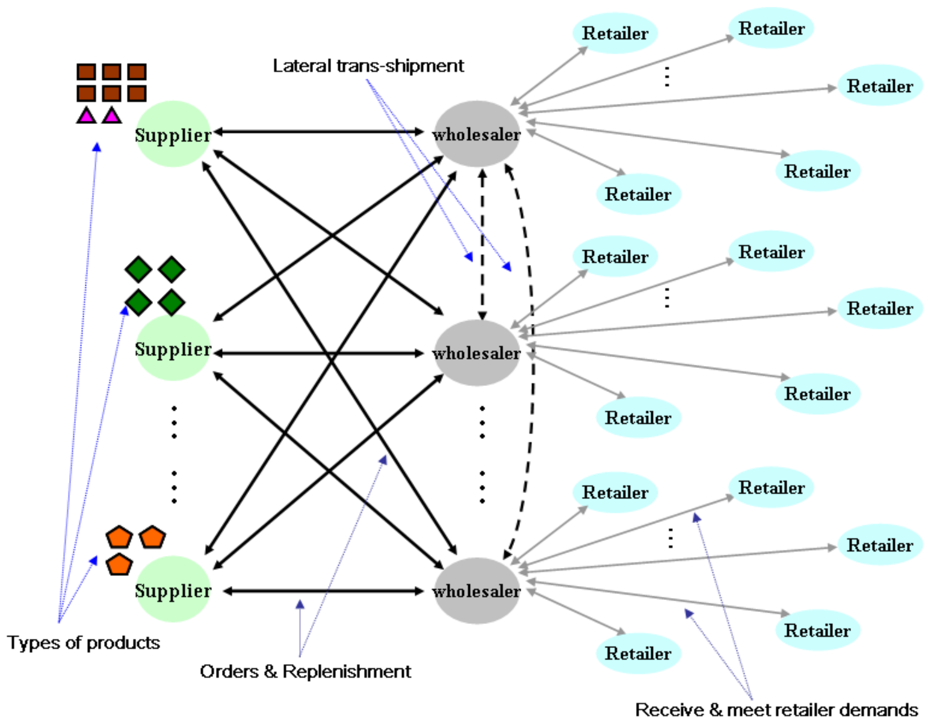


Figure 2.3 The schematic diagram of a multi-echelon supply chain network.

There are many papers dealing with lateral trans-shipment. We will review the selected research articles related to such lateral trans-shipment in chronological order. These papers reflect the issues that were important in lateral trans-shipment at that time.

The earliest emergency lateral trans-shipment model was proposed by Krishnan and Rao (1965), who derived optimal order-up-to quantities under the assumption of there being a single-period review. Das (1975) developed the concept of lateral transfer as a provision for a two-location stochastic inventory with periodic review. He used a stochastic dynamic program to optimize the transfer decision rules and stocks. Hoadley and Heyman (1977) studied lateral trans-shipments between inventory locations at the retail level under the emergency conditions. Impressively, such lateral stock transfers can result in substantial cost reductions (Hoadley and Heyman, 1977; Tagaras, 1989). However, in practice it is unusual for retailers to

adopt lateral trans-shipment between each other. Lee (1987) investigated emergency lateral trans-shipment in multi-echelon inventory systems which cover wide geographical areas. If a local warehouse cannot satisfy customer demands, lateral trans-shipment is then made from another warehouse with adequate stock in the same group (i.e. company). If such lateral trans-shipment is impossible, the demands will be backordered. Lee made a balance between the level of backorders and the size of emergency lateral trans-shipments and in doing so, proved that applying lateral trans-shipment reduces total cost. Moreover, he also considered the case of non-zero trans-shipment lead times. Axsäter (1990) also studied emergency lateral trans-shipment in the same two-echelon inventory system as Lee's. Axsäter' s method focused on modeling the demands at a base following a Poisson demand distribution with the modification of assuming that bases within each group are not identical. He derived steady-state probability by assuming exponentially distributed replenishment time.
In addition, some researchers employed lateral trans-shipment to balance stocks among different locations (Jönsson and Sliver, 1987; Diks and De Kok, 1996; Bertrand and Bookbinder, 1998). It can be regarded as preventive lateral trans-shipment that aims to reduce risk by redistribution between retailers before the arrival of customers' demands (Tagaras, 1999). However, some people note that excessive trans-shipment to balance stocks in certain environments may have a negative effect on the cost (Bertrand and Bookbinder, 1998).

In recent years, Alfredsson and Verrijdt (1999) considered a two-echelon inventory system for service levels by normal supply and lateral trans-shipment and they constructed an analytical model to evaluate the relevant performance. Grahovac and Chakravarty (2001) investigated the advantages of lateral trans-shipment in a specific supply chain where a manufacturer supplies expensive and low-demand items to vertically integrated or autonomous retailers via one central depot. The manufacturer's lead time was assumed to be determined by the geographical distance from the market or a combination of low volumes, high variety, and inflexible production processes. They concluded that sharing and trans-shipment of items could reduce the total costs of holding, shipping, and waiting. Another interesting result they found is that cost reductions sometime result from increasing the overall inventory. Axsäter (2003) proposed a new decision rule to determine the lateral trans-shipment in a single-echelon inventory system consisting of a number of parallel local warehouses facing compound Poisson demand. Holding costs, backorder costs and ordering costs are all considered together. It gives a number of alternative decisions for the warehouse to consider. The approach has been evaluated and the results are encouraging. Köchel et al. (2003) paid attention to the importance of organizing trans-shipments of resource units between the nodes of the logistics network. Weber (2004) analyzed the complementarity and substitutability of lateral trans-shipments in shipment related problems. Burton and Banerjee (2005) examined the cost effectiveness of two lateral trans-shipment approaches in a two-echelon supply chain network and discovered that a lateral shipment approach was considerably superior to a policy of no such shipments, albeit at the expense of increased transportation activity. Minner and Silver (2005) evaluated two simple extreme trans-shipment strategies and developed an analytical approach for approximately estimating the total expected costs. More recently, Lee et al. (2007) described an effective lateral trans-shipment policy to improve service levels in the supply chain. This much more efficiently responded to customer demands. More significantly, Yang and Qin (2007) proposed the idea of virtual lateral trans-shipment for optimal control of a firm with two incapacitated manufacturing plants situated in two remote geographical regions. As they used the virtual source, the base did not need to have non-negative inventory levels throughout the trans-shipment processes. Table 2.4 lists some classical papers related to lateral trans-shipment in past times and also some new developments in recent years.

Table 2.4 Review of papers related to lateral trans-shipment by year.

Before 1980s	**1980s**	**1990s**	**2000s**
Krishnan and Rao, 1965 Das, 1975 Hoadley and Heyman, 1977 Karmarkar and Patel, 1977;	Lee, 1987 Karmarkar, 1987 Jönsson and Silver, 1987 Tagaras, 1989	Axsäter, 1990 Robinson, 1990 Archibald et al, 1997 Bertrand and Bookbinder, 1998 Alfredsson and Verrijdt, 1999	Grahovac and Chakravarty, 2001 Rudi et al., 2001 Herer and Tzur, 2001 and 2003 Axsäter, 2003 Köchel et al., 2003 Weber, 2004 Dong and Rudi, 2004 Burton and Banerjee, 2005 Minner and Silver, 2005 Lee et al., 2007 Yang and Qin, 2007

Many existing studies in this field consider relatively simple cost structures. For example, they usually assumed two stock locations or a single planning period (Das, 1975; Herrer and Rashit, 1995) while in the real world firms have to compete on the open market and sources of lateral trans-shipment are certainly not limited to one neighboring partner. As Guinet (2001) suggested, it will be a multi-site trans-shipment problem, and more attention need to start to focus on it. Complex cost structures and other considerations (i.e. more reflective of real situation), are necessary to substantiate decision making process for lateral trans-shipment.

Furthermore, many researchers assume that lateral trans-shipment only happen under emergency conditions or actual shortages (Lee, 1987; Axsäter, 1990 and 2003) For instance, some authors assumed a decision rule is applied for lateral trans-shipment when a warehouse cannot supply goods to a retailer (Axsäter, 2003).

Lateral trans-shipment may be considered as a regular and potential source to meet customer demands, rather than a temporary and emergency one in the future research. It can be observed from the above related works that decision rules were separately and independently applied. Actually subjects that those decision rules are applied to are closely related to each other and tiny changes in these subjects may generate a significant difference in the total cost. Separate consideration of these decision rules probably offers good local optimal solutions but poor-quality global optimal solution. To overcome this shortcoming, the decision-making process for joint optimization, which provides the optimal replenishment solution, should be addressed in the future research. Moreover, as the computational cost involved in the new decision-making process is huge, efficient optimization methods should be utilized to search good-quality solutions for the decision problems.

2.5 Trans-shipment Policies

As described in the previous section, lateral transshipment can be regarded as the redistribution of stock from retailers with stock on hand to retailers that cannot meet customer demands or to retailers that expect significant losses due to high risk. However, typical supply chain networks are usually too complex to analyze, let alone optimize globally. Researchers usually concentrate on smaller or simplified supply chain network, thus making it easier to obtain a full understanding of such network. One of the research focuses is on a local distributing supply chain network, which includes multiple retailers and a central distribution center (Tagaras and Cohen, 1992; Tagaras, 1999; Herer, Tzur and Yucesan, 2006, Olsson, 2009). Another research focus is on a proactive redistribution of available inventory within a supply chain network, with an objective to prevent stock-out at retailers (Gross, 1963; Jonsson, 1987; Diks and De Kok, 1996). Consequently, two types of lateral transshipment policies have been engendered, namely Proactive Lateral Transshipment (PLT) and Reactive Lateral Transshipment (RLT). PLT reduces potential risk by redistributing inventory in the same echelon that foresee stock-out before the realization of retailer demands, while RLT execute inventory redistribution from one party to another party that has reached stock-out.

The first researcher to consider RLT was Krishnan and Rao (1965). They consider a periodic lateral transshipment model, where its objective is to minimize cost through transshipments once all demand is known, and with an assumption of negligible transshipment times. Robinson (1990), Hu et al. (2005), Herer et al. (2006) and Nonås and Jörnsten (2007) continue the development of this type of RLT model, where their objectives are to provide an optimal solution for a multi-location, multi-period model with different constraints.

While the search of an optimal transshipment based on observed demand give useful insights in this kind of RLT problem, in practice continuous demand is often observed and each instance may trigger a reactive transshipment. Archibald et al. (1997, 2007, 2009, 2010) has conducted a number of researches in RLT problems, such as consider a multi-location system where each experiences Poisson demand. Their research results have illustrated that dynamic programming can be used to determine optimal policy and the preferred location(s) where demand should be fulfilled. Tang and Yan (2010) have conducted research on managing replenishments to a number of stocking points, which can be modeled as a RLT problem. Their focus is in determining whether ordering decisions should be reactively triggered by the stocking points individually or as a collective. Kukreja and Schmidt (2005) and Huo and Li (2007) study similar RLT problem in spare parts environment, under (s,S) replenishment policy and (R,Q) order policy respectively. Both have employed heuristics techniques to determine the optimal base levels for the stock locations.

The first researcher to consider PLT was Gross (1963). Based on a simplified environment with two stock locations with negligible lead time, he derives a transshipment policy that minimizes average shortage and inventory, based on initial inventory levels. Karmarkar and Patel (1977) expand this model with a multi-location case. For a large number of locations they propose a linear programming based technique which they find to be robust. While both Gross's model and Kararkar's model are examined in a single period interval, Karmarkar (1980) provide the multi-period expansion and find that the characteristics of the optimal solutions are similar to the single period case. Diks and de Kok (1996) and Diks and de Kok (1998) conduct similar PLT investigations, but their main objective is to compare several heuristics techniques for determining the amounts to transship when distributing at reorder moments.

Agrawal et al. (2004) illustrate that a dynamic transshipment policy often outperforms a static one with respect to costs, saving up to 30% based on numerical study. Similar cost saving outcomes have been obtained by Banerjee et al. (2003) and Burton and Banerjee (2005). An extended policy investigation has been carried out by Lee et al. (2007), which has included an additional proactive heuristic, called the Service Level Adjustment (SLA) policy. The SLA policy defines that, at the beginning of each sub-period, the probability of no stock-out during the lead time of the next replenishment order is computed; the location with the largest surplus stock will proactively replenish the one with the highest requirement. A simulation study illustrates that this additional SLA policy leads to a better cost performance than types of transshipment policies when transportation costs are sufficiently low.

The adoption of lateral transshipment policies has proved to be an effective tool to measure and improve service level of the entire supply chain or of an individual retailer (Tagaras, 1989; Tagaras, 1999). From the company's point of view, inventory management is an integrated approach to monitor raw materials and finished goods throughout the entire supply chain network. Pressures from low-cost and the new global competitive environment require companies to be more productive, react faster to market changes, and maintain smaller inventories (Burton and Banerjee, 2005). The situation requires that for value to reach the customers, efficiency must be evident even in the suppliers, the distribution channel, and all associated activities and partners. Competition is no longer between individual businesses, but between groups of companies that are linked together in a chain for delivering customer value (Hameri and Palsson, 2003).

Therefore, apart from focusing on in-house inventory management policies, companies should also pay more attention on their collaborative policies with other supply chain partners. There is no doubt that good collaborative policies can enhance companies' supply chain network performance, and an allowance of lateral transshipment is one way to improve relationship among supply chain partners. Professional adoption of lateral transshipment simultaneously reduces the total system cost via effectively resources pooling to reduce the risk of shortage (Herer et al., 2002). The adoption of lateral transshipment strategy can improve a company's system availability while reducing the total system costs. (Kranenburg, 2006; Fredrik Olsson, 2008).

2.6 Forecasting

Forecasting has generally been regarded as a useful planning tool to assist managerial staff to cope with the uncertainty of the future, based on historical transactions and trend analysis (Bates & Grange, 2000; Ballou, 2002). Makridakis, Wheelwright, and McGee (1989) have foreseen the important roles of management's knowledge in the expected development of forecasting. Since then, forecasting has become an emerging research area and has received lots of attentions (Armstrong, 1988; DeRoeck, 1991; Mahmoud et al, 1992). Makridakis (1989) and Chase (1993) have concluded that statistical method is the most popular technique for forecasting approaches in early times and could play prominent roles in forecasting research and application development. For example, McCarthy et al (2006) have concluded that an effective forecast could reduce inventory level, thus enhancing enterprises' competitiveness. However, the popularity of using statistical method has been reduced, because it could not offer effective explanations for qualitative factors such as the seasonal factors and changes in social behaviors (Frees & Miller, 2004; Thomassey & Happiette, 2007; Shih & Chung, 2008; Lee, 2010).

As modern business environment are becoming increasingly complex, researchers are using Artificial Intelligence (AI) techniques to deal with forecasting problems because of their fault tolerant and high-speed computing ability. For example, Neural Networks (NN) has been applied in sales forecasting and have shown promising performance in the areas of material data test handling, friction behavioral analyses, processing control and pattern recognition (Velten et al, 2000; Cai et al, 2005; Vassilopoulos et al, 2007; Chau, 2007). Originally developed to mimic basic biological neural systems – the human brain particularly, are composed of a number of interconnected simple processing units, which simulates the structure and function of the nervous system of the human brain. It is some abstraction and simplifier of the human brain, but not completely true (Peng, 1997). It is a mathematical model of the theorizing human brain nerve network, highly nonlinear, and can carry out complex logic operation and the nonlinear relationship system. The fitting ability of the complex and nonlinear relation between each factors in prediction is very strong, and the prediction precision and efficiency are high (Conejo et al, 2005).

Numerous researchers have performed a comparison between NN and conventional methods of sales forecasting and have concluded NN is better off. Weigend et al. (1991) introduced the eight-elimination back propagation learning procedure to sunspots and an exchange rate time series to deal effectively with problem of over fitting. The NN has shown adequate performance in terms of control and pattern recognition when applied to forecasting. For example, Winklhofer & Diamantopoulos (2003) has successfully employed NN technique to find the relationship between input data and output data without complete information, and such NN has the ability of using estimators to replace the true variance components with short data training. Most companies manage the forecasting function but lack involvement in the forecasting process of the numerous functions that have information critical to effective forecasting (McCarthy et al, 2006; Lee et al, 2010). Forecasting performance will not improve until companies commit the resources to create an adequately funded, cross-functional sales forecasting process that is populated with personnel trained in the use of sales-forecasting techniques (Lee & Lin, 2010).

2.7 Summary of the Literature Review

In this chapter, we briefly reviewed of the literature relating to supply chain management, decision rules for lateral transshipment, transshipment policies and forecasting. It is divided into two categories by its being defined either from the perspective of purchasing and supply management or the perspective of logistics and delivery functions. However this difference in its definition is not always clear as some articles integrate both sides when investigating supply chain management. We conclude that although many papers in the field of supply chain management studies are mainly conceptual description and empirical analysis, there is a lack of an adequate theoretical framework. The advancement of supply chain management in theory is imperative. As a result, we will next review supply the theory of supply chain models as well as the theoretical approaches they use. Especially, we will summarize inventory models, one fundamental sub-field of supply chain modeling, using mathematical techniques. In addition, while researchers have been conducted numerous investigations in model development and overall system costs minimization, the determination of an appropriate timing to execute stock redistribution is still not fully understood.

In conclusion, we find that lateral trans-shipment, which is as old as supply chain modeling, is quite popular in the academic community with various new promising developments from the year 2000 onwards while there are relatively few practical applications of lateral trans-shipment in the industrial community. The possible reason for this is that simple cost structures can not reflect complicated practical situations and the unusual replenishment methods that only happen in an emergency. It is necessary to pay much more attention to this topic in future research and point out its future research directions.

Chapter 3 Development of a Decision Rule Model for Trans-shipment in a Supply Chain Network

3.1 Introduction

With the increasing competition in the wholesale business sector, there has been a significant growth in using supply chain management concepts to streamline the flow of goods. It is well known that with the supply chain concept many enterprises, especially in the wholesale section, will always want to keep a low inventory for the purpose of buffering, in order to minimize the storage cost. This strategy is considered as one of the critical elements for the success of an enterprise, especially in today's globalized business environment. Thomas and Griffin (1996) reviewed the literature addressing coordinated planning between two or more stages of the supply chain, placing particular emphasis on models that would lend themselves to a total supply chain model. Erenguc et al. (1999) concluded that even if a given supply chain network is under a single ownership and centralized control, the integrative view of supply chain management obligates its managers to solve multiple stage inventory problems of a scale for which researchers have yet to identify consistently efficient solution procedures. While Köchel et al. (2003) stressed the importance of organizing shipments of resource units between the nodes of the logistics network; Weber (2004) provided complementarily and substitutability in the shipment related problem. Burton and Banerjee (2005) examined the cost effects of two lateral transshipment approaches in a two-echelon supply chain network and discovered that a lateral shipment approach was considerably superior to a policy of no such shipments, albeit at the expense of increased transportation activity. Minner and Silver (2005) evaluated two simple extreme transshipment strategies and developed an analytical approach for estimating the approximate total expected costs. There are many papers that deal with goods replenishment issues such as Alfredsson and Verrijdt (1999), Guinet (2001), Rudi and Pyke (2001), Dong and Rudi (2004), Wong et al. (2005), Koster (2007), Nagy and Salhi (2007), Young et al (2007).

Most authors assume a decision rule is applied when asking for a shipment from other wholesalers. According to Axsäter (1990), in the case where a wholesaler cannot supply goods to a retailer, lateral transshipment will take place and under these circumstances, he proposed a method for optimizing the control policy of inventory replenishment. Archibald et al. (1997) suggested using a stochastic dynamic program to optimize the decision to laterally transship. A simulation with a heuristics approach was evaluated by Tagaras and Cohen (1992).

Based on Axsäter's (2003) idea, a new approach has been developed. This approach deals with multiple suppliers and variable lead times in delivering goods together with the cost of trans-shipment. In this approach the replenishment quantity from the supplier and the trans-shipment quantity from other wholesalers can be computed, consequently the most cost effective decision can be obtained.

3.2 Inventory Management Policies

When the demand for an item is independent to other demand items, we can treat the inventory of each item separately. For the inventory management policies, they usually include the specification of decision rules with respect to the point in time when a re-ordering of the inventory should be initiated.

The most common inventory situation faced by companies is that stock levels are depleted over time and then are replenished by the arrival of a batch of new units. A simple inventory management policy representing this situation is names as Economic Order Quantity policy (EOQ policy). Such policy is a technique for determining the best answers to the how much and when questions. It is based on the premise that there is an optimal order size that will yield the lowest possible value of the total inventory cost (Heizer and Render, 2011).

Generally speaking, it should be noted that the basic EOQ policy assumes that demand rate is constant and predictable (i.e. deterministic demand). When a company can foresee a stock-out, it would place a replenishment order in a timely fashion, and consequently such replenishment order would be used to cover the stock-out. However, real demand rates are seldom completely predictable, thus usually have been regarded as stochastic demands. As a result, it is highly possible that the company may have stock-out before the replenishment order arrives. In view of these stochastic demand situations, two commonly approaches are adopted. One approach assumes that for each replenishment, the timing is fixed with the amount ordered varies. Another approach assumes the amount ordered is fixed, but the timing varies. The first approach has usually been classified as periodic review policy and has usually been regarded as Safety Stock (s, S) policy. The second approach has usually been classified as continuous or perpetual review policy and has usually been regarded as Reorder-point, order-Quantity (R, Q) policy (Hillier and Lieberman, 2008). Table 3.1 describes the details of each inventory management policies.

Table 3.1 Details of (s, S) policy and (R, Q) policy

	(s, S) policy	(R, Q) policy
Characteristics	Based on a constant time between orders	Based on a constant order size
Parameter 1	Review period or order interval (T)	Reorder-point (R)
Parameter 2	Target inventory (S)	order-Quantity (Q)
Objective	Periodic review refers to the fact, that once every order period, it reviews the inventory level to see the ordered quantity.	Continuous review refers to the fact, that the inventory level must be constantly observed to see if it is time yet to place an order.
Advantages	· Joint shipping advantage with multiple items from same source. · It does not require constant monitoring.	· It provides tighter control over inventory items. · Less safety stock is needed.
Disadvantages	· It requires more safety stock. · Occasional small orders may result. · It provides looser control over inventory items.	· It requires constant monitoring. · There may be problems with multiple items from same source (many items arrive in separate shipments).

Under a classic (s, S) inventory policy, when the on hand inventory for an item under study drops to some level σ that is below the reorder point s (i.e., $\sigma \le s$), an order for $(S - \sigma)$ units is placed to replenish inventory levels back up to the order-up-to level S. In other words, the (s, S) policy has no EOQ concept and just produce items until reaching S level and stop producing.

Under a classic (R, Q) inventory policy, when the on hand inventory for a product under study drops to some level R or below, an order quantity of Q (typically the calculated EOQ) is placed to replenish inventory levels. This approach uses a fixed order quantity of Q, rather than the potentially variable order quantity of (S – σ) as discussed above for the classic (s, S) inventory policy.

Since the turn of the century, more companies (e.g. wholesalers) have increasingly moved to adopt (R,Q) policy (Elmaghraby, & Keskinocak, 2003; Chan et. al, 2004; Chen & Simchi-Levi, 2004; Graves & Willems, 2008). Three reasons are listed:

- The economic globalization has enabled an increase in economic interdependence of national economies across the world through a rapid increase in cross-border movement of goods, service, technology, and capital (Joshi, 2009).
- The continuous evolvement of information technologies and transportation facilities enable quickly-replenish activities.
- It makes sense from the financial point of view. Since less safety stock is needed, less warehouse spaces are required (lower holding costs), thus enhancing the liquidity of the company.

As a result, this research study is aimed for business suitable for (R, Q) policy and (s, S) policy is not within the scope of study, and therefore not to be further investigated.

3.3 Problem Description

Consider a certain (finite) number of wholesalers that operate independently of each other in a certain local area. The wholesalers supply goods to local retailers whose requests for orders from the wholesalers are assumed to follow independent compound Poisson distributions[1] as described by Axsäter (2006). The wholesalers usually replenish their stock from a supplier. The lead time of the supplier follows some probability distribution. In addition, trans-shipment from other wholesalers (being in the same cost centre) is also a convenient and feasible option to partially/fully meet retailer demands. We define such transfer of products between wholesalers belonging to the same cost centre as trans-shipment, i.e. we call the lateral trans-shipment between two wholesalers of the same cost centre, as trans-shipment. Due to the close proximity between the individual wholesalers, compared with the normally large distances from their suppliers, trans-shipments are usually assumed to have no lead time, but they do incur additional cost.

We assume that all wholesalers apply a continuous review policy descibed by Rosenshine and Obee (1976) to replenish from external suppliers. To formulate the continuous review policy, we review the unsatisfied demands in the previous period, the inventory position, and the expected demand in the current period, and then make the order at the beginning of this period. Unsatisfied demands or surplus orders of this period will be regarded as initial demands or will be added to inventory position of the next period. If the wholesaler does not employ a (R,Q) review policy, its inventory position could be lower than R of (R,Q) policy or even near zero, which can decrease the holding costs of the wholesaler. However, the wholesaler that uses a

[1] For consistency, we assume the same distribution of retailer demands as Axsäter (2003) but we note that our mathematical model as well as the decision rule for trans-shipment is also applicable to other discrete retailer demand distributions with simple substitution.

continuous review policy has the possibility that its inventory position may be lower than zero. This potentially increases the back-order cost. One possible solution is to make trans-shipment from other wholesaler so as to make the inventory position of the wholesaler non-negative as soon as possible.

A detailed description of the present model is as follows. Let $W_1, \ldots, W_M$ be M wholesalers in a certain local region. Let n be the number of retailers requesting goods from wholesaler W_i $(i = 1, \cdots, M)$ in a time interval of length t. It has a Poisson distribution with a known arrival intensity λ_i. that is,

$$P_{i,t}(n) = \frac{e^{-\lambda_i t}(\lambda_i t)^n}{n!}, \quad n = 1,2,\ldots,$$

where λ_i is the retailer arrival intensity at wholesaler i.

Let S_{ij} $(j = 1, \cdots N_i)$ represent any supplier of W_i with unit goods prices p_{ij}; let L_{ij} be delivery lead time of S_{ij}; let $g_{ij}(t)$ be the probability mass function of L_{ij}. L_{ij}^{max} is an upper bound on the delivery lead time of supplier S_{ij}. This assumption of a finite value for L_{ij}^{max} is consistent with the fact that no supplier will take an infinite time to deliver its goods. A reasonable (finite) value for L_{ij}^{max} always exists for each S_{ij}.

In our model, the period to update the wholesaler is set to the maximal lead time of the given supplier. So all the orders made should be received in the period. W_i therefore there will be no outstanding orders from its suppliers at the initial point of a new period, which will simplify the total cost model and decision rules for trans-shipment. So the inventory level of the wholesaler is equal to its inventory position.

For reasons related to the efficiency of operations and management, it will also be assumed that once wholesaler W_i has taken a decision not to make any trans-shipment, it will place an order for goods with one single supplier instead of using a combination of suppliers. Likewise, once wholesaler W_i has taken a decision to make any trans-shipment, it will place an order with one single wholesaler instead of using a combination of wholesalers (see Figure 2.3 for the illustration of the relationships of suppliers, wholesalers, and retailers). It is assumed that all the wholesalers belong to the same cost centre. The dashed black lines represent the possible trans-shipment within the cost centre.

We shall model the dependence of the total cost of the operation imposed on one wholesaler in regard to trans-shipment, i.e. we provide the cost function of one wholesaler with respect to the variable, size of trans-shipment, and determine an appropriate order action for the wholesaler. Naturally, the cost function provides a useful decision rule model for trans-shipment and the size of trans-shipment by obtaining its minimization.

In the present model multiple suppliers are allowed to replenish goods for each wholesaler. This assumption is consistent with the real-life situation in supply chains where each wholesaler is serviced by a host of goods suppliers. Secondly, one may consider the general case of variable supply lead time. Such consideration is also realistic as goods supplied from far-away suppliers are invariably subject to all kinds of unforeseen transport and traffic conditions that may either hasten or delay the arrival of the goods. By considering the probability mass functions of the lead times of suppliers, the variability of the arrival times of goods can be taken into account. Another significant advantage of this model is the ease of implementation of the decision rule model, which stems from the basic available information of the wholesalers and their suppliers. All calculations can be done in a straightforward manner using mathematics software by simply plugging in the required inputs.

Note that the lead-time probability mass functions of the suppliers are assumed to be known either precisely from information supplied by the suppliers or approximately from past experience with the suppliers.

3.4 Cost Model for the wholesaler with trans-shipment

Let $x\,(0 \le x \le d_i(0) - \ell_i(0))$ be the number of goods units that are trans-shipped from wholesaler W_k to W_i ($k \ne i$) to partially meet the demand $d_i(0)$ at W_i with the initial inventory level $\ell_i(0)$, with the remaining portion $d_i(0) - \ell_i(0) - x$ being satisfied by one of the suppliers. For ease of reference, the notations used in the model are summarized below:

M = the total number of wholesalers

W_i = the ith wholesaler

N_i = the total number of suppliers to W_i

S_{ij} = the jth supplier of W_i

P_{ij} = the unit selling price by S_{ij} to W_i

q_k = the unit trans-shipment price from W_i to W_k

b_i = the back-order cost rate at W_i per unit item per unit time

h_i = the holding cost rate at W_i per unit item per unit time

t_0 = the initial time

t = the tth unit time interval after t_0

$g_{ij}(t)$ = the delivery lead time probability mass function of S_{ij}.

L_{ij} = the lead time of S_{ij} with duration equal to L_{ij} times unit time interval.

L_{ij}^{max} = the maximal lead time of S_{ij} with duration equal to $L_{ij}^{\max}$ times unit time interval.

$d_i(0)$ = the initial retailer demand appearing at W_i

$\lambda_i(t)$ = the retailer arrival intensity of the tth time interval at W_i

$f_{i,m}^{n}$ = the probability of n retailers at W_i with a total demand of m

$\hat{d}_i(t)$ = the expected retailer demand at wholesaler W_i in the tth time interval

$\hat{D}_{ij}$ = the expected retailer demand at wholesaler W_i over L_{ij}^{max}

$P_{ijk}(x)$, $B_{ijk}(x)$, $H_{ijk}(x)$ $C_{ijk}(x)$ are the purchase cost, the back-order cost, holding cost, and the total cost to W_i for trans-shipping x units from W_k and supplying the remainder of demands from S_{ij}, respectively.

Under the consideration of the current supply/trans-shipment model for any time interval, such as the tth, and any fixed supplier S_{ij},

$$\hat{d}_i(t) = e^{-\lambda_i(t)} \sum_{m=1}^{+\infty} \sum_{n=1}^{m} \frac{m(\lambda_i(t))^n}{n!} f_{i,m}^{n}.$$

Firstly, Given the tth time interval ($0 \le t \le L_{ij}^{max}$) and n retailers, the conditional probability that n retailers require m demands is

$$P_{d_{i,t}}(m \mid n) = f_{i,m}^{n}.$$

Meanwhile, given the th time interval ($0 \le t \le L_{ij}^{max}$), the probability of n retailers arriving at W_i follows the Poisson distribution,

$$P_{d_{i,t}}(n) = e^{-\lambda_i(t)} \frac{(\lambda_i(t))^n}{n!}.$$

The probability of retailer demands at W_i over the tth time interval is thus given by

$$
\begin{aligned}
P_{d_{i,t}}(m) &= \sum_{n=1}^{m} P(m\ demands\ under\ condition\ of\ n\ retailers\ at\ W_i)P(n\ retailers\ at\ W_i) \\
&= \sum_{n=1}^{m} P_{d_{i,t}}(m \mid n) P_{d_{i,t}}(n) \\
&= \sum_{n=1}^{m} f_{i,m}^{n} P_{d_{i,t}}(n) \\
&= \sum_{n=1}^{m} f_{i,m}^{n} e^{-\lambda_i(t)} \frac{(\lambda_i(t))^n}{n!}
\end{aligned}
$$

Therefore, the expected retailer demand at W_i by time interval t is given by

$$
\begin{aligned}
\hat{d}_i(t) &= \sum_{m=1}^{+\infty} m P_{d_{i,t}}(m) \\
&= e^{-\lambda_i(t)} \sum_{m=1}^{+\infty} \sum_{n=1}^{m} \frac{m(\lambda_i(t))^n}{n!} f_{i,m}^{n}.
\end{aligned}
$$

Since there is no infinite demand at wholesaler i in practice, we set $d_i^{\max}$ as the upper bound of retailer demands at wholesaler i in the numercial simulation.

It also follows that the expected retailer demand at W_i over the maximal lead time of S_{ij} (i.e. L_{ij}^{max} times unit time intervals) is given by the sum of all the expected demands above,

$$
\begin{aligned}
\hat{D}_{ij} &= \sum_{k=1}^{L_{ij}^{\max}} \hat{d}_i(k) \\
&= \sum_{k=1}^{L_{ij}^{\max}} e^{-\lambda_i(k)} \sum_{m=1}^{+\infty} \sum_{n=1}^{m} \frac{m(\lambda_i(k))^n}{n!} f_{i,m}^{n}.
\end{aligned}
$$

Furthermore, if the ith wholesaler makes its orders from the jth supplier, the expected delivery lead time is

$$
E(L_{ij}) = \sum_{t=1}^{L_{ij}^{\max}} t g_{ij}(t),
$$

Our mathematical model will determine an appropriate course of action for W_i in response to the appearance of $d_i(0)$ that would minimize its operation cost, as follows.

Over one scheduling period (i.e. the maximal lead time), the expected retailer demands for the *i*th wholesaler is $\hat{D}_{ij}$. The purchase cost of the *i*th wholesaler is therefore composed of the cost to purchase from the supplier, S_{ij} and cost to purchase from the other wholesaler, W_k[2]. Hence,

$$P_{ijk}(x) = \left(d_i(0) - \ell_i(0) - x + \hat{D}_{ij}\right)p_{ij} + q_k x.$$

Consider $0 < \ell_i(0)$. In this case, W_i has no backlogged orders. The appearance of $d_i(0)$ at t_0 adds to the backlog. If $0 < d_i(0) \le \ell_i(0)$, then no trans-shipment is needed. On the other hand, if $\ell_i(0) < d_i(0)$, then that the total number of back-ordered units at W_i at the initial time is $d_i(0) - \ell_i(0)$. Now x units of the required goods have just arrived from a nearby wholesaler W_k ($k \neq i$), so the number of back-ordered units at W_i is in fact $d_i(0) - \ell_i(0) - x$.

The goods by trans-shipment arrive at the wholesaler with zero lead time, which will not produce back-order cost, while the remaining goods from the supplier are expected to arrive at the wholesaler after the expected lead time, $E(L_{ij})$, which will generate some back-order cost. Among the remainging goods, some goods ($d_i(0) - \ell_i(0) - x$) are demanded at $t = 0$ so the back-order time is $E(L_{ij})$ while the

[2] It is assumed that the wholesaler has the stocks on hand but its available stocks, s_k may be less or more than $d_i(0) - \ell_i(0)$. The actual number of trans-shipment $\mu_k = \min((d_i(0) - \ell_i(0), s_k)$.

other demands $\hat{D}_{ij}$ appear over the whole period. If those demands happen before the ordered goods arrive, the wholesaler will suffer from the back-order cost; if they happen after the arrival of goods the wholesaler has to carry the burden of the holding cost. Consequently, according to the delivery time of ordered goods we devide L_{ij}^{max} into two sub-intervals, [0, $E(L_{ij})$] and ($E(L_{ij})$, L_{ij}^{max}]. Next, we prove the back-order cost is due to expected demands. Consider the expected demand over unit time interval, such as the *h*th time interval, the expected demand over this day is $\hat{d}_i(h)$. The back-order cost for this demand is given by $b_i d_i(h)(E(L_{ij})-h)$, as presented in Figure 3.1, and then the back-order cost for all expected demand over the interval $[(0, E(L_{ij})]$ is calculated by its sum.

Thus,

$$B_{ijk}(x) = b_i\left(d_i(0) - \ell_i(0) - x\right)E(L_{ij}) + b_i \sum_{t=0}^{E(L_{ij})} \hat{d}_i(t)(E(L_{ij}) - t).$$

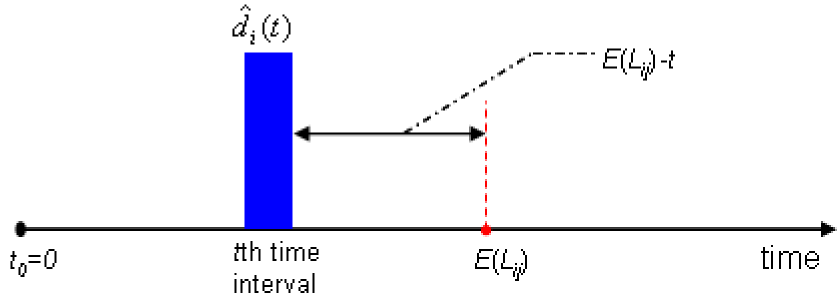


Figure 3.1 Schematic of the expected demand at the *t*th day and its lead time.

We formularize the holding cost for the demands generated over the sub-interval, $(E(L_{ij}), L_{ij}^{\max}]$ in the same way, as follows

$$H_{ijk}(x) = h_i \sum_{t=E(L_{ij})}^{L_{ij}^{\max}} \hat{d}_i(t)(t - E(L_{ij})).$$

Finaly, the total cost of wholesaler *i* over one review period is

$$\begin{aligned} C_{ijk}(x) &= P_{ijk}(x) + B_{ijk}(x) + H_{ijk}(x) \\ &= (d_i(0) - \ell_i(0) - x + \hat{D}_{ij})\, p_{ij} + q_k x + b_i (d_i(0) - \ell_i(0) - x) E(L_{ij}) \\ &\quad + b_i \sum_{t=0}^{E(L_{ij})} \hat{d}_i(t)(E(L_{ij}) - t) + h_i \sum_{t=E(L_{ij})}^{L_{ij}^{\max}} d_i(t)(t - E(L_{ij})). \end{aligned}$$

We state our first decision rule model for trans-shipment as a proposition.

Proposition. For the current supply/trans-shipment model, if the condition $0 < d_i(0) \le \ell_i(0)$ is not satisfied, and then for the given supplier S_{ij}, W_i should make an trans-shipment from W_k $(k \ne i)$ to satisfy the demand $d_i(0)$ only if

$$q_k < p_{ij} + b_i E(L_{ij}) \,(k \ne i).$$

Proof

Clearly, if the condition $0 < d_i(0) \le \ell_i(0)$ is not satisfied, then the total expected cost of W_i for trans-shipping x units from W_k $(k \ne i)$ and supplying the remainder of $d_i(0)$ from S_{ij} is $C_{ijk}(x)$. The result follows by rewriting the expression for $C_{ijk}(x)$ as

$$\begin{aligned} C_{ijk}(x) &= P_{ijk}(x) + B_{ijk}(x) + H_{ijk}(x) \\ &= \left(q_k - \left(p_{ij} + b_i E(L_{ij})\right)\right)x + \left(d_i(0) - \ell_i(0)\right)\left(p_{ij} + b_i E(L_{ij})\right) \\ &\quad + \hat{D}_{ij} p_{ij} + b_i \sum_{t=0}^{E(L_{ij})} \hat{d}_i(t)(E(L_{ij}) - t) + h_i \sum_{t=E(L_{ij})}^{L_{ij}^{\max}} \hat{d}_i(t)(t - E(L_{ij})). \end{aligned}$$

The total cost function of W_i with respect to x is a linear function with the form $y = Ax + B$. So, if $q_k - (p_{ij} + b_i E(L_{ij})) < 0$, the total cost function is decreasing function regarding the variable x. The more goods are trans-shipped from the other wholesaler, the more costs are saved. However, if $q_k - (p_{ij} + b_i E(L_{ij})) > 0$, the total cost function is an increasing function regarding x. Under this condition the trans-shipment from the other wholesaler raises the cost of W_i.

Given the fixed supplier S_{ij} our decision rule model for trans-shipment therefore is $q_k - (p_{ij} + b_i E(L_{ij})) < 0$. If this decision rule model is not satisfied, then W_i should satisfy the demands $d_i(0)$ by using supplier S_{ij}.

Furthermore, we give a corollary to estimate the favorite wholesaler to make trans-shipment.

Corollary. It is assumed that the preceding decision rule model is valid. For any fixed supplier S_{ij} the trans-shipment should be ordered from W_{k^*}, where k^* (not necessarily unique) is such that

$$q_{k^*} - \left(p_{ij} + b_i E(L_{ij})\right) = \min\left(q_k - (p_{ij} + bE(L_{ij}))\right)$$

for all the wholesalers exclusive wholesaler i.

Proof

The cost function above is a linear function about the size of trans-shipment and its slope is $q_k - (p_{ij} + b_i E(L_{ij}))$. Given the fixed x $(x \neq 0)$, if $q_{k^*} - (p_{ij} + b_i E(L_{ij}))$ is the minimal, $C_{ijk}(x)$ is correspondingly the lowest by trans-shipment from W_{k^*}.

It is natural that if we decide to make trans-shipment we prefer to trans-ship from the wholesaler that provides the lowest price. So our model is consistent with the practical considerations. As we mentioned, the trans-shipped amount should be $\mu_k = \min((d_i(0) - \ell_i(0)), s_k)$ where s_k is the available stocks of the kth wholesaler. So we have to consider both factors: the selling price of the wholesaler and its available stocks, and make the trade-off between them. Let C_{ij} be the minimal cost of W_i that makes partial or full orders from the given S_{ij}. We thus obtain another decision rule model for estimation of the favorite wholesaler that

$$C_{ij} = \min_{k \neq i} \min_{1 \leq x \leq \mu_k} \{C_{ijk}(x)\}.$$

As the ith wholesaler is allowed to obtain their supplies from a wide choice of available suppliers, not limited to the certain supplier, the total cost of W_i achieves the global minimization by

$$C_i = \min\{C_{i1}, \cdots, C_{ij} \cdots C_{iN_i}\},$$

where the suffix N_i is the number of the suppliers of wholesaler i.

Consequently, by minimization of both $C_{ijk}(x)$ and C_{ij} we can determine the optimal solution of wholesaler i to satisfy the retailer demands. We will explain our decision rules and minimization of the total cost of one wholesaler by simulation study.

3.5 Numerical Illustrations

In this section, the developed model is illustrated with three examples. For simplicity, only identical wholesalers are considered and retailer arrival intensity at different unit time intervals is assumed to be the same, i.e. $\lambda(t) = \lambda$ (constant)for any t. Also, in the absence of specific information about retailer ordering patterns, it is reasonable to assume that the probability mass function $f_{i,m}^{n}$ is the same as the assumption of Axsäter (2003), where a retailer demand of size m follows the geometric distribution,

$$f_{i,m}^{1} = p(1-p)^{m-1} \quad m = 1,2,3,\cdots.$$

3.5.1 Initial Case

We first consider a hypothetical region where there are only two wholesalers for a certain line of products, W_1 and W_2 and one supplier to replenish them. Without loss of generality, since the two wholesalers are assumed to be identical, one need only consider the problem of trans-shipment from the point of view of any wholesaler, W_1 say. Therefore take W_1 as fixed and consider the decision-making process at W_1. Furthermore, take $b_1 = 2$, $h_1=1$, $\lambda_1 =1$, $p=0.8$, $p_{11}=2.2$, and $D_{\max} =30$[3]. The unit time interval can be defined as one week, one day, or even half of either. There is exactly one product supplier, S_{11} for W_1, and it has variable lead time with $L_{11}^{\max} = 5$. Finally, the current inventory level at W_1 is $\ell_1(0) = 0$ and the initial demand at W_1 is $d_1(0) = 6$. Under assumption that another wholesaler has the adequate stocks the case is divided into four groups that differ in the trans-shipment price from W_2 and expected lead time from S_{11}. Group one has $q_2 = 5$ and $E(L_{11}) = 3$, Group two has $q_2 = 9$ and $E(L_{11}) = 3$, Group three has $q_2 = 7$ and $E(L_{11}) = 4$, and

[3] Since a retailer demand $f_{i,m}^{1}$ follows the geometric distribution and $f_{i,m}^{n}$ is obtained by m-fold convolution, $f_{i,m}^{n}$ deceases quickly and goes to zero when m become large. Given p=0.8 in the simulation, $D_{\max}$ =30 is large enough.

Group four has $q_2 = 7$ and $E(L_{11}) = 2$. For simplicity, we do not define the probability mass function of the supplier but directly give its expected lead time. Application of our decision rule model for trans-shipment is shown in Table 3.2. All costs are for the wholesaler W_1. Each line gives the results for each group.

Table 3.2 Results for the initial case. *X* represents the size of trans-shipment.

Total Cost of Wholesaler 1								
q_2	$E(L_{11})$	x=0	x=1	x=2	x=3	x=4	x=5	x=6
5	3	60.4	57.2	54	50.8	47.6	44.4	41.2
9	3	60.4	61.2	62	62.8	63.6	64.4	65.2
7	4	74.7	71.5	68.3	65.1	61.9	58.7	55.5
7	2	47.9	48.7	49.5	50.3	51.1	51.9	52.7

In Group three the decision rule model is satisfied and the cost of W_1 keeps decreasing with more trans-shipments while in Group four the decision rule model is not satisfied. However, the cost of W_1 in Group four is quite a bit lower than that of Group three. This is related to the problem of supplier selection the related discussion of which is given in Section 3.5.3.

Figure 3.2 clearly illustrates the tendency of total cost of W_1 with increasing trans-shipments for Group one and two. Zero in the x-axis means no trans-shipment between wholesalers. When the decision rule model is satisfied (Group one), W_1 saves its cost by trans-shipment. However, when the decision is not satisfied (Group two) W_1 has to increase its cost with trans-shipment from W_2, and then W_1 should order products from its supplier, rather than from another wholesaler.

In Section 3.5.2 and 3.5.3 we consider a different variation of 3.5.1. In the present subsection we suppose that the stocks of the wholesaler which is asked for trans-shipment is enough to satisfy its counterpart. Section 3.5.2 considers the case that the trans-shipped wholesaler has limited stocks. That is, we need to employ another decision rule model to decide from which wholesaler to make trans-shipment under the assumption that there are more than two available wholesalers in the local area.

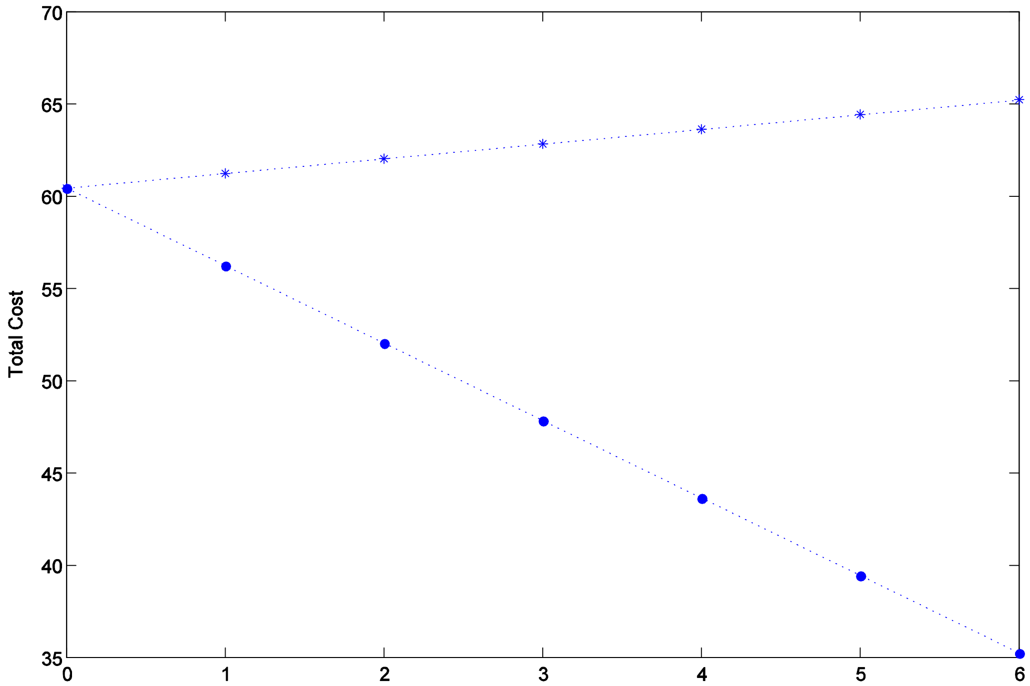


Figure 3.2 The total cost function with a variable, size of trans-shipment. Dots denote the total costs of W_1 for Group one; Stars denote the total costs of W_1 for Group two.

3.5.2 More Wholesalers with Limited Stocks

Here we consider that there are four wholesalers W_1, W_2, W_3 and W_4 and one supplier for them. We also investigate the second decision-rule process at W_1. Take b_1, h_1, λ_1, p, p_{11}, D_{max}, $\ell_1(0)$ and $d_1(0)$ are the same as those in section 3.5.1. The supplier, S_{11} for W_1 has variable lead time with $L_{11}^{max} = 10$ and $E(L_{11}) = 3$. This case is divided into three groups according to the other three wholesalers: Group one has $q_2 = 8$ and $\mu_2 = 6$, Group two has $q_3 = 7$ and $\mu_3 = 5$, and Group three has $q_4 = 6.5$ and $\mu_4 = 3$. Clearly, we should make a trade-off between wholesalers' selling prices and their stocks. This can also be verified in Figure 3.3.

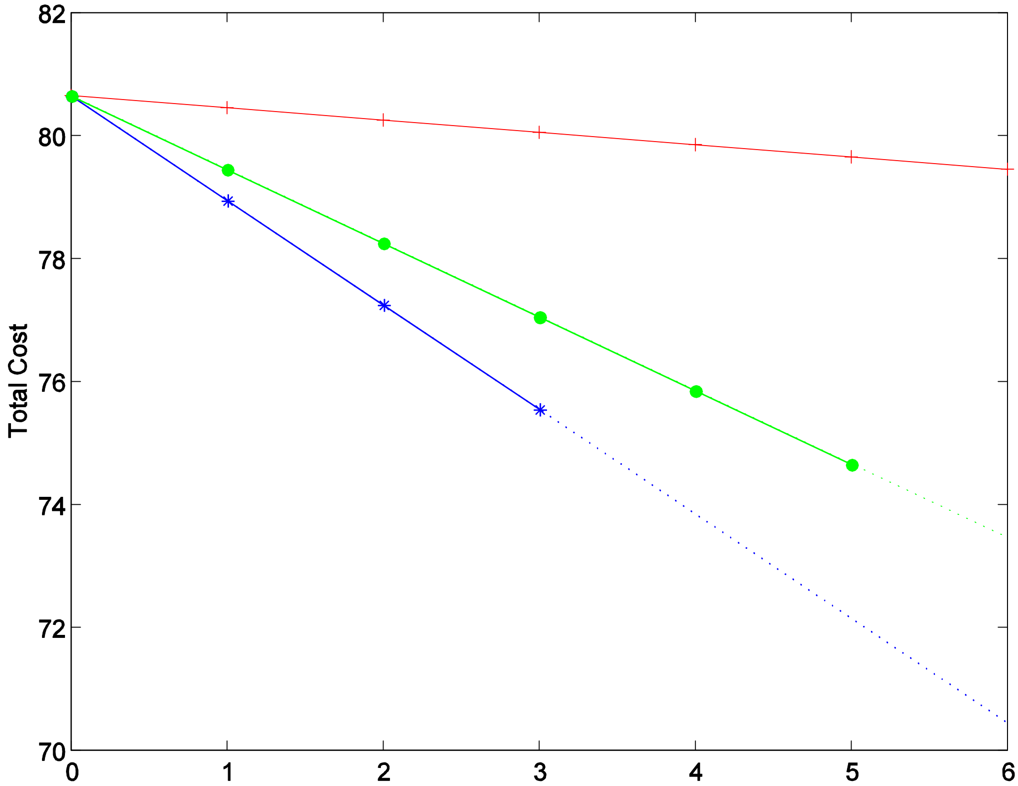


Figure 3.3 Trends of total costs of W_1 with trans-shipment from W_2, W_3, and W_4, denoted by crossing line, dot line and star line respectively.

As shown in Figure 3.3, the first decision rule model is satisfied for each group, i.e. W_1 benefits from trans-shipment from W_2, W_3, or W_4. Note that the dashed lines represent the total costs of W_1 if it makes more trans-shipments from W_3 and W_4. Now we need to decide from which one to order trans-shipment so as to minimize the cost of W_1. By the corollary, W_4 is the best choice but taking its stocks into consideration we find that W_1 does not benefit the most from W_4 by trans-shipment. On the contrary, W_2 has adequate stocks to satisfy the full demands at W_1 but its selling price is relatively expensive. According to the second decision rule model, $C_{113}(5)$ is the minimal. Consequently, W_1 should make trans-shipment from W_3 and order all the available stocks at W_3.

3.5.3 Multi-supplier and Multi-wholesaler

In this subsection we consider another variation of the previous cases. There are four wholesalers W_1, W_2, W_3 and W_4 in a local area and three suppliers to replenish them. For consistency, we still take W_1 as the object of study. For fair comparison we use $max\{L_{11}^{\max}, L_{12}^{\max}, L_{13}^{\max}\} = 5$ as the review period so we ignore their respective maximal lead times given in the tables below. All the other parameter values are the same as those in the previous subsection.

In Table 3.3 the cost in each cell is calculated under the condition that the demands of W_1 are satisfied by a combination of the given supplier and wholesaler. For example, the value 56.7 represents the total cost of W_1 by making three orders from W_2 and the rest from S_{13}. The blank cells indicate that the wholesaler cannot provide trans-shipments of more than its stocks. The global minimum in Table 3.3 (i.e. 56.7) indicates the optimal solution for W_1 to make orders. In addition given S_{11} and S_{12}, W_1 will save the most with trans-shipment from W_3 and W_2 respectively, as presented in Table 3.3. We also give Figure 3.4 to describe the contents in this table.

From Figure 3.4, given supplier 1, $C_{11} = C_{113}(5)$ is the minimal; given supplier 2, $C_{12} = C_{122}(3)$ is the minimal; given supplier 2, $C_{13} = C_{132}(3)$ is the minimal. By the formula, $C_i = \min\{C_{i1}, \cdots, C_{ij} \cdots C_{iN_i}\}$ we obtain

$$C_1 = \min\{C_{11}, C_{12}, C_{13}\} = C_{13} = C_{132}(3).$$

Consequently, under the condition above, W_1 achieves the minimal cost by ordering from S_{13} and W_2; and the size of trans-shipment is 3.

Table 3.3 The total cost of W_1 by making orders from certain suppliers and wholesalers.

	Total Cost of Wholesaler 1								
	Supplier 1 p_{11}=2.6 $E(L_{11})$=4			Supplier 2 p_{12}=2.8 $E(L_{12})$=3			Supplier 3 p_{13}=3.3 $E(L_{13})$=2		
Trans-shipment Size	W_2 q_2=7	W_3 q_3=8	W_4 q_4=9	W_2 q_2=7	W_3 q_3=8	W_4 q_4=9	W_2 q_2=7	W_3 q_3=8	W_4 q_4=9
0	78.2	78.2	78.2	65.7	65.7	65.7	57.6	57.6	57.6
1	74.6	75.6	76.6	63.9	64.9	65.9	57.3	58.3	59.3
2	71.0	73.0	75.0	62.1	64.1	66.1	57.0	59.0	61.0
3	67.4	70.4	73.4	60.3	63.3	66.3	56.7	59.7	62.7
4		67.8	71.8		62.5	66.5		60.4	64.4
5		65.2	70.2		61.7	66.7		61.1	66.1
6			68.6			66.9			67.8

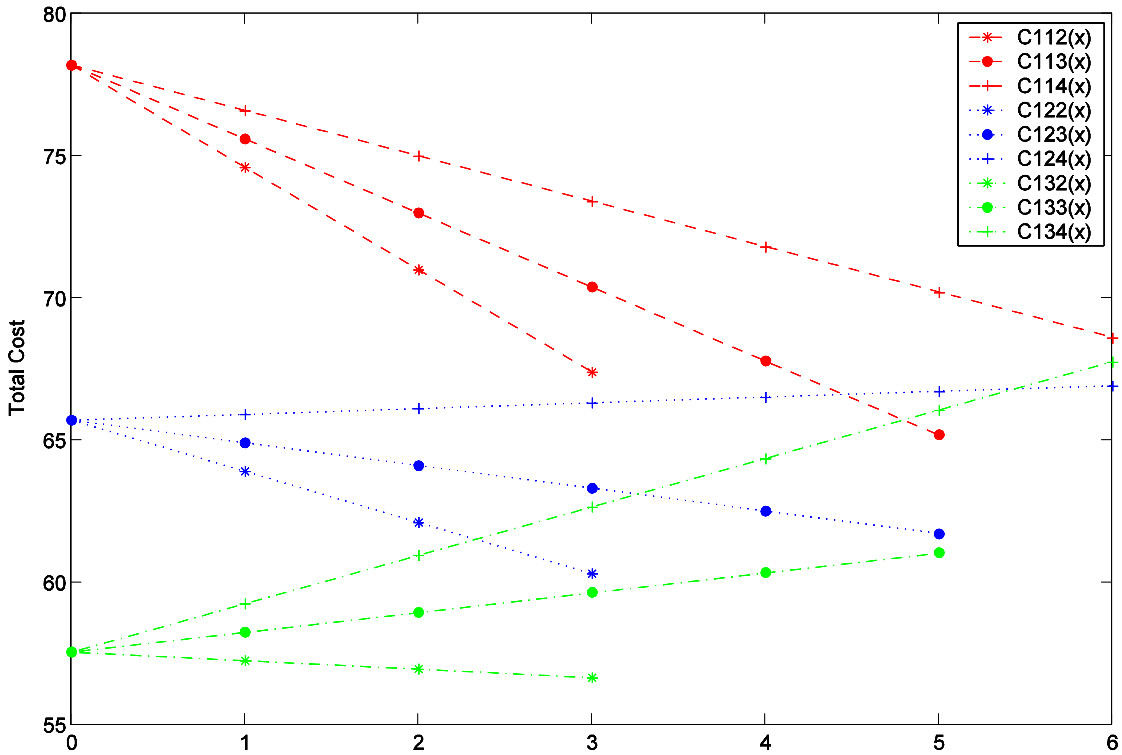


Figure 3.4 Results for the case of multi-supplier and multi-wholesaler. x represents the size of the trans-shipment.

In the case of multi-suppliers and multi-wholesalers any wholesaler, like W_1, first of all, needs to determine which supplier to replenish from. That is, we estimate the total cost of W_1 by full replenishment from each supplier. Given the supplier, the wholesaler then determines whether it will make an trans-shipment and which wholesaler it will order from.

Table 3.4 describes a special case in that the decision rule model for trans-shipment is not satisfied and thus there is no trans-shipment for wholesaler 1. This is equivalent to select only the favorite supplier. Here we set b_1 = $1, max\{L_{11}^{\max}, L_{12}^{\max}, L_{13}^{\max}\} = 6$ and keep all the other parameter values unchanged.

As presented in Table 3.4, W_1 need to make all the replenishment from S_{13} in order to minimize its operation cost. Hence, our model also provides a decision rule model for selection of suppliers to wholesalers without trans-shipment.

Table 3.4: The total cost of W_1 by making orders from the combination of one supplier and one wholesaler.

	Total Cost of Wholesaler 1								
	Supplier 1 p_{11}=6.7 $E(L_{11})$=3			Supplier 2 p_{12}=5.5 $E(L_{12})$=4			Supplier 3 p_{13}=4.3 $E(L_{13})$=5		
Trans-shipment Size	W_2 q_2=10	W_3 q_3=12	W_4 q_4=14	W_2 q_2=10	W_3 q_3=12	W_4 q_4=14	W_2 q_2=10	W_3 q_3=12	W_4 q_4=14
0	85.8	85.8	85.8	80.6	80.6	80.6	76.5	76.5	76.5
1	86.1	88.1	90.1	81.1	83.1	85.6	77.2	79.2	81.2
2	86.4	90.4	94.4	81.6	85.6	89.6	77.9	81.9	85.9
3	86.7	92.7	98.7	82.1	88.1	94.1	78.6	84.6	90.6
4	87.0	95.0	103.0	82.6	90.6	98.6	79.3	87.3	95.3
5	87.3	97.3	107.3	83.1	93.1	103.1	80.0	90.0	100.0
6	87.6	99.6	111.6	83.6	95.6	107.6	80.6	92.7	104.7

Chapter 4 Development of Decision Rule Model on Wholesaler Lateral Trans-shipment and Supplier Replenishment to Meet Retailer Demands

4.1 Introduction

The previous chapter explains the development of a decision rule model for trans-shipment in a supply chain network. In this chapter, we explain the development of another decision rule model with an expanded scope.

In a supply chain network comprising suppliers, wholesalers, and retailers, ordering products can take place between (a) suppliers and a wholesaler, and (b) a wholesaler and other wholesalers (i.e. lateral trans-shipment [Axsater, 1990; Axsater, 2003]); meeting retailer demands can take place between (c) a wholesaler and its retailers. Figure 4.1 presents a schematic of the whole supply chain process for a wholesaler.

Each wholesaler faces stochastic Poisson retailer demand and it may replenish them from various suppliers with finite supply or receive them from other wholesalers through lateral transshipment. Storage of products at a wholesaler incurs holding cost, temporarily lack of products for fulfilling retailers' demands incurs backorder cost, and shortage of products for meeting retailers' demands incurs shortage cost.

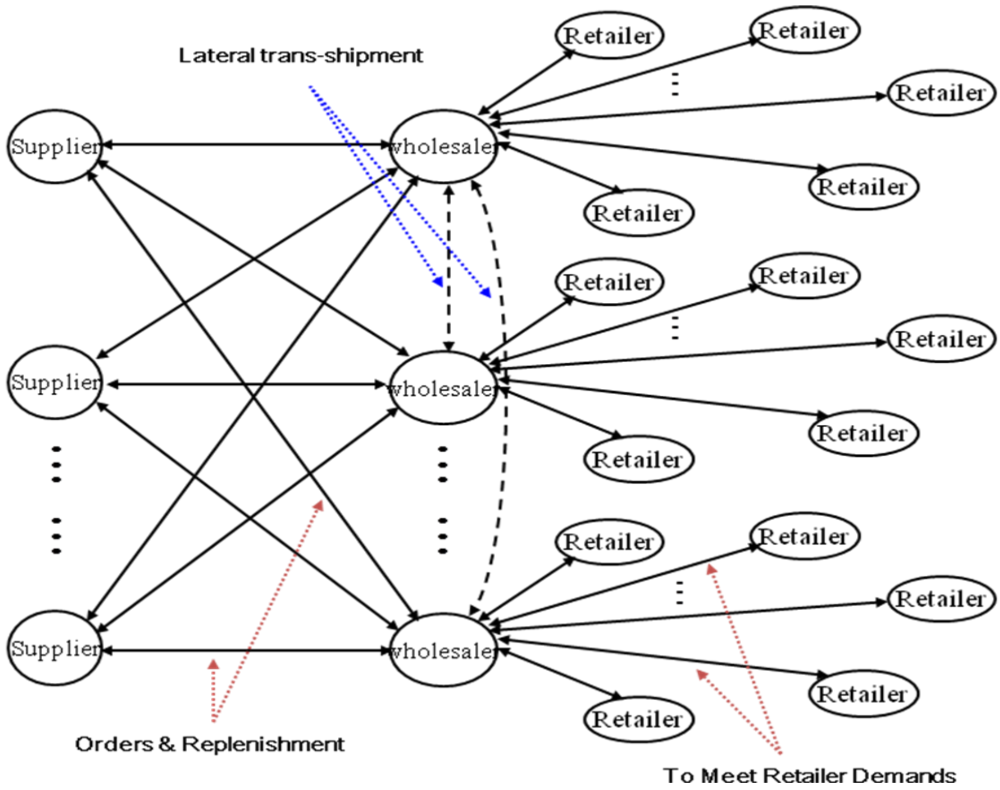


Figure 4.1. An integrated decision model of a supply chain network.

Literature review reveals that in most of past studies, decisions were separately and independently applied to the above relationships (Carter & Price, 2001; Chien et al, 2002; Lee et al, 2007; Türkyilmaz & Özkan, 2007). Ghodsypour and Brien (2001) studied the supplier selection problem in the case of multiple suppliers. It was aimed at minimizing the total cost of logistics, including net price, storage, transportation and ordering costs. Davidrajuh discussed the main elements involved in selection of suppliers as part of electronic commerce systems implementation (Davidrajuh, 2000).There are many papers dealing with lateral trans-shipment, which focus on a stochastic dynamic program to optimize the decision of lateral trans-shipment (Archibald et al, 1997), optimizing the control policy of inventory systems (Axsater , 1990; Axsater, 2003) or a heuristic approach (Tagaras & Cohen, 1992). J. Lamothe *et al.* (2006) aimed to select a product family and design its supply chain in order to minimize the comprising fixed cost. Ghodsypour and O'Brien (1998) describe a decision support system for choosing the best suppliers and placing the optimum order quantities among them such that the total value of purchasing becomes maximum. Furthermore, an integrated framework has been proposed for user interface prototyping and evaluation for the development of information systems to improve user satisfaction of information systems (Lee et al, 2006). K. Leslie *et al.* (2003) presented an integrated conceptual model of supply chain flexibility for analyzing the components of supply chain flexibility.

It can be observed from the above related work that three decisions were separately applied in past studies. Actually subjects that those decisions are applied on are closely related to each other and tiny changes on these subjects may generate significant difference on the total cost spent. If one merely considers a specific decision rule he cannot obtain the global optimization in a supply chain network. For example, the decision whether lateral transshipment takes place between any two wholesalers (i.e. decision in (b)) will change the number of various products from supplier(s) (i.e. the ordering cost from supplier(s)), involved in the decision (a) and to reduce or avoid the shortage cost (i.e. decision in (c)) should overwhelm the probably generated ordering cost from supplier(s) and wholesaler(s) (i.e. decisions in (a) and (b)). Separate consideration of these decisions probably offers only poor-quality local optimal solutions. As a result, we propose an integrated multi-product decision model simultaneously involving the three factors for the wholesalers so as to achieve better solutions.

Moreover, consider that a wholesaler has a limited number of stocks on hand. These stocks can fulfill only some retailers' needs. Since each retailer has a priority degree for the arrival of their ordered products, a shortage cost representing unfulfilled retailers, which is proportional to the number of units of a product, is incurred when the wholesaler cannot deliver products to a retailer. In order to minimize the total shortage cost, demanded retailers must be served with their priority. That is, limited stocks at the wholesaler must be firstly offered to retailers with high priority. We therefore consider adding the item of shortage cost to the integrated decision model. The flowchart of the joint optimization process for a wholesaler, considered in a supply chain shown in Figure 4.1, is depicted in Figure 4.2.

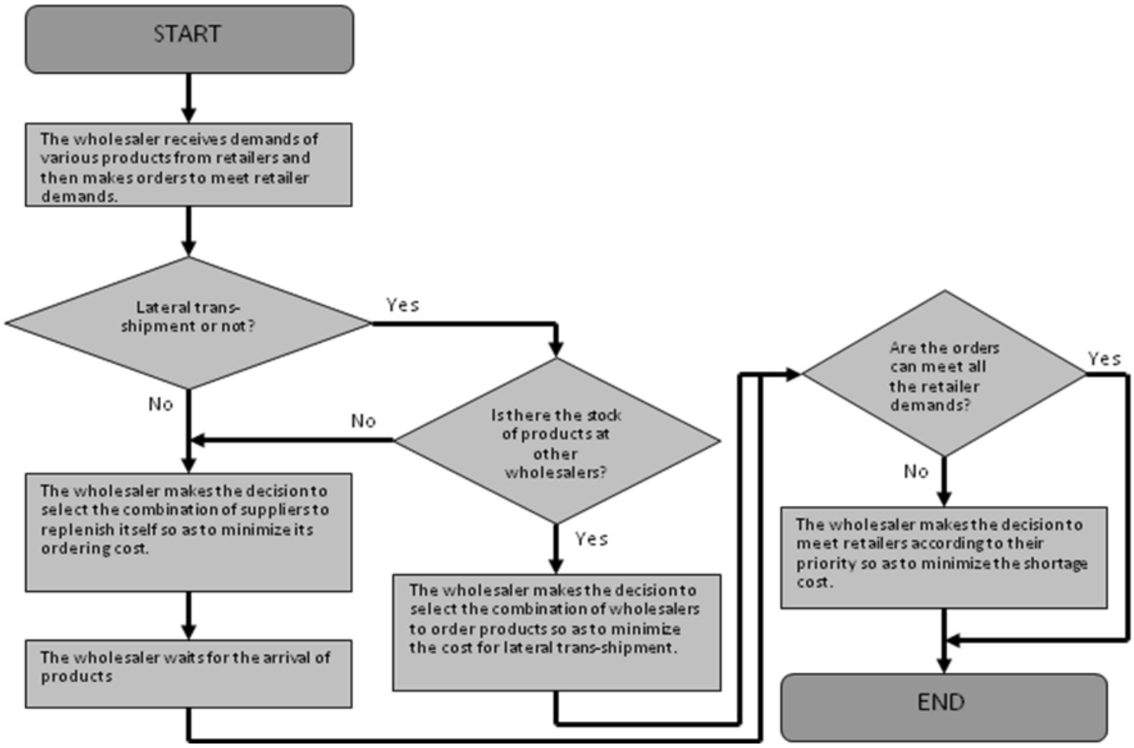


Figure 4.2. The flowchart of the process of the joint optimization in the whole supply chain.

Using stochastic based search techniques such as tabu search (Renaud et al., 1996), genetic algorithm (Holland, 1975; Goldberg, 1989), fuzzy logic guided genetic algorithms (McClintock, 1997; King et al., 2004), and simulated annealing algorithm (Zomaya, 2003) a sub-optimal solution can be easily found for a large-size problem in a reasonable time but the optimal solution usually cannot be obtained. Exhaustive search can quickly compare all the possible solution and give the optimal one for the small/medium-size problem.

In this chapter, we aim to validate the proposed idea of joint optimization rather than to show the power of current search technique so we construct a small supply chain network that is composed of tens of suppliers and wholesaler. Hence, we adopt the exhaustive search technique to find the optimal solution for all the scenarios.

4.2 Notation for the decision rules

The considered decision model will be formulated mathematically and this model comprises important decision rules. The notations and mathematical formulation of each of these three decisions are given as follows:

Notation	Meaning
N	Total number of suppliers
M	Total number of wholesalers
O_i	Total number of products required by wholesaler *i*
S	Index set of suppliers, $S = \{1,2,...,N\}$
P	Index set of required products, $P = \{1,2,...,O_i\}$
W	Index set of wholesalers, $W = \{1,\ldots i-1, i+1,\ldots,M\}$
d_{il}	Quantity of demands for product *l* at wholesaler *i*, $(l \in P)$
x_{il}	Quantity of product *l* of wholesaler *i* satisfied by lateral trans-shipment
p_{jl}	Unit cost of product *l* supplied by supplier *j*, $(j \in S, l \in P)$
q_{kl}	Unit cost of product *l* supplied by wholesaler *k*, $(k \in W, l \in P)$
b_i	Back-order cost rate at wholesaler *i* per unit item per unit time
h_i	Holding cost rate at wholesaler *i* per unit item per unit time
L_j	Lead time of supplier *j* to the wholesaler
s_{jl}	Total number of items of product *l* that supplier *j* can supply
w_{kl}	Total number of items of product *l* that wholesaler *k* can provide
T_i	Expected waiting time for retailers demands arriving at wholesaler *i*

$F_i^{\max}$	Maximum allowed number of suppliers for wholesaler *i*
$G_i^{\max}$	Maximum allowed number of wholesalers for wholesaler *i*
f_i^{jl}	$f_i^{jl} = 1$ if wholesaler *i* orders product *l* from supplier *j*; 0 otherwise
g_i^{kl}	$g_i^{kl} = 1$ if wholesaler *i* make trans-shipment of product *l* from wholesaler *k*; 0 otherwise

4.3 Cost Model for the Wholesaler with Trans-shipment and Supplier Replenishment

4.3.1 Scenario One

Consider that a supply chain network comprise suppliers, wholesalers and retailers. Retailers ask various types of products from its wholesaler, and then the wholesaler makes such orders from a series of suppliers so as to satisfy its retailer demands. In addition, the wholesaler may make the lateral trans-shipment from other wholesalers. First we consider a simple case that a wholesaler makes all the orders from combination of suppliers and satisfies the full retailer demands. We investigate the problem of supplier replenishment from the point of view of any wholesaler, W_{i} say.

The total cost function of wholesaler *i* is given by

$$f_i = \underbrace{\sum_{j \in S} \sum_{l \in P} d_{il} \cdot p_{jl} \cdot f_i^{jl}}_{\text{A}} + \underbrace{\sum_{j \in S} \sum_{l \in P} d_{il} \cdot b_i \cdot (T_i - L_j)^- \, f_i^{jl}}_{\text{B}} + \underbrace{\sum_{j \in S} \sum_{l \in P} d_{il} \cdot h_i \cdot (T_i - L_j)^+ \cdot f_i^{jl}}_{\text{C}} \qquad (1)$$

where the notations $(y)^{-} = \max(-y,0)$ and $(y)^{+} = \max(y,0)$.

Part A in Equation 1 is the cost of wholesaler *i* to order types of products (for example, the number of product *l* is denoted by d_{il} and the price of product *l* offered by supplier *j* is p_{jl}) ordered from suppliers. The maximal numbers of suppliers which wholesaler *i* can order from is determined by the constraint, C_2. The goods from the supplier are expected to arrive at the wholesaler after the expected lead time, L_j, which will generate the back-order cost, while retailer demands will arrive at wholesaler *i* in an average time, T_i .So the back-order time is the deviation, $L_j - T_i$, as shown in Figure 4.3. Such back-order cost is calculated by Part B in Equation 1. Obvioursly, if retailer demands arrive at wholesaler i earlier than products, and then it will produce the back-order cost while if retailer demands arrive at wholesaler i later than products, and then there is no back-order cost but it will produce a new cost, holding cost. So we use $(T_i - L_j)^{-} = \begin{cases} L_j - T_i & T_i < L_j \\ 0 & T_i > L_j \end{cases}$ to represent the deviation between them. Part C in the above equation is the holding cost, which is generated by the negative deviation of $L_j - T_i$. So $(T_i - L_j)^{+} = \begin{cases} 0 & T_i < L_j \\ T_i - L_j & T_i > L_j \end{cases}$.

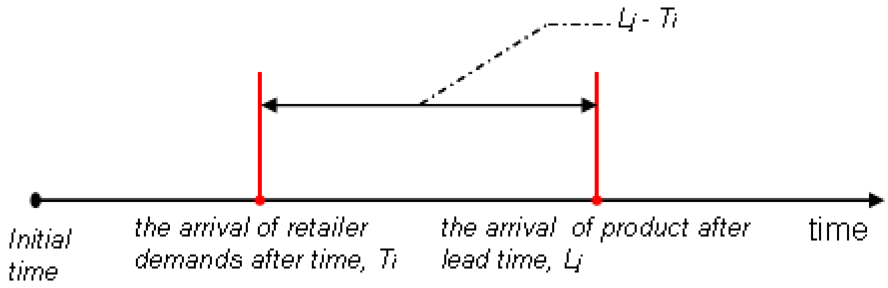


Figure 4.3 the back-order time between the arrival time of retailer demands and the lead time of supplier *j*.

Subject to

$$d_{il} \leq \sum_{k \in W} \sum_{j \in S} s_{jl} f_i^{jl} \quad (C_1)$$

$$\sum_{j \in S} f_i^{jl} \leq F_i^{\max} \quad (C_2)$$

$$f_i^{jl} \in \{0,1\} \quad (C_3)$$

Constraint (C_1) requires that the demand of each product must be less than or equal to the total supply of the product from all selected suppliers. Constraint (C_2) requires that the wholesaler must order each product from at most $F_i^{\max}$ suppliers. Constraint (C_3) requires that the values of the decision variables must be limited to be 0 or 1 only, which means that the given supplier may be selected to make replenishment or may not.

4.3.2 Scenario Two

Here we assume that the wholesaler can not satisfy all the retailer demands, and penalty cost has to be paid to unfulfilled retailers. Consider that a wholesaler has a limited number of stocks on hand for a type of products. These stocks can fulfill only some retailers' needs, but not all. Since each retailer has a different degree of tolerance of waiting for the arrival of their ordered products, a penalty cost representing retailer dissatisfaction, which is proportional to the number of units of a product, is incurred when the wholesaler cannot deliver products to a retailer. In order to minimize the total penalty cost, serving priority must be given to the demanded retailers. That means the limited number of stocks on hand must be first delivered to retailers with minimum degree of tolerance. As a result, we proposed to modify the preceding decision rule by adding the total retailer dissatisfaction penalty costs. The total retailer dissatisfaction penalty cost is mathematically derived, as follows.

As the ith wholesaler have shortage of t_{il} ($\geq$ 0) units of product l, the total numbers of retailers that they cannot fulfill are

$$r_i = \arg\max_{1 \leq m_i \leq R_{il}} \left\{ \sum_{e=1}^{m_i} (d_{il})_e - t_{il} \middle| \sum_{e=1}^{m_i} (d_{il})_e \geq t_{il} \right\} \tag{2}$$

where R_{il} is the total numbers of demanded retailers for product l at wholesaler i, m_i and is the retailer index, and $(d_{il})_e$ is the demands of the eth retailer in the sorted retailer lists.

The operation $\arg\max\{\ \}$ denotes the index of the first retailer whose demands can not be fulfilled. Since each retailer has been labeled with indexes according to their degree of tolerance in descending order the index of one retailer represent the accumulative number of retailers from the first to this retailer inclusive. Then, the total retailer dissatisfaction penalty costs for the *i*th wholesalers are

$$\sum_{e=1}^{r_i-1}\gamma_i\cdot\left(d_{il}\right)_e+\gamma_i\cdot\left(t_{il}-\sum_{e=1}^{r_i-1}\left(d_{il}\right)_e\right) \tag{3}$$

Thus, the new total cost function of wholesaler i with consideration of the penalty cost is

$$f_i=\underbrace{\sum_{j\in S}\sum_{l\in P}(d_{il}-t_{il})\cdot p_{jl}\cdot f_i^{jl}}_{A}+\underbrace{\sum_{j\in S}\sum_{l\in P}(d_{il}-t_{il})\cdot b_i\cdot(T_i-L_j)^{-}\cdot f_i^{jl}}_{B}$$
$$+\underbrace{\sum_{j\in S}\sum_{l\in P}(d_{il}-t_{il})\cdot h_i\cdot(T_i-L_j)^{+}\cdot f_i^{jl}}_{C}+\underbrace{\sum_{e=1}^{r_i-1}\gamma_i\cdot(d_{il})_e+\gamma_i\cdot\left(t_{il}-\sum_{e=1}^{r_i-1}(d_{il})_e\right)}_{D}, \tag{4}$$

where γ_i is the penalty cost rate per product unit at wholesaler i.

Part A, B, and C in the above equation are defined the same as those in Equation 1. As the stocks of suppliers for product l ($d_{il}-t_{il}$) can only meet some of retailers others have to suffer from shortage. Part D in Equation 4 is used to calculate the shortage cost, where the content in the bracket denotes the number of unfulfilled retailers. The penalty cost rate, γ_i is linearly determined by retailer priority level that is between zero and one. That is, the penalty cost rate for the retailer with highest priority level is also highest and vice versa.

Subject to

$$d_{il}>\sum_{k\in W}\sum_{j\in S}s_{jl}f_i^{jl} \quad (C_4)$$

$$\sum_{j\in S}f_i^{jl}\le F_i^{\max} \quad (C_5)$$

$$f_i^{jl}\in\{0,1\} \quad (C_6)$$

Constraint (C_4) requires that the demand of each product must be larger than the total supply of the product from all selected suppliers, which ensure that not all the retailer demands can be satisfied. Constraint (C_5) is the same as (C_2) that requires that the maximal number of supplier for the wholesaler is $F_i^{\max}$. Constraint (C_6) requires that the values of the decision variables must be limited to be 0 or 1 only.

4.3.3 *Scenario Three*

In this case a wholesaler makes the orders from not only combination of suppliers but also combination of wholesalers[1] (i.e. it also makes lateral trans-shipment) and still satisfies the full retailer demands. x_{il} is defined as the size of lateral trans-shipment for product l made by wholesaler i. We give the total cost of W_i with the consideration of its lateral trans-shipment.

$$\begin{aligned} f_i = & \underbrace{\sum_{j\in S}\sum_{l\in P}(d_{il}-x_{il})\cdot p_{jl}\cdot f_i^{jl}}_{\text{A}} + \underbrace{\sum_{j\in S}\sum_{l\in P}(d_{il}-x_{il})\cdot b_i\cdot(T_i-L_j)^{-}\cdot f_i^{jl}}_{\text{B}} \\ & + \underbrace{\sum_{j\in S}\sum_{l\in P}(d_{il}-x_{il})\cdot h_i\cdot(T_i-L_j)^{+}\cdot f_i^{jl}}_{\text{C}} + \underbrace{\sum_{k\in W}\sum_{l\in P}x_{il}q_{kl}g_i^{kl}}_{\text{D}} + \underbrace{\sum_{k\in W}\sum_{l\in P}x_{il}h_iT_ig_i}_{\text{E}} \end{aligned} \tag{5}$$

Since the size of lateral trans-shipment for product l is x_{il}, $d_{il}-x_{il}$ product l will be ordered from suppliers. It correspondingly results in the purchase cost and back-order cost or holding cost, as listed in Equation 5. Part D represents the cost to

[1] First of all, one should decide whether the wholesaler can benefit from the lateral transshipment and then make the lateral transshipment if it is worthwhile. The decision could be made by comparison of the total cost of the wholesaler with and without later transshipment. We have described a mathematical formulization for the lateral transshipment in a supply chain network of the same cost centre.

order products (i.e. lateral trans-shipment) from other wholesaler. The goods by trans-shipment arrive at the wholesaler with zero lead time, which will not produce the back-order cost. However, as the average time that retailer demands come to wholesaler *i* is T_i, the time to hold products from other wholesalers is also T_i and thus the holding cost generated by lateral trans-shipment is calculated by Part E in Equation. The total cost of wholeasler *i* with lateral trans-shipment is the sum of all these costs.

$$d_{il} \le \sum_{k \in W} \sum_{j \in S} (s_{jl} f_i^{jl} + w_{kl} g_i^{kl}) \quad (C_7)$$

$$x_{il} \le \sum_{k \in W} w_{kl} g_i^{kl} \quad (C_8)$$

$$\sum_{j \in S} f_i^{jl} \le F_i^{\max} \quad (C_9)$$

$$\sum_{k \in W} g_i^{kl} \le G_i^{\max} \quad (C_{10})$$

$$f_i^{jl} \in \{0,1\} \text{ and } g_i^{kl} \in \{0,1) \quad (C_{11})$$

Constraint (C_7) requires that the demand of each product must be less than or equal to the total supply of the product from both selected suppliers and wholesalers. Constraint (C_8) requires the size of lateral trans-shipment for each product must be less than or equal to the total supply of the product from the selected wholesalers. Constraint (C_9) requires that the wholesaler must order each product from at most $F_i^{\max}$ suppliers. Constraint (C_{10}) requires that the wholesaler must make the trans-shipment of each product from at most $G_i^{\max}$ wholesalers. Constraint (C_{11}) requires that the values of the decision variables must be limited to be 0 or 1 only.

4.3.4 Scenario Four

This subsection describes a general case that a wholesaler makes the orders from both combination of suppliers and combination of wholesalers but suffers from the shortage of products (retailer demands). The total cost of the wholesaler will be formularized by summarization of the previous three formulas.

$$
\begin{aligned}
f_i = & \underbrace{\sum_{j\in S}\sum_{l\in P}(d_{il}-x_{il}-t_{il})\cdot p_{jl}\cdot f_i^{jl}}_{\text{A}} + \underbrace{\sum_{j\in S}\sum_{l\in P}(d_{il}-x_{il}-t_{il})\cdot b_i\cdot(T_i-L_j)^{-}\cdot f_i^{jl}}_{\text{B}} \\
& + \underbrace{\sum_{j\in S}\sum_{l\in P}(d_{il}-x_{il}-t_{il})\cdot h_i\cdot(T_i-L_j)^{+}\cdot f_i^{jl}}_{\text{C}} + \underbrace{\sum_{k\in W}\sum_{l\in P}x_{il}\cdot q_{kl}\cdot g_i^{kl} + \sum_{k\in W}\sum_{l\in P}x_{il}\cdot h_i\cdot T_i\cdot g_i^{kl}}_{\text{D}} \qquad (6) \\
& + \underbrace{\sum_{e=1}^{r_i-1} r_i(d_{il})_e + r_i\left(t_{il}-\sum_{e=1}^{r_i-1}(d_{il})_e\right)}_{\text{E}}
\end{aligned}
$$

If wholesaler i merely orders from suppliers, the stocks of them for product l, ($d_{il}-t_{il}-x_{il}$), can just meet retailer demands. The shortage size for product l is ($t_{il}+x_{il}$), and then more shortage cost is required. However, in this scenario the lateral trans-shipment is allowed so wholesaler i can meet more retailer demands for product l. The shortage size is decreased to t_{il}, and the shortage cost is still calculated by Part E in Equation 6. The cost of lateral trans-shipment (i.e. Part D) and cost to order from suppliers (i.e. Part A, B, and C) are calculated in the same way as the section 3.3 and section 3.2 respectively.

Subject to

$$d_{il} > \sum_{k \in W} \sum_{j \in S} (s_{jl} f_i^{jl} + w_{kl} g_i^{kl}) \quad (C_{12})$$

$$x_{il} \leq \sum_{k \in W} w_{kl} g_i^{kl} \quad (C_{13})$$

$$\sum_{j \in S} f_i^{jl} \leq F_i^{\max} \quad (C_{14})$$

$$\sum_{k \in W} g_i^{kl} \leq G_i^{\max} \quad (C_{15})$$

$$f_i^{jl} \in \{0,1\} \text{ and } g_i^{kl} \in \{0,1) \quad (C_{16})$$

Constraint (C_{12}) requires that the demand of each product is large than the total supply of the product from both selected suppliers and wholesalers. So the wholesaler fulfills only some retailers' needs. Constraint (C_{13}) requires the size of lateral trans-shipment for each product must be less than or equal to the total supply of the product from the selected wholesalers. This ensures that the size of lateral trans-shipment is lower or equal to the available stocks of selected wholesalers. Constraint (C_{14}) requires that the wholesaler must order each product from at most $F_i^{\max}$ suppliers. Constraint (C_{15}) requires that the wholesaler must make the trans-shipment of each product from at most $G_i^{\max}$ wholesalers. Constraint (C_{16}) requires that the values of the decision variables must be limited to be 0 or 1 only.

4.4 *Numerical Simulation*

In this section, we illustrate the proposed decision rules under four scenarios with case study. We consider the mathematical techniques to find the solution for each scenario, i.e. search the optimal combination of suppliers (and wholesalers) to minimize the objective total cost functions.

5 different products, 10 available suppliers, and 6 wholesalers are considered in four scenarios. $F_i^{\max} = 3$ and $G_i^{\max} = 2$. In scenario two and four, 20 retailers are considered to make demands for products and only part of them with high priority level can be fulfilled.

4.4.1 *Initial Case*

In the first decision rule (scenario one), different ranges of parameters of product *l* offered by each supplier were shown in Table 4.1, where the ordering prices, stocks, and lead time of each supplier are randomly generated. All the retailer demands for this product are 450.

Table 4.1 Parameters for product *l* required in the first decision rule.

Parameter	Value
$stock_{jl}$	Randomly generated between [100, 500]
$purchase_{jl}$	Randomly generated between [20, 30]
$lead_j$	Randomly generated between [1, 5] (unit: day)

As we know, only supplier 7 can provide product *l* more than retailer demands. According to Eq. 1, we obtain the total cost of the wholesaler by replenishment from this supplier is 10210. The wholesaler may make orders from combination of two supplier so as to decrease its total cost, as presented in Table 4.2.

Table 4.2 the total cost of the wholesaler by replenishment from combination of two wholesalers.

	s1	**s2**	**s3**	**s4**	**s5**	**s6**	**s7**	**s8**	**s9**	**s10**
s1	0	11988	12345	12869	12683	0	12108	12900	12419	12967
s2	11216	0	10209	10591	10456	0	**10037**	10614	10263	10663
s3	11898	10421	0	11169	11012	0	10523	11196	10787	11254
s4	12380	11331	11547	0	11751	11280	11404	11882	11592	11923
s5	11979	11115	11292	11553	0	11072	11175	11568	11329	11602
s6	0	0	0	11186	10914	0	10066	11232	10524	11332
s7	0	0	0	0	0	0	0	0	0	0
8	12122	11719	11802	11924	11881	11700	11747	0	11819	11947
s9	11100	10815	10874	10960	10929	10801	10835	10965	0	10976
s10	12166	11965	12006	12067	12045	11955	11979	12070	12015	0

In the above table, s1, s2,..., s10 represent the supplier indexes. By selecting supplier 2 and 7, the wholesaler achieved lower cost (i.e. 100037). It means that the wholesaler orders 299 product *l* from supplier 2 and 151 product *l* (450-299) from supplier 9. If the wholesaler replenish itself from three supplier, there would be much more combinations which correspondingly produce different cost. Here we merely give the table with the optimal solution.

Table 4.3 Total cost of the wholesaler for product l by replenishment from combination of three wholesalers. The minimal cost is obtained by ordering 299, 145, and 6 product *l* from supplier 2, 6 and 7.

	s1	s2	s3	s4	s5	s6
s1	0	0	0	0	0	11964
s2	0	0	0	0	0	**9892.4**
s3	0	0	0	0	0	10379
s4	0	0	0	0	0	0
s5	0	0	0	0	0	0
s6	11964	**9892.4**	10379	0	0	0

In the above, we demonstrate the optimal supplier selection for one given product. If we repeat those procedures, we can achieve the optimal solution for all the different products (for example, 5 kinds of products in this simulation) required at the wholesaler, as shown in Table 4.4.

Table 4.4 Optimal combination of suppliers to replenish the wholesaler.

	p1	**p2**	**P3**	**p4**	**p5**
s1					
s2	299	2|24	70	665	
s3		31	310|327		
s4		37		679	
s5					
s6	145				1113
s7	6|459				1887|1898
s8				56|789	
s9					
s10					
Cost	9892.4	8018	6258.7	20906	1.60E+05

In Table 4.4, the symbol 6|459 denotes that the available stocks at the supplier are 459 but the wholesaler just orders 6 of them. The last column is the minimal total cost of the wholesaler by the optimal replenishment solution. Note that it is natural that the wholesaler may achieve its minimal cost by replenishment from two or even one supplier.

4.4.2 Wholesaler with Shortage

In this section we simulate one case that the retail demands are greatly larger than the stocks of the individual supplier. An example is presented Figure 4.4, where retailer demands are sorted out according their priority level and then demands of 11 retailers can be satisfied.

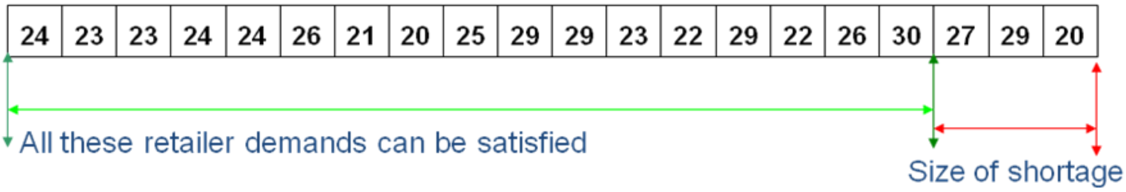


Figure 4.4 Satisfaction and dissatisfaction of retailer demands

As the wholesaler cannot satisfy all the retailer demands, it prefers to make orders from as many suppliers as possible in order to reduce the penalty cost caused. So we give optimal replenishment of the wholesaler for all the products, as follows. Number of retailers for fulfilled demands denotes how many retailers can be served.

Table 4.5 Optimal solution for the wholesaler replenishment under consideration of its shortage.

	p1	p2	P3	p4	p5
s1		57		20	
s2				25	
s3					52
s4	131		72		
s5		76			
s6	138		54		56
s7			74		
s8		67			
s9					42
s10	151			22	
Number of retailers for fulfilled demands	**11**	**16**	**17**	**8**	**15**
Cost	10549	4064.5	4686	1485	8.65E+03

4.4.3 Wholesaler with Lateral Transshipment

Wholesalers are usually serviced by a number of goods suppliers that have varying purchase prices and goods delivery lead time. In addition to their suppliers, wholesalers are also allowed to replenish their supplies among other wholesalers by lateral trans-shipment at mutually agreed but fixed prices. Such kind of order is assumed to be available immediately If the lateral trans-shipment is possible, the wholesaler will try to make the orders from the combination of suppliers as well as the possible combination of other wholesalers so as to minimize its operation cost.

Above all, One decision that must be taken is whether or not a lateral trans-shipment should be used to meet the demand and also on the optimum amount of this trans-shipment, if needed. There are many literautre to discuss decision rules for lateral trans-shipment in the supply chain (Axsater, 2003; Herer & Tzur, 2003; Wong et al. 2005). Here we only consider the case that the lateral trans-shipment is worthwhile and we study the selection of combination of wholesalers to further reduce the cost of lateral trans-shipment. For one product, such as product *l*, the stocks and prices offered by each wholesaler is listed in Figure 4.5. We estimate the operation cost at wholesaler 6.

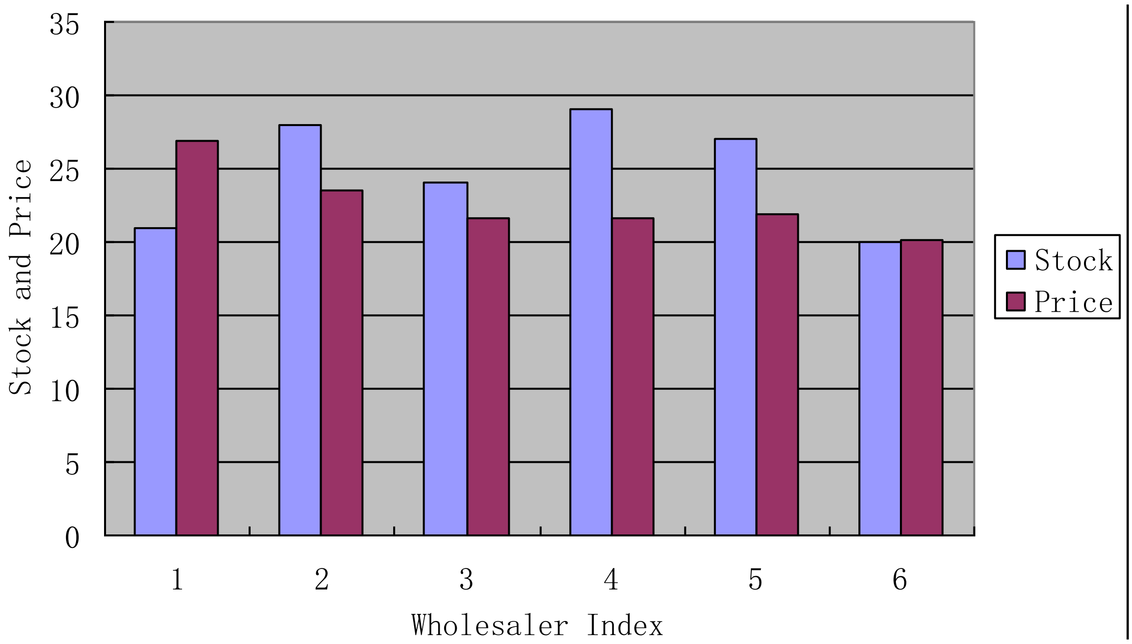


Figure 4.5 Information of product *l* provided by all the wholesalers.

If wholesaler 6 order 40 product *l* from its two neighbors (as $G_i^{\max} = 2$), we can obtain the cost by lateral trans-shipment, as follows.

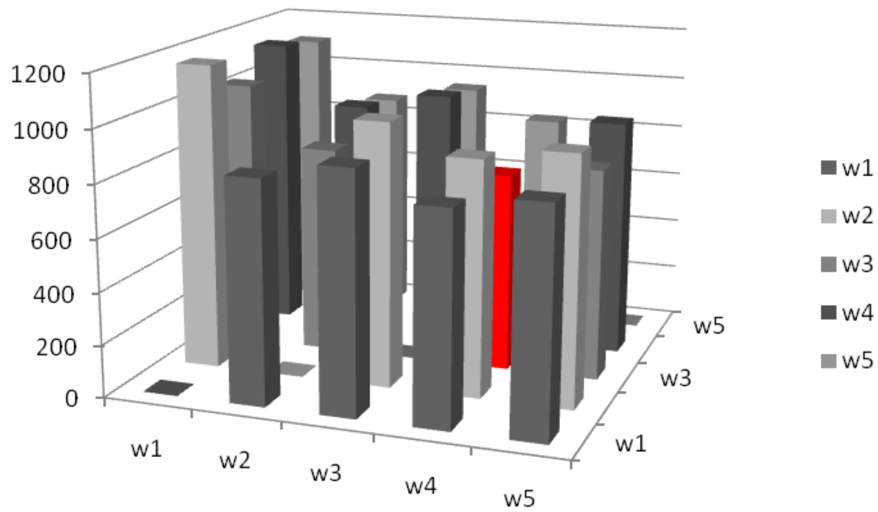


Figure 4.6 Cost of wholesaler 6 for the lateral trans-shipment.

The minimal cost for lateral trans-shipment highlighted by the red bar is 756.97. Taking the above trans-shipment into consideration, the wholesaler merely needs to order the rest demands for product *l* from combination of suppliers. The minimal cost of the wholesaler using combination of two suppliers is 10854, and the minimal cost using combination of three suppliers is 10732. We knew that in Section 4.1 without lateral trans-shipment the wholesaler has to order all retailer demands for product *l* from combination of suppliers and the minimal cost is 11644.

For product *l*, when we make transshipments (40 product l) from wholesaler 3 and part of wholesaler 4 and order the rest (350) from supplier 5, supplier 6, and part of supplier 4 we obtain the minimization of total cost of wholesaler 6. So we can give the optimal solution for the replenishment of wholesaler 6 under the condition of this fixed trans-shipment size.

4.4.4 Wholesaler with Lateral Trans-shipment and with Shortage

It is obvious that this case is the integration of the previous two cases. We use the same information of product *l* as Section 4.2. Assumed that retail demands are still larger than the sum of stocks of any three individual suppliers, partial retailer demands can be satisfied and lateral trans-shipment will help to reduce shortage of the wholesaler and meet more retailer demands. An example is illustrated in Figure 4.7.

Figure 4.7 Satisfaction and dissatisfaction of retailer demands by replenishment from suppliers and lateral trans-shipment

Obviously, lateral trans-shipment can decrease the shortage cost but it also generate the cost for such action. In theory, one can compare both costs and then decide to make the lateral trans-shipment or not but in practice the wholesaler prefer to make lateral trans-shipment in a relatively reasonable or even higher price so as to save its reputation and retrieve retailers' trust. Table 4.6 shows an example with the minimal cost, where the wholesaler orders 450 product *l* from combination of supplier 2 and other two suppliers.

The wholesaler should order all the stocks from supplier 5 and 6, and part from supplier 2 to achieve the minimal cost for such number of products. However, these orders merely meet sixteen retailer demands and the rest retailers suffer from shortage. Lateral trans-shipment is an option to meet more retailer demands. The cost of later trans-shipment is referred to Figure 4.5. The minimal cost for 40 product *l* by lateral trans-shipment is 756.97. Such order can satisfy the 17^{th} retailer demands and part of the 18^{th} retailer demands. Substituting those values into Eq. 3 we obtain the shortage cost saved is 1407. Hence, the optimal solution to meet retailer demands of product *l* is that the wholesaler makes the replenishment from supplier 5, 6 and par of supplier4, and trans-shipment from wholesaler 3 and part of wholesaler 4.

Table 4.6 Cost of the wholesaler by replenishment from some combination of suppliers.

0	11753	11988	0	11131	11442	12853	11613	11925	12395
11753	0	11639	0	10782	11093	12504	11264	11576	12045
11988	11639	0	0	11018	11328	12739	11499	11811	12281
0	0	0	0	0	0	0	0	0	0
11131	10782	11018	0	0	10471	11882	10642	10954	11424
11442	11093	11328	0	10471	0	12193	10953	11265	11734
12853	12504	12739	0	11882	12193	0	12364	12676	13145
11613	11264	11499	0	10642	10953	12364	0	11436	11905
11925	11576	11811	0	10954	11265	12676	11436	0	12218
12395	12045	12281	0	11424	11734	13145	11905	12218	0

Chapter 5 The Intelligent Supply Chain System (ISCS)

5.1 Introduction

This chapter presents an Intelligent Supply Chain System (ISCS), which is based on the Minimum Description Length-optimal (MDL-optimal) neural network combined with the surrogate data method for "learning" the underlying pattern and predicting future demands. The ISCS will act as a guide to forecast the coming retailer demands and thus improve supply chain network.

5.2. Model and Methodology

Demands forecasting plays an important role in the supply chain management. Accurate demand prediction is a vital component of an effective supply chain. It can help make a moderate inventory level, and achieve the objective of just-in-time business workflow. It is, therefore, necessary to apply advanced techniques to capture the pattern from historical data and to determine the future trend.

The traditional ARMA model family, like autoregressive moving average (ARMA) and autoregressive integrated moving average (ARIMA) has been widely used to solve the problem of time series prediction, with success (Box, 1994). Furthermore, the primary limitation of ARMA models is the assumption of the linear relation between independent and dependent variables (Kuo & Reitsch, 1995; Dorffner, 1996). ARMA models are applicable only to stationary time series modeling. Those constraints, therefore limit the application range and prediction accuracy of the ARMA models (Zhang, 2003). Chang & Wang (2006) surveyed typical traditional methods of sales forecasting and their main drawbacks, and discussed the promising Artificial Intelligent (AI) techniques and the tendency of application of such techniques to sales forecasting.

Advanced artificial intelligence technologies, like artificial neural networks, genetic algorithms, fuzzy logic, and their integration produce more advanced generic model with more flexibility, which can accurately capture the characteristics of practical data in various industrial fields. Doganis et al. (2006) developed a nonlinear time series sales forecasting models for shelf-life food products, where they combined the neural network and genetic algorithm. Chang et al. (2006) proposed a hybrid system by evolving a case-based reasoning system with a genetic algorithm for a wholesaler's returning book forecasting. This hybrid model outperformed the back propagation neural network, a conventional case-based reasoning without artificial intelligence, and the linear modeling. They demonstrated that the traditional approach of sales forecasting integrated with the appropriate artificial intelligence was highly competitive in the practical business service. Thomassey and Fiordaliso applied the decision tree and clustering techniques to an apparel industry (Thomassey et al., 2005; Thomassey & Fiordaliso, 2006).

However, some prediction of their models deviated from the real sales profiles of future items. Due to this fact they suggested advanced AI techniques such as neural networks, genetic programming or fuzzy logic to make possible improvement in the future works. Significantly, Chang et al. carried out series of works that incorporated fuzzy logic into different AI techniques, such as clustering (Chang et al, 2006), case-based reasoning (Chang, 2008) and neural networks (Chang, 2006) for sales forecasting. Fuzzy logic shows the potential advantages of handling variables with flexible linguistic expression but deliberate selection of fuzzy sets is required since design of fuzzy sets and their membership functions is usually empirical and especially fuzzy membership function shapes take influence on the variation in decision making (Ozen & Garibaldi, 2011). Lertpalangsunti et al. (1999) constructed a comprehensive toolset of a hybrid intelligent forecasting system, including common intelligent techniques with focus on water demands prediction. In addition, artificial intelligence has been widely employed to support various manufacturing workflows so as to enhance product quality (Acciani et al., 2006; Chen et al., 2007).

Note that over-fitting has long been recognized as a problem endemic to sophisticated nonlinear models with a number of parameters. Over-fitting means the model accurately follows the training data but fails to respond properly to novel data or even gives worse estimation. It widely occurs in any resultant model above, in particular neural networks. This leads to the consequence that the performance of neural networks in some comparative experiments is not superior to or as good as other AI techniques. Albeit with this, neural networks are still considered as the primary AI techniques to solve forecasting problems in supply chain network (Dorffner, 1996; Faraway & Chatfield, 1998; Aburto & Webber, 2003). Aburto and Weber developed a hybrid model combining the neural network and ARIMA to predict the future demands for a Chilean supermarket (Aburto & Webber, 2007). The neural network significantly improved the prediction accuracy of the ARIMA model. Although the proposed model exhibits improvements in customer service and inventory level they did not further integrate their model with the company’s decision policy. Actually neural networks are considered as the primary and auxiliary problem solving methodology for optimization, forecasting and decision support in supply chain management (Leung, 1995). Remarkably, neural networks are quite effective in modeling nonlinearity between the input and output variables and in particular the multi-layer feed-forward neural network is able to approximate any nonlinear function under certain conditions (Hill et al., 1996). The neural networks can model more complex time series (i.e. the nonlinear process) and do not, theoretically, require certain features of the time series.

Nevertheless, the high-degree freedom in the neural network architecture provides the potential to model any function but it also generates the uncertain conditions. So the crucial issue in developing a neural network is generalization of the network. The usual methods to avoid stopping on the local minima of the respective error function is early stopping and statistical regularization (Zhao & Small, 2006). But they just make the improvement to the known neural network while they can not directly determine the optimal model. Certainly, the improved neural networks are sub-optimal models. We take an alternative novel approach, the Minimum Description Length (MDL), to exactly estimate the optimal neural network for the time series prediction, which is defined as the MDL-optimal neural networks.

There are other model selection methods, such as the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) (Akaike, 1974; Barron & Rissanen, 1998). They both perform well for the linear models while MDL information criterion is better for nonlinear models (Nakamura et al., 2006). The utilization of the MDL also is based on our familiarity with it and the fact that it maintains good robustness against noise or stochastic disturbance (Judd & Mees, 1995). This is particularly useful to the practical case where the original recordings are usually contaminated with observational noise and stochastic factors somewhat.

Moreover, our MDL method with reasonable approximation has the great advantage of small computational costs.

There have been relatively few attempts at identifying the characteristics of demands. A number of articles in the literature about demands forecasting always assume that those demands are predictable and then describe corresponding models to forecast the future demands (Yoo & Pimmel, 1999; Terwiesch et al., 2005; Aburto & Webber, 2007). Actual demands depend on lots of stochastic elements, which very probably result in completely stochastic demands. Meanwhile, some kinds of demand data in which deterministic patterns dominate appear to be random, and then people are very likely to ignore the investigation of those demands. To address this problem, we introduce the technique developed in the field of nonlinear dynamics, the surrogate data method (Theiler et al., 1992; Small & Tse, 2003) to test and identify the dynamics (pattern characteristics) of the specific retailer demands. We can confirm the predictability of those demands with statistical evidence.

5.3. System architecture of ISCS

The generic architecture of the ISCS, which can facilitate a reliable operation with low inventory costs, is illustrated in Figure 5.1.

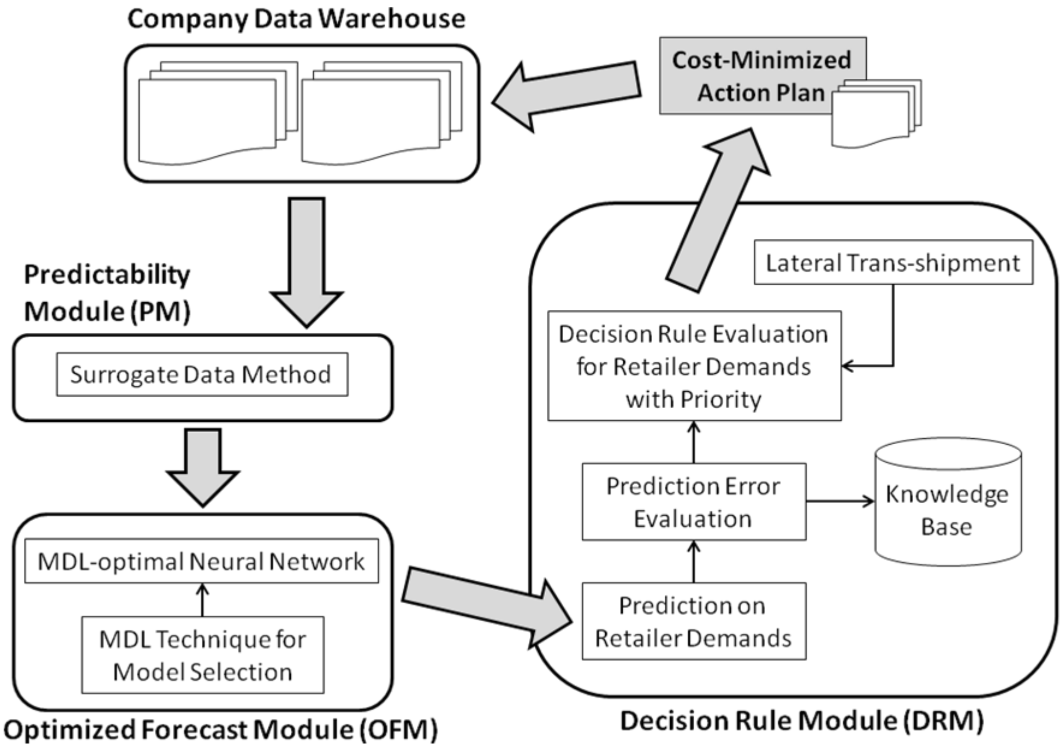


Figure 5.1 Constituent of the Intelligent Supply Chain System (ISCS) to meet retailer demands.

5.3.1 Predictability Module (PM)

First of all, data collection is a crucial step in the whole of any intelligent system. As Banks et al states, the analyst needs to employ a way to represent the elements (Banks et al., 2001). The measurement module is responsible for collecting demands from each retailer of the supply chain, assuming that the demand data is considered as deterministic and independent. The task of identifying the characteristics of the collected data belongs to the predictability module that utilizes the surrogate data method.

The surrogate data method originally came from the Monte Carlo hypothesis tests, and was standardized by Theiler et al. (1992). The rationale of surrogate data hypothesis testing is that it generates an ensemble of artificial surrogate data (surrogates in short) of the original data, which are consistent with the certain hypothesis. One then applies some test statistic to both surrogates and the original data. If the statistical value of the data is different from the ensemble of values estimated for surrogates, one thus rejects the given hypothesis as being the likely origin of the data. If the statistic for the data is not distinct from that for surrogates, one may consider that the original data follows the given hypothesis. The concept of the standard surrogate data method is visualized in Figure 5.2.

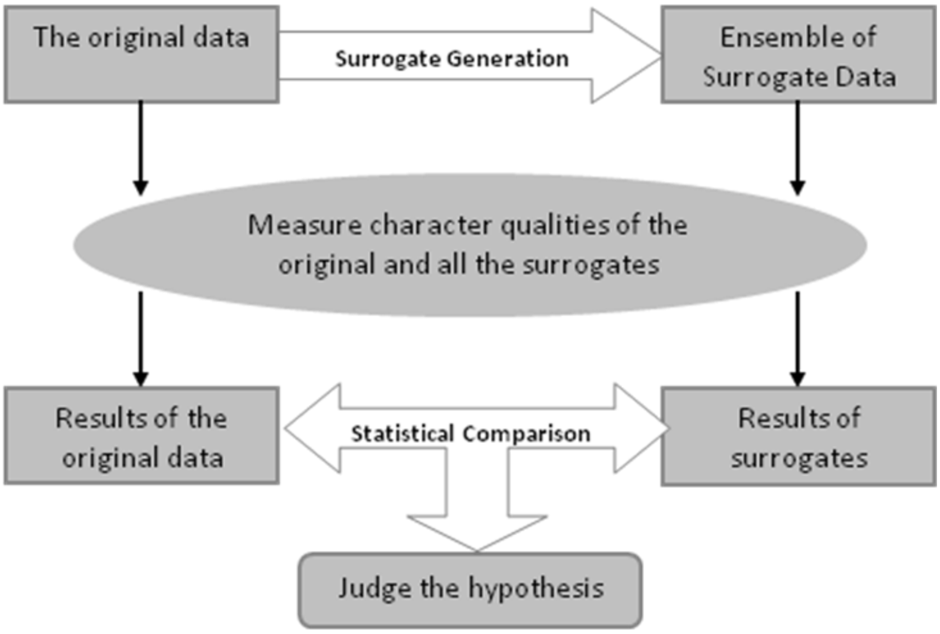


Figure 5.2 Framework representation of the surrogate data method testing for the hypothesis.

These commonly employed hypotheses are known as NH0, NH1 and NH2 [19]: NH0: the data is independent and identically distributed (i.i.d.) noise, such as Gaussian noise, NH1: the data is linearly filtered noise, and NH2: the data is a static monotonic nonlinear transformation of linearly filtered noise. There are three classical surrogate generation algorithms, Algorithm 0, 1, and 2, corresponding to the hypotheses above to generate surrogate data. For example, given the hypothesis of NH0, the surrogate data method will randomly shuffle the order of the original data. Such shuffling should destroy any temporal correlation of consecutive data points, and the generated surrogates are random data consistent with NH0. As an example, Figure 5.3 illustrates one sinusoid plus slight uncorrelated Gaussian noise, the recording of retailer demands, and their typical surrogate data. Both surrogates that appear to be random are consistent with NH0.

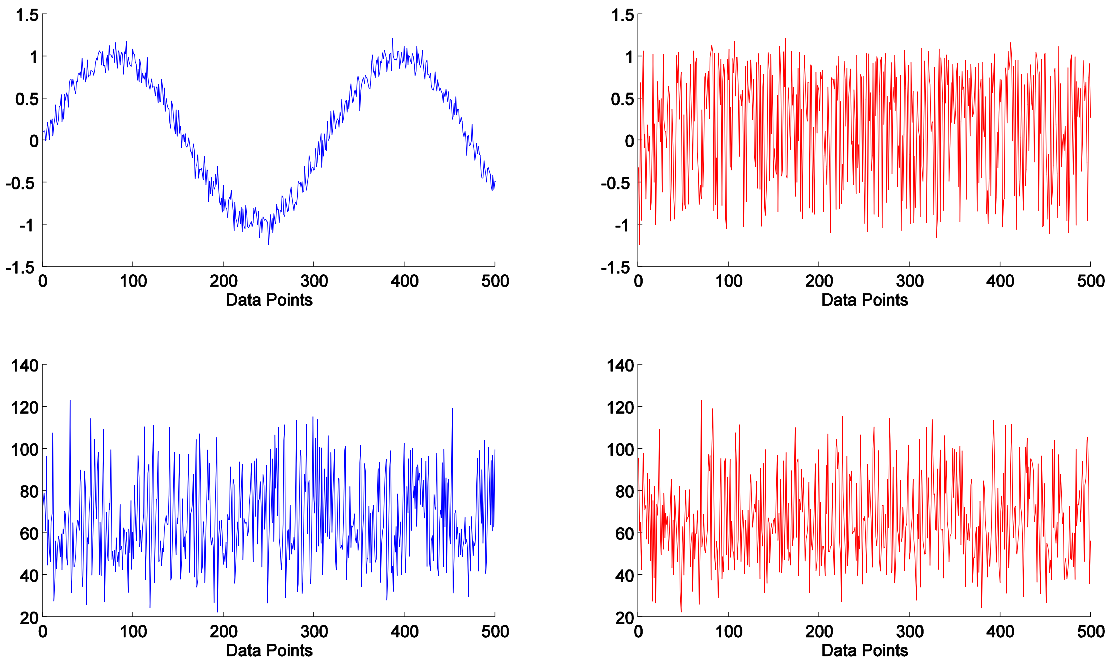


Figure 5.3 Original data sets in blue color and their corresponding surrogate data in red color.

As the surrogate generation algorithm randomly shuffles the original data points, we can obtain various surrogates by implementation of the generation algorithm. We then calculate the certain statistic of the original data and its surrogates. There is an ensemble of statistical values for the surrogates, which forms a probability distribution with respect to these statistical values.

In addition, Algorithm 1 feeds the original data to an *AR*(*p*) process described by the equation, $x_{t+1} = \alpha + \sum_{i=0}^{p-1} c_i x_{t-i} + \beta\xi_t$, where $\alpha, \beta, \{c_i\}$ are unspecified parameters and $\{\xi_t\}$ are i.i.d. noise. Its output is the surrogate data. The surrogate generation algorithm for NH2 is open to the problem, which cannot keep surrogates stationary. It results in fake rejection and wrong decisions.

We originally propose the surrogate data method to examine whether the interesting demand data comes from the same origin as NH0 and NH1. It, therefore, is enough to determine whether the neural network is applicable to predict such data and whether it is more suitable to such data than ARMA models. Firstly, the surrogate data method with the hypothesis of NH0 is proposed to test the given data. If these data are consistent with NH0 (i.e. random noise) it appears that no modeling technique can predict them while if they are confirmed to exclude from the random noise one then consider to select the appropriate model. Secondly, we are interested in feasibility of application of the ARMA model to these data. Although the ARMA model may have large prediction errors it will not become overfitted. The performance of the sophisticated nonlinear model could be worse once it becomes overfitted. We, therefore, proposed the surrogate data method with another hypothesis, NH1 to the data that have been confirmed not to be random. If the data is consistent with NH1 (i.e. originates from the linear process) the linear modeling techniques, like ARMA should be suitable to model them while if they do not come from the linear process nonlinear modeling techniques should outperform the linear counterparts. However, sophisticated nonlinear models are not as robust as the linear since they easily become over-fitted. So the crucial issue of application of nonlinear models is to ensure their adequate generalization, which we will discuss in the next subsection.

In the ISCS, the predictability module that comprises the surrogate data method will identify the characteristics of the recorded retailer demands. Those data that are identified as the predictable data are then fed to the following optimized forecast module for forecasting while others which are considered as the stochastic data will be excluded since it is impossible to make forecast on stochastic data.

5.3.2 Optimized Forecast Module (OFM)

The potential prediction ability of the neural network with a large number of neurons stimulates people to create large artificial neural networks. It correspondingly leads to over-fitting of the resulting model. Therefore, the adequate generalization of neural networks for a specific application is the primary element to ensure the success of their application in practice. We take a novel technique, the minimum description length, to select the optimal neural networks with adequate generalization. The minimum description length principle is rooted in the theory of algorithmic complexity for efficient data compression (Rissanen, 1989). We develop its trade-off strategy to estimate the optimal model according to the equilibrium (i.e. minimum) of description length. That is, the description length of a model includes two parts: the cost describing of both the model parameters and its prediction errors.

E(*k*) denotes the description length of the model prediction errors for a given model whose model size is *k*, and *M*(*k*) is the description length of model parameters of the same model. The description length of this model is then given by the sum, $D(k) = M(k) + E(k)$.

For the prediction of retailer demands, we define that $\{p_i\}_1^N$ are the *N* recording of the retailer demands over the *i*th day. $f(p_{i-1}, p_{i-2}, ..., p_{i-d}; \Lambda_k)$ is a scalar function of *d* variables, where p_{i-d} represents the retailer demand of the (*i-d*)th day, and Λ_k is the set of coefficients of $f(\cdot)$. Note that the neural network used in this chapter is the three-layer feed-forward neural network, and its architecture is illustrated in Figure 5.4.

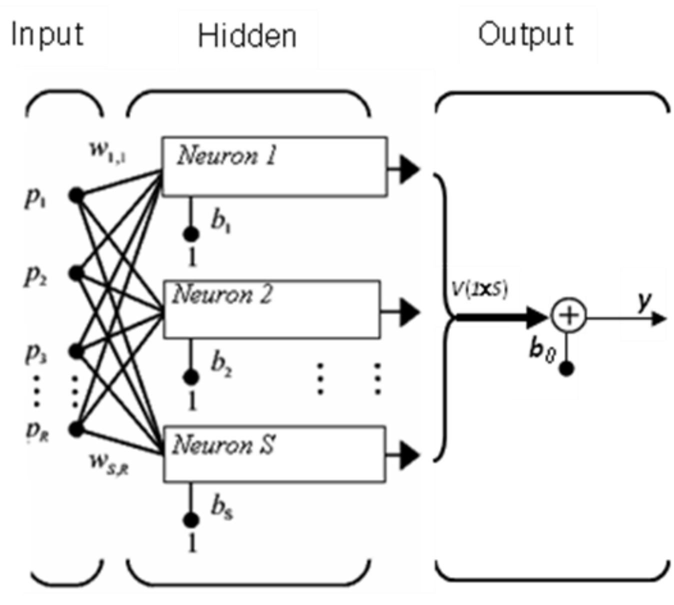


Figure 5.4 The multilayer network is composed of the input, hidden and output layers.

There are S neurons in the hidden layer and one linear function in the output layer. $W=\{w_{ij} \mid i=1,\dots,R \ \ j=1,\dots,S\}$ and $V=\{v_i \mid i=1,\dots,S\}$ denote weights and $b=\{b_i \mid i=0,\dots,S\}$ are the biases.

Input vectors with the size of R denoted by $\{p_1, p_2, \dots, p_R\}$ are fed to the neural network, and the network finally gives its output denoted by y. With the given input vector, the number of parameters (i.e. weights and biases) is only determined by the number of neurons. As shown in Figure 5.4, given the number of neurons is S, Λ_S is completely described by those parameters of the neural network, i.e. $\Lambda_S = \{w_{ij}, v_i, b_i \mid i=1,\dots,R \quad j=1,\dots,S\}$. $y = f(p_{i-1}, p_{i-2}, \dots, p_{i-d}; \Lambda_S)$ is the output of the neural network with S neurons. So the description length of the parameters of the neural network is the function regarding to the variable, the number of neurons. That is, the variable k of $M(k)$ is the number of neurons. For the parameters of the network with k neurons, Λ_k, $M(k)$ is given by Small & Tse (2005):

$$M(k) = L(\Lambda_k) = \sum_{i=1}^{k} \ln \frac{\gamma}{\delta_j}, \qquad (1)$$

where γ is represents the number of bits required in the exponent of the floating point representation and δ_j is interpreted as the optimal precision of the parameters λ_j.

We then define the prediction error $e_i = f(p_{i-1}, p_{i-2}, ..., p_{i-d}; \Lambda_S) - p_i$, where p_i is the original retailer demand of the ith day and the function is $f(\cdot)$ is the prediction on the original one. So the description length of the model prediction errors is relevant to the model parameters, and these parameters are determined by the number of neurons in the network. Finally, for the given neural network the description length of the prediction errors is also the function regarding to the number of neurons. We, therefore, establish the function of description length of the network with respect to the variable, the number of neurons.

For the calculation of $E(k)$, the distribution of prediction errors defined before is generally unknown, which leads to quite complicated or even unfeasible computation to $E(k)$. We are required to make necessary and reasonable assumption that the model errors follow Gaussian distribution. Its distribution is then converted to the normalized Gaussian distribution with mean zero and standard deviation one. The cost for the model prediction errors is approximated to the following equation,

$$E(k) = \frac{N}{2} + \ln\left(\frac{2\pi}{N}\right)^{N/2} + \ln\left(\sum_{i=1}^{N} e_i^2\right)^{N/2} \qquad (2)$$

Notations used in the calculation of description length are tabulated as follows:

Table 5.1 Summary of notations in the calculation of description length

Notation	Definition
k	Number of neurons in a neural network
d	Number of inputs to a neural network
p_i	The *i*th input (i.e. retailer demand at the *i*th day)
e_i	The prediction error for the *i*th day
N	Total number of measurements
Λ	The model parameters, including:
	$w_{s,r}$, the weights between the input vectors and neurons
	b_j, the bias for each neuron and the final output
	v_r, the weights between the neurons and the output

Typical behavior of $E(k)$ and M(k) is that when the neural network has more neurons (i.e. k increases) it has more parameters and the description length of these parameter, $M(k)$ increases while the prediction errors should decrease and then the description length of these prediction errors, $E(k)$ decreases. There will be one minimal point in the sum of both description length for a series of candidate networks. The variable, k which minimizes the total description length, $D(k)$ indicates the optimal number of neurons (i.e. the optimal neural network among all the candidates). So the MDL method makes equilibrium between the model size and its prediction errors, and the MDL-optimal network can provide adequate generalization and avoids over-fitting.

We take an example to describe how to select the MDL-optimal model. For example, there are twenty neural networks with different neurons from one to twenty. After a neural network is well trained we then calculate its description length, and thus for all the twenty candidates we obtain a description length curve with respect to the number of neurons. The certain neural network that minimizes the description length curve is selected as the optimal neural network. If the neural network with 9 neurons has the minimum description length among all the candidates and then this network is the MDL-optimal neural network.

The MDL-optimal neural networks can provide adequate generalization and perform well for various time series predictions (Zhao et al., 2006; Zhao et al., 2008). The MDL-optimal neural network developed for the given supply chain also proves effective in the certain retailer demand forecasting. As suggested, the prediction module works closely with the company’s decision rules aiming to minimize its operation cost, which is completed in the decision rule module.

5.3.3 Decision Rule Module (DRM)

The Decision Rule Module (DRM) deals with calculation of the wholesaler's inventory cost based on the output of the Optimized Forecast Module (OFM). Since the theories, corollaries and illustrations for the DRM development has already been covered in chapter 3 and chapter 4, it will not be explained again in this section. The output of DRM will be an action plan, which usually includes the issue of purchase orders (if necessary) and trans-shipment orders (if necessary).

In this chapter, the analysis of each module allows a systematic evaluation of the performance of neural networks in terms of prediction accuracy and inventory cost. It also allows an estimation of optimal parameters including the optimal model size and prediction time lag. The optimal parameters obtained are saved in the knowledge base and will be assigned to the prediction module when the matched retailer demands come. Therefore, the ISCS can automatically identify data characteristics, select the optimal neural network for the given data, and optimize the prediction settings by minimization of the total cost. Figure 5.5 summarizes the workflow in ISCS framework.

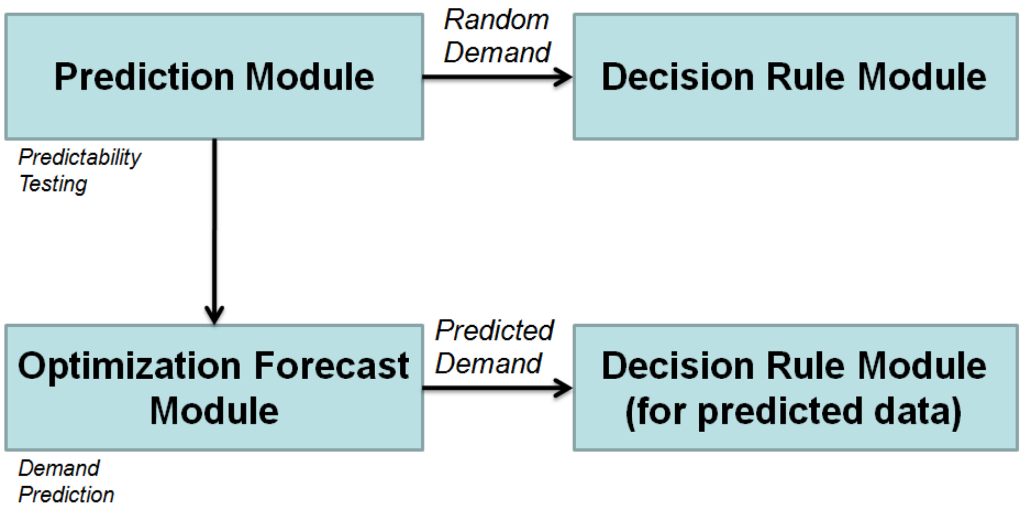


Figure 5.5 The workflow in ISCS framework.

Chapter 6 Case Study

6.1 Introduction

With the increasing competition in the wholesale business sector, there has been a significant growth in using supply chain management concepts to streamline the flow of goods. It is well known that with the inventory control concept, many enterprises (especially the wholesaler section) will always want to keep a low inventory for buffering in order to save the storage cost. This strategy is considered as one of the critical elements of success for an enterprise, especially in today's globalized business environment. On the other hand, the ever-changing economic situation and the fierce (retail) business competition require the wholesaler section to be more cautious about cost and speed of delivery in order to remain competitive. Thus, the most challenging task for such section is to decide whether it is more appropriate to order the required quantity of goods from the list of suppliers, or to ask for a lateral-shipment from other wholesalers within the enterprise. To validate the feasibility of adopting the Intelligent Supply Chain system (ISCS) in providing systematic evaluation of the supply chain network performance, a case study has been conducted in a Hong Kong based company: a food distributor (wholesaler). Although the case company has already been regarded as a successful company in its industry, it is still searching for an appropriate approach to achieve continuous improvement in all decision makings. This chapter provides a profile of the case company, the existing practices of the company, and the roadmap for the implementation of ISCS is proposed and discussed.

6.2. Case Study in a food distributor company (wholesaler)

Gunter Supply Limited is a Hong Kong food wholesaling company. The company (wholesaler) offers a variety of food products (about 150 different food products) purchased from several suppliers located in the Mainland China. Its retailers are dispersed over Hong Kong and Macau. The supply chain network of this company comprises suppliers, retailers and itself: ordering products takes place between suppliers and the wholesaler and meeting retailer demands takes place between the wholesaler and its retailers. Figure 6.1 presents a schematic diagram of the whole supply chain process from the point of view of the wholesaler.

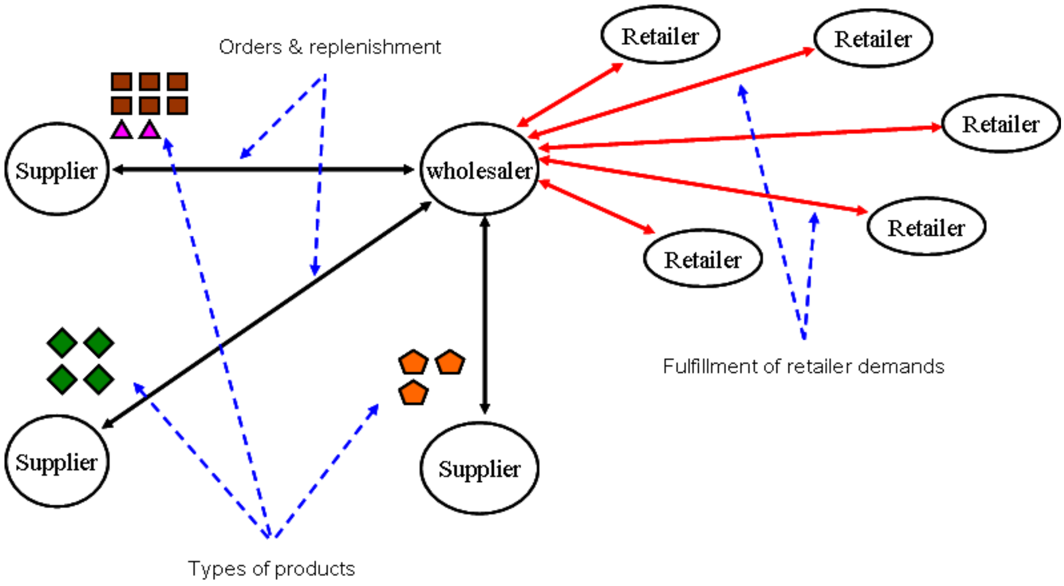


Figure 6.1 An integrated decision model of the given supply chain network.

The wholesaler faces retailer demands and replenishes its stock from suppliers who have abundant stock, which incurs purchasing costs. Storage of products at the wholesaler's end incurs holding costs. A temporary lack of products for fulfilling retailers' demands incurs back-order costs. Shortage of products for meeting retailers' demands incurs shortage costs.

The aim of this company is to manage efficiently all those retail demands. It wishes to quickly respond to the retailer demands or even prepare for some typical kinds of product demands in advance so as to provide the best service to its retailers at relatively high prices. Reviewing the historical data flow generated by its retailers, the wholesaler may make the decision on how much to order before the arrival of the actual demand, and on how many days in advance to make the order. The task, however, is difficult as retailer demands depend on many factors and then the pattern hidden in those demands is unknown or too complicated for the managers of this company to understand.

6.3 Predictability evaluation of demand data

Consider two kinds of retailer demands through data collection. One is the daily demand for Product 0397 (Chinese soft drinks) and another is the daily demand for Product 1582 (Chinese noodles). It is difficult for managers to determine which kind of demand is consistent with the random noise and which contains deterministic dynamics by direct observation of the original data. If people hastily try to model the stochastic retailer demand and predict the future tendency, it has to result in unexpected extra cost based on their prediction. On the other hand, if people empirically or customarily regard the deterministic retailer demand contaminated with observational noise as the stochastic one, and do not analyze the underlying tendency, it also wastes the opportunity to significantly reduce the cost. Therefore, we propose the statistical hypothesis testing by the surrogate data method to examine the characteristics of retailer demands we are curious about. Figure 6.1 and 6.2 illustrate the application of the proposed technique.

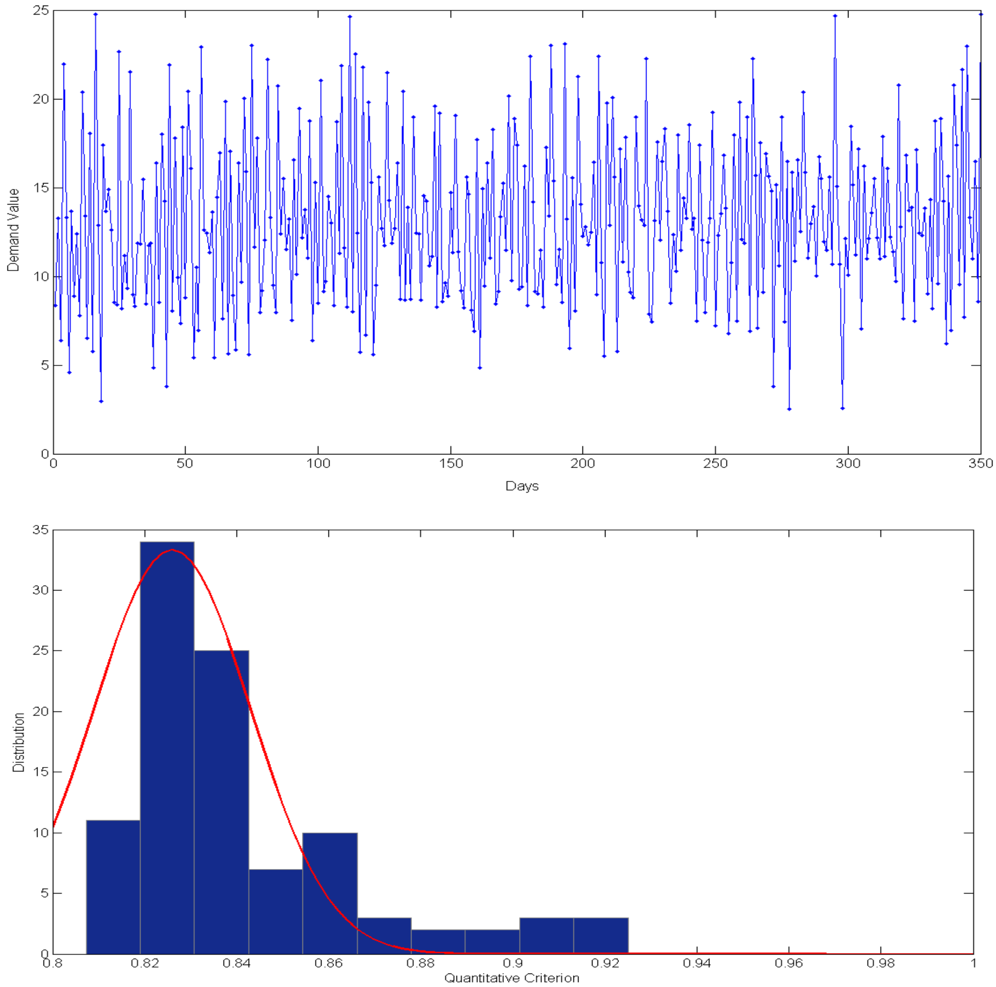


Figure 6.2 One type of retailer demand (top panel) with application of the surrogate data method (bottom panel).

We generate 100 surrogates of the original retailer demand, which are consistent with NH0. One popular statistical criterion, correlation dimension (Yu et al., 2000) is applied to both surrogates and the original data. Blue bars in Figure 6.2 show the probability distribution of statistical values for all the surrogates and the red curve is a Gaussian distribution curve fitting to this distribution. The mean and standard deviation of the fitted distribution are the same as those of the distribution of surrogates. We note that the correlation dimension of the original data is not shown in this figure as its value (1.0367) is out of the range of results of surrogates (i.e. 0.8~0.93) and is even larger than the mean of the fitted Gaussian distribution plus its three-times standard deviation. We therefore reject the hypothesis that the retailer demand of Product 0397 is a random noise with almost 100 percent confidence probability. That is, the rejection indicates that the given data is of a deterministic character and is suitable to predict.

However, application of the surrogate data method to another retailer demand (Chinese noodles) reveals that this data set is consistent with NH0 since its result (the star in Figure 6.3) is in the centre of the distribution for surrogates' results. So people should be careful to select the modeling technique that is suitable for analyzing such data. We exclude it from the following prediction module. We also tested the hypothesis of NH1 on the first retailer demand, and we found that the former retailer demand does not follow the linear process, which means that the linear techniques are not suitable for approximating this kind of data with acceptable prediction error.

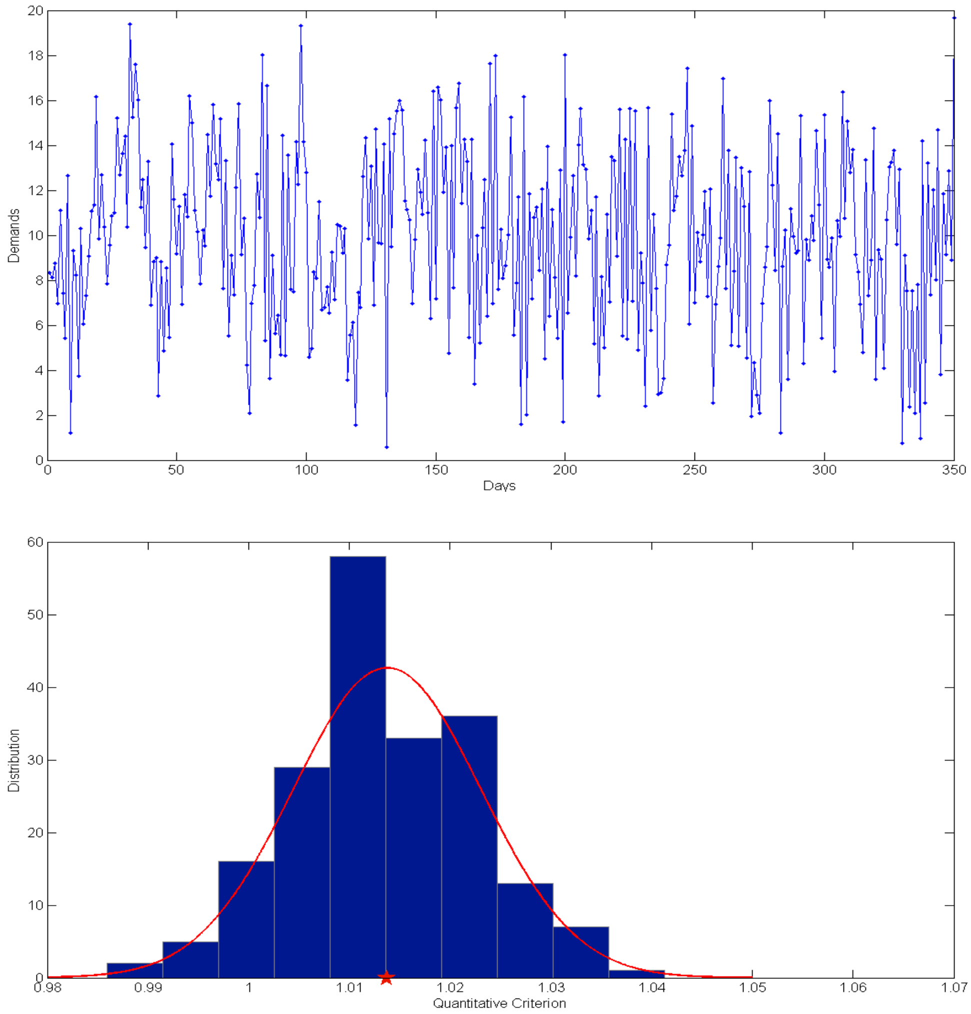


Figure 6.3 Another type of retailer demand (top panel) with application of the surrogate data method (bottom panel).

The possible explanation for both results is that the Chinese soft drinks like the soy bean milk are very popular in Hong Kong and customers are inclined to order them with their meals (many retailers also provide a meal package with these soft drinks) while rice, Chinese noodles and other foreign noodles are the primary choices in daily food. It seems that there is no obvious consumption habit related to this food.

6.4 *Forecast analysis*

In the Optimized Forecast Module (OFM), we employ twenty neural network candidates. That is, the number of neurons in these twenty networks is from one to twenty. Each neural network has the same input architecture: past daily retailer demands from the last k days and binary variables to indicate special events. The value of k is calculated by the autocorrelation of the current data point with its previous kth data point in comparison with the given threshold. The output of each neural network is the future retailer demand.

We construct the neural network utilizing MATLAB neural network toolbox. For fair comparison, the same 600 daily retailer demand data is used as the training data with the next 500 demand data as the test data. Neurons in the hidden layer use the sigmoid transfer function. Note that the training iteration time is set long enough to ensure adequate training.

Consider that the past retailer demands: $x(t)$, $x(t\text{-}1)$, $x(t\text{-}2)$, …, $x(t\text{-}k)$ are the input vector to the neural network. The output of the neural network will be the prediction on the demand of the $(t+1)$th day, $x(t+1)$. We denote the prediction value as $\hat{x}(t+1)$. Now we introduce a concept, time lag by an example. The unit of time lag is day. If time lag is one, it means the model makes one-step prediction on the demand of the next day. So the prediction value is $\hat{x}(t+1)$. If time lag is three, the model needs to predict the retailer demand of the $(t+3)$th day. The prediction value,

$\hat{x}(t+3)$ is obtained from the following sequence: $\hat{x}(t+1)$ predicted from $x(t)$, $x(t\text{-}1)$, $x(t\text{-}2)$, …, $x(t\text{-}k)$, then $\hat{x}(t+2)$ predicted from $\hat{x}(t+1)$, $x(t)$, $x(t\text{-}1)$, $x(t\text{-}2)$, …, $x(t\text{-}k+1)$ and finally $\hat{x}(t+3)$ predicted from $\hat{x}(t+2)$, $\hat{x}(t+1)$, $x(t)$, $x(t\text{-}1)$, …, $x(t\text{-}k+2)$.

6.4.1 Prediction performance

We give an example of the model prediction with time lag equal to 2. That is, given $x(t)$, $x(t\text{-}1)$, $x(t\text{-}2)$, …, $x(t\text{-}k)$ we make the prediction, $\hat{x}(t+2)$. We calculate the description length of each model and obtain a description length curve for all the twenty candidates, as shown in Figure 6.4.

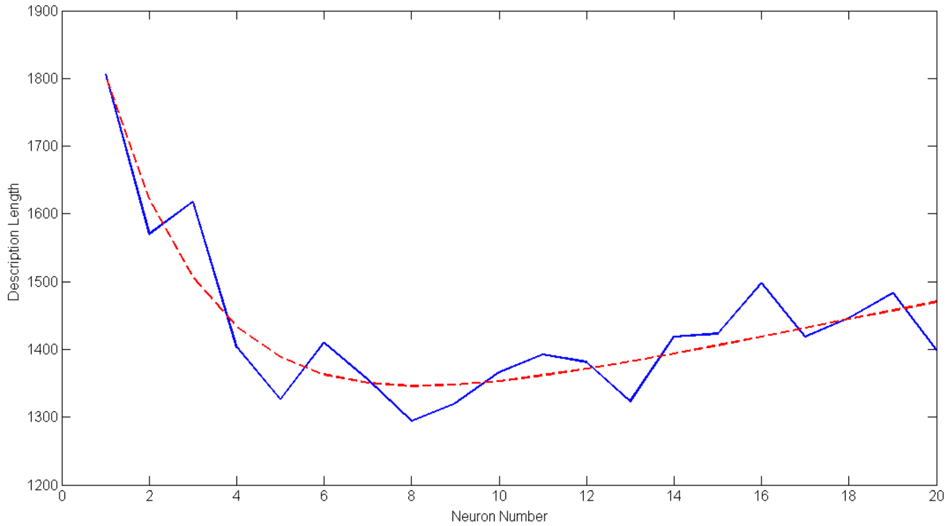


Figure 6.4 The description length curve of twenty neural network candidates (solid line) and its nonlinear fitting curve (dashed line).

Due to the independent construction of neural networks the description length fluctuates somewhat. We adopt the nonlinear curve fitting technique matching the true behavior of the original curve in order to smooth out the fluctuations. The candidate neural network with eight neurons is selected as the optimal one. The right panel in Figure 6.4 presents the prediction of this model for testing retailer demands, which follows the future retail demand (blue curve) very well.

There are some criteria to evaluate the performance of the model, such as mean absolute percentage error (MAPE) and normalized mean square error (NMSE) given by Chatfield & Haya (2008) $\frac{1}{N}\sum_{i=1}^{N}\left|\frac{x_i - \hat{x}_i}{x_i}\right|$ and $\frac{\sum_{i=1}^{N}(x_i - \hat{x}_i)^2}{\sum_{i=1}^{N}(\hat{x}_i - \bar{x})^2}$ respectively, where N denotes the number of prediction, x_i is the original data, $\hat{x}_i$ is its prediction, and $\bar{x}$ is the mean of all the original data.

The MDL-optimal neural network outperforms all the other candidates under both measurements. As the prediction accuracy plays the vital role in the cost saving we select to test the performance of each model by the comparison between its prediction error and the one-fourth standard deviation of the historical data. If the prediction error of the specific day is lower than the given threshold, the corresponding prediction is accepted as one correct prediction. Table 6.1 presents the accuracy rate for the selected models, including the MDL-optimal one.

Table 6.1 Prediction accuracy of neural networks for testing retailer demands.

Prediction Accuracy (percentage)										
NN with 1neurons	NN with 3neurons	NN with 5neurons	NN with 6neurons	NN with 7neurons	NN with 8neurons	NN with 9neurons	NN with 10neurons	NN with 12neurons	NN with 13neurons	NN with 16neurons
11.80%	54.90%	56.90%	66.70%	82.40%	96.10%	94.10%	90.20%	82.40%	88.20%	92.20%

6.4.2 *Integration with decision rule model*

The Decision Rule Module (DRM) deals with calculation of the wholesaler's inventory cost based on the output of the Optimized Forecast Module (OFM). For generality, we define the wholesaler as wholesaler *i*. The decision policy that the company considered is formulated mathematically and the notations in the decision rules are tabulated as follows:

Notation	Meaning
N	Total number of suppliers
S	Index set of suppliers, $S = \{1,2,\dots,N\}$
O_i	Total number of products required by wholesaler i
P	Index set of required products at wholesaler i, $P = \{1,2,\dots,O_i\}$
d_{il}	Quantity of demands for product l at wholesaler i, $(l \in P)$
$\hat{d}_{il}$	Quantity of prediction on the demands for product l at wholesaler i

p_{jl}	Unit price of product *l* supplied by supplier *j*, $(j \in S, l \in P)$
b_i	Back-order cost rate at wholesaler *i* per unit item per unit time
h_i	Holding cost rate at wholesaler *i* per unit item per unit time
c_i	Penalty cost rate retalted to prediction accurancy at wholesaler *i*
L_j	Lead time of supplier *j* to the wholesaler
T_i	Time lag of the prediction for retailer demands
f_i^{jl}	$f_i^{jl} = 1$ if wholesaler *i* orders product *l* from supplier *j*; 0 otherwise

Actually this wholesaler ranks its retailers according to their priority (i.e. the degree of tolerance they have in waiting for the arrival of the products ordered). A shortage cost representing retailer dissatisfaction, which is proportional to the number of units of a product, is incurred when the wholesaler cannot deliver products to a retailer. In order to minimize the total shortage cost, a serving priority must be given to the retailers who are demanding the product. The limited amount of stock on hand must be delivered first to those retailers with the highest priority. As a result, we take retailer dissatisfaction penalty costs into consideration. This cost is mathematically derived, as follows:

As the *i*th wholesaler has a shortage of t_{il} (≥ 0) units of product *l*, the total number of retailers that they cannot serve are

$$r_i = \arg\max_{1 \le m_i \le R_{il}} \left\{ \sum_{e=1}^{m_i} (d_{il})_e - t_{il} \middle| \sum_{e=1}^{m_i} (d_{il})_e \ge t_{il} \right\} \tag{3}$$

where R_{il} is the total number of retailers demanding product l at wholesaler i, m_i is the retailer index, and $(d_{il})_e$ is the demands of the eth retailer in the sorted retailer lists.

The operation $\arg\max\{\ \}$ denotes the index of the first retailer whose demands can not be fulfilled. Since each retailer has been labeled with an index according to their degree of tolerance in descending order, the index of one retailer represents the accumulated number of retailers from the first up to and including this retailer. So r_i indicates that the demands of retailers 1, 2, …, and $r_i - 1$ definitely cannot be met and part of the demand of retailer r_i cannot be met either. The total shortage costs for the ith wholesalers are then given by

$$\overbrace{\sum_{e=1}^{r_i - 1} \gamma_i \cdot (d_{il})_e}^{A} + \overbrace{\gamma_i \cdot \left(t_{il} - \sum_{e=1}^{r_i - 1} (d_{il})_e \right)}^{B}. \tag{4}$$

Part A in Equation 4 is the shortage cost due to failure to satisfy the demands of retailers 1, 2, …, and $r_i - 1$; part B is the shortage cost due to failure to satisfy part of the demand of retailer r_i.

Fortunately, the shortage usually does not happen if retailers are willing to wait longer for their demands. The last event of shortage at this wholesaler was the time when rice was out of stock in April and May 2008, in Hong Kong. But we should point out that long waiting would oblige those retailers to order from other distributors. It is imperative to shorten the back-order time and save the lead time based on prediction of the future retailer demands. The Mainland partners deliver the various ordered products to the wholesaler by road transportation every day. So the transportation cost can be assumed to be constant. Hence, given that no shortage occurs for retailer demands we formulize the wholesaler's operation costs considering the ordering cost, back-order cost, holding cost and penalty cost related to the prediction error, as follows:

$$
\begin{aligned}
f_i = & \sum_{j\in S}\sum_{l\in P}\hat{d}_{il}\cdot p_{jl}\cdot f_i^{\,jl} + \sum_{j\in S}\sum_{l\in P}\hat{d}_{il}\cdot b_i\cdot(L_j - T_i)\cdot f_i^{\,jl} + \sum_{j\in S}\sum_{l\in P}(d_{il}-\hat{d}_{il})^{+}\cdot b_i\cdot L_j\cdot f_i^{\,jl} \\
& + \sum_{j\in S}\sum_{l\in P}(d_{il}-\hat{d}_{il})^{+}\cdot p_{il}\cdot f_i^{\,jl} + \sum_{j\in S}\sum_{l\in P}(d_{il}-\hat{d}_{il})^{-}\cdot h_i\cdot T_i\cdot f_i^{\,jl} \\
& + \sum_{l\in P}(d_{il}-\hat{d}_{il})^{+}\cdot c_i + \sum_{l\in P}(d_{il}-\hat{d}_{il})^{-}\cdot c_i,
\end{aligned}
$$

(5)

where the notations $(y)^{-} = \max(-y,0)$ and $(y)^{+} = \max(y,0)$.

It is feasible to make a short-term prediction on the deterministic data or even a chaotic data using suitable modeling techniques. However, the longer prediction the model makes the larger prediction error it has. If the neural network wants to predict the retailer demands for the distant future the resulting prediction error will be large. The long prediction can save the back-order cost but relatively large prediction error has to generate extra cost. So the prediction time lag and corresponding prediction accuracy is a contradiction. Equation 5 describes the trade-off between the time lag and prediction error. With the given prediction values Equation 5 can be regarded as a cost function with respect to one variable, time lag. Minimization of this cost function gives the optimal time lag.

Figure 6.5, 6.6 and 6.7 illustrate the increasing prediction errors of MDL-optimal neural networks with increasing time lags for the same demand data, where the green lines are the prediction errors.

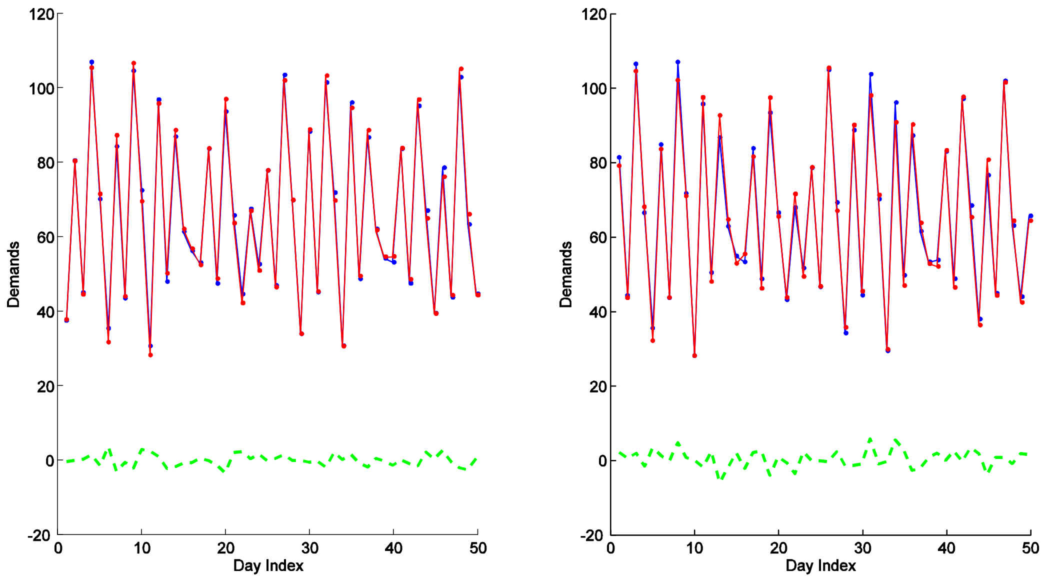


Figure 6.5 The prediction obtained by the MDL-optimal neural network with time lag equal to one (left panel) and two (right panel)

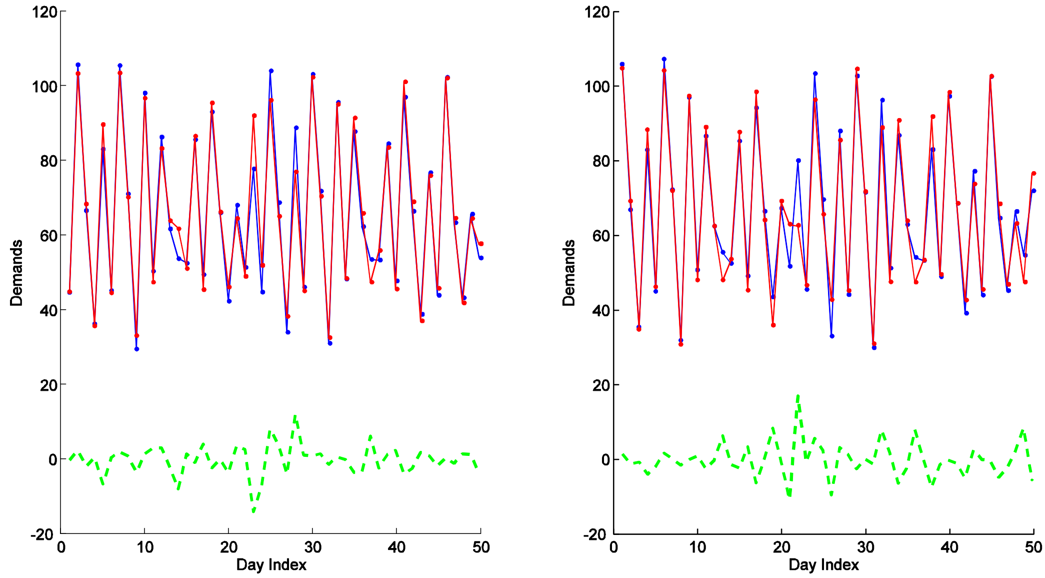


Figure 6.6 The prediction obtained by the MDL-optimal neural network with time lag equal to three (left panel) and four (right panel).

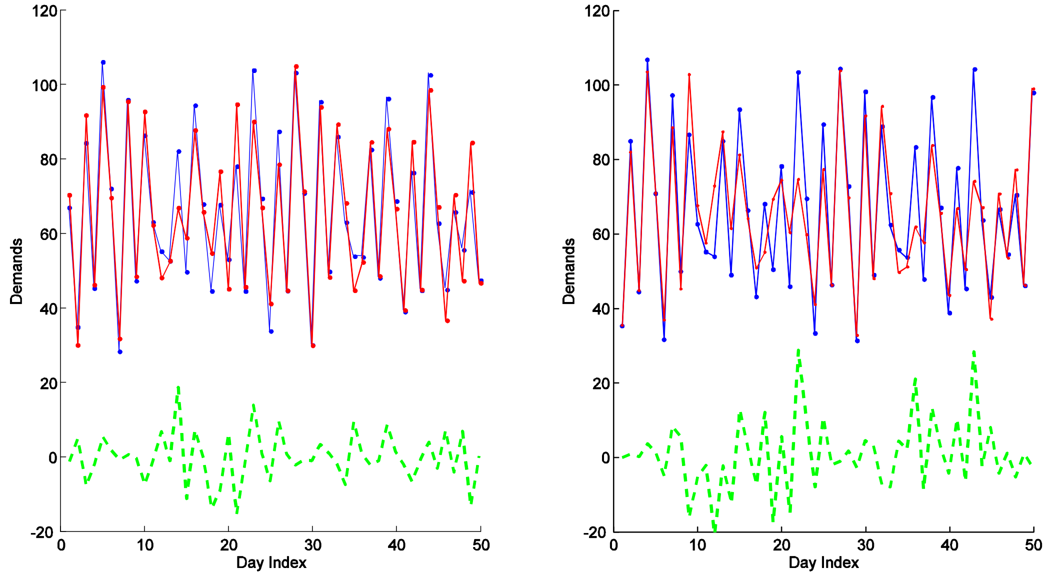


Figure 6.7 The prediction obtained by the MDL-optimal neural network with time lag equal to five (left panel) and six (right panel).

For brevity we do not present longer time-lag predictions of MDL-optimal neural networks since those predictions become much more stochastic. Figure 6.8 describes the prediction accuracy rate of MDL-optimal neural networks vs. different time lags (from one to ten). The prediction accuracy rate is calculated in the same way as the previous section.

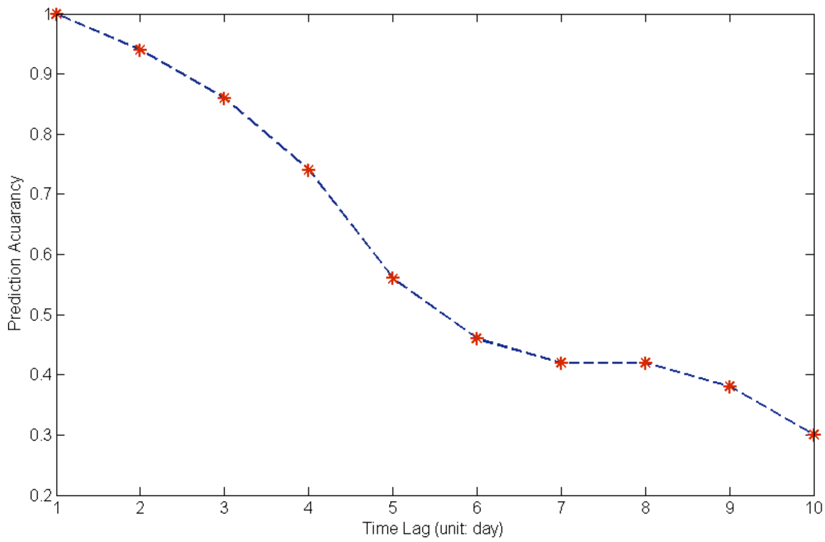


Figure 6.8 Prediction accuracy rate of MDL-optimal networks with changing prediction time lags.

Note that the lead time of the supplier for delivering products is nine days. So it is unnecessary to predict the retailer demands for this product for more than ten days ahead. But in numerical simulation we compute the prediction errors when the time lag is equal to ten or more.

Substituting the required parameters, including prediction values into Equation 5, we can evaluate the most suitable time lag that minimizes the total cost. We implement the prediction for each time lag in 50 days and compute the cost in this period. We wish to estimate the optimal prediction time lag for the long-term cost. Table 6.2 summarizes these results. Calculation of the cost can be regarded as an objective function with respect to the variable, the time lag, which seeks for some kind of trade-off between the prediction errors and saving lead time.

Table 6.2 Total cost to the wholesaler using prediction with different time lags (unit: day).

Total Cost								
Time lag =1	Time lag =2	Time lag =3	Time lag =4	Time lag =5	Time lag =6	Time lag =7	Time lag =8	Time lag =9
52125	49373	46809	43002	39376	42956	45583	50217	64830

From this table, the prediction module can minimize the wholesaler's operation costs by predicting the fifth day retailer demand from the current day. Consider the scenario in which no prediction technique is used. The wholesaler orders the products when the retailer demand arrives. This produces a total cost of 56752. It is much larger than the cost when the prediction of demand is used. In particular, note that prediction of retailer demands of 5 days ahead (i.e. time lag equal to 5) can obtain 44.1% cost saving.

6.5 Observation

The research data has been collected through interviews of company owners and logistics managers. The historical data was collected from the information management system of the food wholesaling company. The company itself is considered a small and medium enterprise (SME) which is seeking optimal resources allocation. This case study can be regarded as a good example to illustrate the ISCS framework is not only applicable to large enterprises.

The analysis of each module allows a systematic evaluation of the performance of neural networks in terms of prediction accuracy and inventory cost. It also allows an estimation of optimal parameters including the optimal model size and prediction time lag. The optimal parameters obtained are saved in the knowledge base and will be assigned to the prediction module when the matched retailer demands come. Therefore, the ISCS can automatically identify data characteristics, select the optimal neural network for the given data, and optimize the prediction settings by minimization of the total cost. (A prototype based on the ISCS framework has been developed, and has been trialed at the food wholesaling company. The user interfaces can be found in Appendix A).

Chapter 7 Discussion

7.1 Discussion on the decision rule model for trans-shipment in a supply chain network

The ever-changing economic situation and the fierce (retail) business competition require the wholesaler section to be very cautious about cost and speed of delivery in order to remain competitive. Thus, the most challenging task for this section is to decide whether it is more appropriate to order the required quantity of goods from the list of suppliers, or to ask for a trans-shipment from other wholesalers within the enterprise.

In chapter 3, we describe a new decision rule model that computes all expected total costs and identifies the optimum arrangement of either to order the quantity needed from the suppliers directly or to replenish the goods from other wholesalers through trans-shipment. In many cases, wholesalers face a dilemma with their operations. When a sudden request for goods from a retailer exceeds the inventory on hand at the wholesaler, a decision has to be made in order to fulfill the demand. The wholesaler needs to evaluate whether it is appropriate to admit the loss generated due to the backorder (by ordering the goods from the suppliers) or to accept a trans-shipment from other wholesalers. The proposed decision rule model is based on the computation and comparison of the total costs of trans-shipping a certain portion of the demand, and in supplying the remaining portion from an external supplier.

7.2 Discussion on the decision rule model on wholesaler lateral trans-shipment and supplier replenishment to meet retailer demands

Due to the fierce competition of supplier replenishment and uncertain factors of retailer demands the wholesaler cannot always achieve the full replenishment in the negotiated lead time and correspondingly cannot fulfill all the retailer demands. This means that future research is needed which will analyze the effect of possible shortage as well as impulse retailer demand, to improve the prediction policy. In view of this issue, a joint optimization based on supplier selection, lateral transshipment, and retailer demands with priority has been studied (chapter 4). Its objective is to:

- select optimal combination of suppliers to order and replenish different types of products in order to minimize the ordering cost spent by a wholesaler;
- select optimal combination of wholesalers to minimize the cost for lateral trans-shipment and reduce the shortage cost if possible;
- meet retailer demands according to their priority so as to minimize the shortage cost.

Examples to illustrate the proposed decision rule model are organized into four scenarios, which generalize the common situation in a supply chain network. Results show that lateral trans-shipment may be made not only to save ordering cost for a wholesaler but also to reduce the shortage cost if necessary. More importantly, joint optimization can provide a globally optimal solution for a wholesaler to meet retailer demands.

7.3 Discussion on Intelligent Supply Chain System (ISCS)

In this research, the Intelligent Supply Chain System (ISCS) is proposed and it is designed to be applied in the cases where a company historical transaction data warehouse is available. The first focus is developing the Predictability Module (PM), which is able to perform predictability evaluation of demand data. The PM that comprises the surrogate data method will identify the characteristics of the recorded demand data. Those data that are identified as the predictable data are then fed to the following Optimized Forecast Module (OFM) for forecasting while others which are considered as the stochastic data will be excluded since it is impossible to make forecast on stochastic data. Understandability, there is an emphasis on the importance of the accuracy of historical transaction. This issue is vital, otherwise the outcomes of the predictability evaluation that are of little use to decision makers due to the incomplete/non consistent nature of the data that they are based upon.

The second focus is developing the OFM for predicting the forthcoming demands by using the developed MDL-optimal neural network algorithm. The experimental results have already demonstrated that the MDL-optimal neural network outperforms other candidate neural networks. However, due to the continuous evolvement of artificial intelligent technologies, a new and improve algorithm is always a possible. It should be emphasized that, under the designed OFM framework, its components can be modified in the future by introducing other artificial intelligent technologies, thus making new attempts to enhance the prediction quality and efficiency. For example, by using stochastic based search techniques, an optimal solution or sub-optimal solution with a better prediction quality may be easily found for relatively large-sized historical data sets in a reasonable amount of time.

The final focus is on developing the Decision Rule Module (DRM), so as to optimize the resource allocation within a supply chain network. In general, for a company with a scaled supply chain network, there may be numerous wholesalers and suppliers within its network. The possible combinations of these can be very large, which is worthwhile to develop DRM. However, if the number of possible combination is small, then development of DRM is not advisable, because a simple calculation using the conventional approach can find the optimal combination. In addition, if the company does not update its transactions on a designed regular basis, then the ISCS is inappropriate and may reduce the reliability of the suggested resource allocating plan.

Chapter 8 Conclusion and Future Work

8.1 Summary of Research Work

In this study, a practical three-echelon supply chain network with focus on the operation of the wholesaler has been investigated. We describe the derivation of the decision rule models that may be used for trans-shipment decision-making in supply chains made up of suppliers, wholesalers and retailers, in any local region. The suggested decision rule models will minimize the total expected future costs of the wholesaler when considering replenishment from one supplier and trans-shipment from one wholesaler. Some major advantages of this approach include the pragmatic inclusion of multiple suppliers for wholesalers as well as variable goods delivery lead times, both of which are important relaxations of the properties of previous models that neglect the central features of real operations in inventory systems. Another advantage of the present model is the straight-forwardness of its implementation which requires only direct calculations and a comparison of total costs. Numerical examples have also been included to illustrate the effectiveness of the technique. Receiving some kind of predictable retailer demands, we employ the information theory approach to estimate the MDL-optimal neural network so as to guarantee accurate prediction under different prediction time lags. Moreover, the prediction results are further combined with the practical inventory decision rules of the wholesaler aiming to minimize its inventory cost. The optimal prediction policy is eventually determined at this step. The optimal prediction policy exhibits the great advantage of saving the wholesaler's inventory cost in comparison with the usual cost without any prediction analysis.

8.2 Contributions of the Research

This research provided a generic methodology for the development of an Intelligent Supply Chain System (ISCS) with predictability evaluation of retailer demand and with a framework to integrate practical inventory decision rules of the company (wholesaler) aiming to minimize its inventory cost. This will help the companies to achieve dramatic improvements in critical business activities. Some new contributions of this research are summarized below:

(i) An innovative approach that formulates decision rule models, which can be used for trans-shipment decision making in supply chains (suppliers, wholesalers and retailers) in any local region. Such approach is based on the theories and corollaries behind the derivation of the decision rule models that explain the achievement in minimizing the total expected future costs of the wholesaler when considering replenishment from one supplier and trans-shipment from one wholesaler.

(ii) Since the real retailer demands depend on many stochastic features, their dynamics are identified by the employment of surrogate data method, so as to exclude the completely stochastic demands from the following predictability evaluation.

(iii) Based on some kind of predictable retailer demands, the employment of the developed MDL-optimal neural network can achieve accurate prediction under different prediction time lags. Experimental results demonstrate that the MDL-optimal neural network outperforms other candidate neural networks.

(iv) In this research, the design and implementation of an ISCS, which incorporates the decision rule models, embraces MDL-optimal neural network and surrogate data method to achieve accurate prediction of retailer demand and optimized resource allocation, has been introduced. Implementing ISCS in a food distributor (wholesaler) have been successful. This indicates that the approach could be used in other industries for achieving the same success.

8.3 Suggestions for Future Work

Some of the characteristics of the proposed algorithm and system to be investigated in future research are as follows.

(i) The proposed ISCS is limited to wholesale sector demonstrated in the case study. However, the principles and techniques can be extended to different industries with modifications. The proposed system still requires experienced engineers to assist in the development of decision rule models in order to obtain reliable improvement in business activities.

(ii) The design of predictability evaluation is a good approach in enhancing the subsequent forecasting performance. However, for a large enterprise with a scaled data warehouse, much effort is still required to perform predictability evaluation of its large demand data sets. In view of this, data mining approach can be adopted, with the objective to quickly downs-sizing the demand data sets.

(iii) Further research on the structural configuration of the system is needed in order to further enhance its benefits. In general, this model paves the way for a novel approach to deal with supply chain management in the area of resource allocation. It is recommended that researchers utilize this innovative novel approach to create value for (logistics) business operators, with the proposed ISCS framework, that ultimately can help the enterprise to achieve inventory control advantages.

References

Aburto, L. and Webber, R. (2003) "Demand forecast in a supermarket using a hybrid intelligent system", *Design and application of hybrid intelligent systems*, IOS Press, Amsterdam, Berlin, pp. 1076-1083.

Aburto, L. and Webber, R. (2007) "Improved supply chain management based on hybrid demand forecasts," *Applied Soft Computing*, vol. 7, pp. 136-144.

Acciani, G., Brunetti G. and Fornarelli, G. (2006) "Application of neural networks in optical inspection and classification of solder joints in surface mount technology," *IEEE Trans. Indus. Inform.*, vol. 2, No. 3, pp. 200-209.

Agrawal, V., Chao, X., Seshadri, S. (2004). "Dynamic balancing of inventory in supply chains". *European Journal of Operational Research*, Vol. 159, pp. 296–317.

Akaike, H. (1974) "A new look at the statistical model identification," *IEEE Trans. Autom. Control*, vol. AC-19, no. 6.

Alfredsson, P., J. Verrijdt. (1999) "Modeling emergency supply flexibility in a two-echelon inventory system", *Management Science*, vol. 45, pp. 1416-1431.

Armstrong, J. S. (1988). "Research needs in forecasting". *International Journal of Forecasting*, Vol. 4, pp. 449–465.

Amundson, S. D. (1998) “Relationships between theory-driven empirical research in operations management and other disciplines”, *Journal of Operations Management*, vol. 16, pp. 341-359.

Archibald T.W., Sassen, A.A.E. and Thomas, L.C. (1997) “An optimal policy for a two-depot inventory problem with stock transfer,” *Management Scienc*, vol. 43, pp. 173-183.

Aviv, Y. (2003) “A time-series framework for supply-chain inventory management, Operation Research”, vol. 51, pp. 210-227.

Axsäter, S. (1990) “Modeling emergency lateral trans-shipments in inventory systems”, *Management Science*, vol. 36, pp. 1329-1338.

Axsäter, S. (2003) “A new decision rule for lateral trans-shipments in inventory systems”, *Management Science*, vol. 49, pp. 1168-1179.

Axsäter, S. (2006) *Inventory Control*, New York, Springer.

Azoury, K.S. (1985) “Bayesian solution to dynamic inventory models under unknown demand distribution”, *Management Science*, vol. 31, pp.1150-1160.

Azoury, K.S. and Miller, B.L. (1984) “A comparison of the optimal ordering levels of Bayesian and non- Bayesian inventory models”, *Management Science,* vol. 30, pp. 993-1003.

Archibald, T.W., A.A.E. Sassen, and L.C. Thomas. (1997) “An optimal policy for a two-depot inventory problem with stock transfer”, *Management Science*, vol. 43, pp. 173-183.

Banks, J., Carson, J.S., Nelson B.L. and Nicol, D.M. (2001) *Discrete-Event System Simulation*, Prentice Hall.

Barron A. and Rissanen, J. (1998) “The minimum description length principle in coding and modeling,” *IEEE Trans. Inf. Theory*, vol. 44, no. 6, pp. 2743–2760.

Ballou, R.H. (1999) *Business Logistics Management: Planning, Organizing, and Controlling the Supply Chain*, London, Prentice Hall.

Ballou, R. H. (2002) *Enterprise Logistics Management – Supply Chain Planning, Organization and Control*, Beijing, China, Mechanical Industry Press.

Baumol, W.J., and Vinod, H.D. (1970) “An Inventory Theoretic Model of Freight Transport Demand”, *Management Science*, vol. 16, pp. 413-421.

Banerjee, A., Burton, J. and Banerjee, S. (2003). “A simulation study of lateral transshipments in a single supplier multiple buyers supply chain network”, *International Journal of Production Economics*, Vol. 81–82, pp. 103–114.

Bates, J. M. and Grange, C. W. (2000) "Review of guidelines for the use of combined forecasts", *European Journal of Operational Research*, Vol.50, pp.190-204.

Berry, D., Towill, D.R. and Wadsley, N. (1994) "Supply chain management in the electronics product industry", *International Journal of Physical Distribution & Logistics Management*, vol. 24, pp.20-32.

Bertrand, L.P. and J.H. Bookbinder (1998) "Stock redistribution in two-echelon logistics systems", *Journal of the Operational Research Society*, vol. 49, pp. 966-975.

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

Box, G.E.P., Jenkins, G.M. and Reinsel, G. (1994) *Time series analysis: forecasting and control*, Prentice Hall.

Boyer, K. K., Frohlich, T. M. and Hult, T. M. G. (2004) *Extending the supply chain: how cutting-edge companies bridge the critical last mile into customers' homes*, New York, American Management Association.

Bradford, J.W. and Sugrue, P.K. (1990) "A Bayesian approach to the two-period style-goods inventory problem with single replenishment and heterogeneous

Poisson demand", *The Journal of Operation Research Society,* vol. 41, pp. 211-218.

Burton, J. and Banerjee, A. (2005) "Cost-parametric analysis of lateral trans-shipment policies in two-echelon supply chains", *International Journal of Production Economics,* vol. 93-94, pp. 169-178.

Cai, K., Xia, J. T., Li, L. T. and Gui, Z. L. (2005) "Analysis of the electrical properties of PZT by a BP artificial neural network", *Computational Materials Science*, Vol.34, No.2, pp. 166-172.

Carter, M. W. and Price, C. C. (2001), *Operations Research: A Practical Introduction*. Boca Raton: CRC Press.

Diks E.B, De Kok A.G. (1996) "Controlling a Divergent Two-echelon Network with Transshipment using the Consistent Share Rationing Policy", *International Journal of Production and Economics,* Vol. 45, pp. 369-79.

Dorffner, G. (1996) "Neural Networks for time series processing," *Neural Network World*, vol. 6, no. 4, pp. 447-468.

Chan, L.M.A., Shen, Z.J.M., Simchi-Levi, D. and Swann, J.L. (2004) *Coordination of Pricing and Inventory Decisions: A Survey and Classification*, Kluwer Academic Publishers.

Chandra, C. and Kumar, S. (2001) "Enterprise architectural framework for supply-chain integration”, *Industrial Management and Data System*, vol. 101, pp. 290-303.

Chang, Y. and Makatsoris, H. (2001) “Supply chain modeling with simulation”, *International Journal of Simulation: Systems, Science & Technology*, vol. 2, pp. 24-30.

Chang, P.C., Liu, C.H. and Wang, Y.W. (2006) “A hybrid model by clustering and evolving fuzzy rules for sales decision supports in printed circuit board industry,” *Decision Support System*, vol. 42, pp. 1254–1269.

Chang, P.C., Wang, Y.W. and Liu, C.H. (2006) “The development of a weighted evolving fuzzy neural network for PCB sales forecasting”, *Expert Systems with Applications*, vol. 32, pp. 86-96.

Chang, P.C., Lai, C.Y. and Lai, K.R. (2006) “A hybrid system by evolving case-based reasoning with genetic algorithm in wholesaler’s returning book forecasting”, *Decision Support Systems*, vol. 42, pp. 1715–1729.

Chang, P.C., Liu C.H. and Lai, R.K. (2008) “A Fuzzy Case-Based Reasoning Model for sales forecasting in Print Circuit Board industries”, *Expert Systems with Applications*, vol. 34, pp. 2049-2058.

Chang, P.C. and Wang, Y.W. (2006) “Fuzzy Delphi and back-propagation model for sales forecasting in PCB industry”, *Expert Systems with Applications*, vol. 30, pp. 715–726.

Chase, C. W. (1993). “Ways to improve sales forecasts”. *Journal of Business*

Forecasting, Vol. 12, pp. 15–17.

Chatfield, D.C. and Haya, J.C. (2008) “All-zero forecasts for lumpy demand: a factorial study”, *International Journal of Production Research*, vol. 45, no. 4, pp. 935-950.

Chau, K. W. (2007) “Reliability and performance-based design by artificial neural network”, *Advances in Engineering Software*, Vol.38, No.3, pp. 145-149.

Chen, F.R. and Song, J.S. (2001) “Optimal policies for multi-echelon inventory problems with Markov-modulated demand”, *Operations Research*, vol. 49, pp. 226-234.

Chen, I. J. and Paulraj, A. (2004) “Understanding supply chain management: critical research and a theoretical framework”, *International Journal of Production Research*, vol. 42, pp.131-163.

Chen, Z.Z., Shan C.H. and Zhu, H.L. (2007) “Adaptive Fuzzy Sliding Mode Control Algorithm for a Non-Affine Nonlinear System,” *IEEE Trans. Indus. Inform.*, vol. 3, no. 4, pp. 302-311.

Chen, X. and Simchi-Levi, D. (2004) "Coordinating inventory control and pricing strategies with random demand and fixed ordering cost", *Operations Research*, vol. 52, no. 6, pp. 887-896.

Chien, Te-king, Su, Chin-Ho and Su, Chao-ton (2002) “Implementation of a customer satisfaction program: a case study”, *Industrial Management and Data*

Systems, vol. 102, pp.252-259.

Choi, T.M., Li, D. and Yan, H.M. (2004) "Optimal single ordering policy with multiple delivery modes and Bayesian information updates", *Computers & Operations Research*, vol. 31, pp. 1965-1984.

Chopra, S. and Meindle, P. (2001) *Supply chain management: strategy, planning, and operation*, NJ: Prentice Hall.

Christopher, M. (1992) *Logistics and Supply Chain Management*, London: Pitman Publishing.

Christopher, M. (2000) "The agile supply chain: Competing in volatile markets", *Industrial Marketing Management*, vol. 29, pp. 37-44.

Christy, D.P., and Grout, J.R. (1994) "Safeguarding Supply Chain Relationships", *International Journal of Production Economics*, vol. 36, pp. 233-242.

Conejo, A. J., Plazas, M. A., Espínola, R. and Molina, A. B. (2005) "Day-ahead electricity price forecasting using the wavelet transform and ARIMA models", *IEEE Trans, Power Systems*, Vol.20, No.2, pp.1035-1042.

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*, vol.4, pp. 13-24.

Cooper, M. C., Lambert, D. M. and Pagh, J. D. (1997) “Supply chain management: More than a new name for logistics”, *The International Journal of Logistics Management*, vol. 8, pp. 1-14.

Copacino, W. C. (1997) *Supply chain management*, FL: Saint Lucie Press.

Coyle, J.J., Bardi, E.J., and Langley, C.J. (2003) *The Management of Business Logistics: A Supply Chain Perspective*, Ohio: South-Western/Thomson Learning.

Croom, S., Romano, P. and Giannakis, M. (2000) “Supply chain management: An analytical framework for critical literature review”, *European Journal of Purchasing & Supply Management*, vol. 6, pp. 67-83.

Das, C. (1975) “Supply and redistribution rules for two-location inventory systems: One period analysis”, *Management Science*, vol. 21, pp. 765–776.

Das, A. and Handfield, R. B. (1997) “A meta-analysis of doctoral dissertations in purchasing”, *Journal of Operations Management*, vol. 15, pp. 101-121.

Davidrajuh R. (2000) “Modelling and implementation of supplier selection procedures for e-commerce initiatives,” *Industrial Management and Data Systems*, vol. 103, pp. 28-38.

DeRoeck, R. (1991). “Is there a gap between forecasting theory and practice? A personal view”. *International Journal of Forecasting*, Vol. 7, pp. 1–2.

Diks, E.B. and De Kok, A.G. (1996) “Controlling a divergent 2-echelon network with trans-shipments using the consistent appropriate share rationing policy”, *International Journal of Production and Economics*, vol. 45, pp. 369-379.

Doganis, P., Alexandridis, A., Patrinos, P. and Sarimveis, H. (2006) “Time series sales forecasting for short shelf-life food products based on artificial neural networks and evolutionary computing,” *Journal of Food Engineering*, Vol. 75, No. 2, pp. 196-204.

Dong, L.X. and Lee, H.L. (2003) “Optimal policies and approximations for a serial multiechelon inventory system with time-correlated demand”, *Operation Research*, vol. 51, pp. 969-980.

Dong, L.X., and N. Rudi. (2004) “Who benefits from trans-shipment? Exogenous vs. endogenous wholesale prices”, *Management Science*, vol. 50, pp.645-657

Elmaghraby, W., and Keskinocak, P. (2003) "Dynamic pricing in the presence of inventory considerations: Research overview, current practices, and future directions", *Management Science*, vol. 49, no. 10, pp. 1287-1309.

Elmuti, D. (2002) “The perceived impact of supply chain management on organization effectiveness”, *Journal of Supply Chain Management*, vol. 38, pp. 49-57.

Erenguc, S.S., Simpson, N. and Vakharia, A.J. (1999) “Integrated production/distribution planning in supply chains: An invited review", *European Journal of Operational Research*. vol. 115, no. 2, pp. 219–236.

Faraway J. and Chatfield, C. (1998) "Time series forecasting with neural networks: a comparative study using the airline data," *Applied Statistics*, Vol. 47, No. 2, pp. 231-250.

Forrester, J. W. (1958), "Industrial dynamics: A major breakthrough for decision makers", *Harvard Business Review*, vol. 38 (July/August), pp.37-66.

Forrester, J.W. (1961), *Industrial Dynamics*, MA: MIT Press.

Fredrik Olsson (2009) "Optimal Policies for Inventory Systems with Lateral Transshipments", *International Journal of Production Economics, Vol. 118, No. 1, pp. 175–184*.

Frees, E. W. and Miller, T. W. (2004). "Sales forecasting using longitudinal data models". *International Journal of Forecasting*, Vol. 20, No. 1, pp. 99–114.

Ganeshan, R., Jack, E., Magazine, M. J. and Stephens, P. (1999), A taxonomic review of supply chain management research, in Tayur, S., Ganeshan, R. and Magazine, M., *Quantitative Models for Supply Chain Management*, pp. 841-879.

Ghodsypour S. H. and O'Brien, C. (1998) "A decision support system for supplier selection using an integrated analytic hierarchy process and linear programming," *International Journal of Production Economics*, vol. 56-57, pp. 199-212.

Ghodsypour S. H. and O'Brien, C. (2001) "The total cost of logistics in supplier selection, under conditions of multiple sourcing, multiple criteria and capacity constraint," *International Journal of Production Economics*, vol. 73, no. 1, pp. 15 – 27.

Gilbert, K. (2005) "An ARIMA supply chain model," *Management Science.*, vol. 51, no. 2, pp. 305-310.

Goldberg, D. E. (1989) *Genetic Algorithms in Search, Optimization, and Machine Learning*, Reading, Mass.: Addison-Wesley.

Grahovac, J. and Chakravarty, A. (2001) "Sharing and lateral trans-shipment of inventory in a supply chain with expensive low-demand items", *Management Science*, vol. 47, pp. 579-594.

Graves, S.C. (1999) "A single-item inventory model for a non-stationary demand process", *Manufacturing & Service Operations Management*, vol. 1, pp. 50-61.

Graves, S.C. and Willems, S.P. (2008) "Strategic inventory placement in supply chains: Nonstationary demand", *Manufacturing & Service Operations Management*, Vol. 10, No. 2, pp. 278-287.

Guinet, A. (2001) “Multi-site planning: A trans-shipment problem”, *International Journal of Production Economics*, vol. 74, pp. 21-32.

Gross D. (1963) “Centralized Inventory Control in Multi-location Supply Systems” *In: Scarf HE, Gilford DM, Shelly MW,* Editors, “Multistage Inventory Models and Techniques”, *Stanford University Press, Stanford*, CA, pp. 47-84.

Hameri, A.P. und Palsson J. (2003). “Supply Chain Management in the Fishing Industry: the Case of Iceland”, *International Journal of Logistics: Research and Application*, Vol. 6, pp. 137-149.

Handfield, R. B. and Melnyk, S. A. (1998) “The scientific theory-building process: A primer using the case of TQM”, *Journal of Operations Management*, vol. 16, pp. 321-339.

Handfield, R. B. and Nichols, E. L. (1999) *Introduction to Supply Chain Management*, Prentice Hall, New Jersey.

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

Harpaz, G., Lee, W.Y., and Winkler, R.L. (1982) “Learning, Experimentation, and the Optimal Output Decisions of a Competitive Firm”, *Management Science*, vol. 28, pp. 589-603.

Heizer, J. and Render, B. (2011) *Principles of Operations Management*, 8th edition, Prentice Hall.

Heizer, J., & Render, B. (2011). *Short-Term Scheduling. In Principles of Operations Management*. Upper Saddle River: Pearson.

Herer, Y.T. and M. Tzur. (2001) “The dynamic trans-shipment problem”, *Naval Research Logistics*, vol. 48, pp.386-408.

Herer Yale T., Tzur Michal, Yucesan Enver (2002). “Transshipments: emerging inventory recourse to achieve supply chain leagility”, *International Journal of Production Economics,* Vol. 80, pp. 201-212.

Herer, Y.T. and M. Tzur. (2003) “Optimal and heuristic algorithms for the multi-location dynamic trans-shipment problem with fixed trans-shipment costs”, *IIE Transactions*, vol. 35, pp. 419-432.

Herrer, Y.T., Rashit, A. (1995) “Lateral stock transshipments in a two-location inventory system”, *Proceedings of the 13th International Conference on Production Research*, Jerusalem, Israel, pp. 593–595.

Herer, Y. T. and Tzur, M. (2003) “Optimal and heuristic al-gorithms for the multi-location dynamic transshipment problem with fixed transshipment costs,” *IIE Transactions*, vol. 35, pp. 419-432.

Hill, T., O’Connor, M. and Remus, W. (1996) “Neural networks for time series forecasts," *Management Sci*ence, vol. 42, no. 7, pp. 1082–1092.

Hill, R.M. (1999) "Bayesian decision-making in inventory modeling", *IMA Journal of Mathematics Applied in Business & Industry*, vol. 10, pp. 147-163.

Hillier, F.S. and Lieberman, G.J. (2002) *Introduction to Operations Research*, 7th edition, McGraw-Hill.

Hoadley, B., Heyman, D.P. (1977) "A two-echelon inventory model with purchases, dispositions, shipments, returns and trans-shipments", *Naval Research Logistics*, vol. 24, pp. 1–19.

Holland, J. H. (1975) *Adaption in Natural and Artificial Systems*, MIT Press.

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

Hugos, M. (2003) *Essentials of Supply Chain Management*, Hoboken, NJ: John Wiley & Sons.

Judd, K. and Mees, A. I. (1995) "On selecting models for nonlinear time series," *International Journal of Physical Distribution and Logistics Management*, vol. 82, pp. 426-444.

Johnson, G.D., and Thompson, H.E. (1975) "Optimality of Myopic Inventory Policies for Certain Dependent Demand Process", *Management Science*, vol. 21, pp. 1303-1307.

Jonsson H. and Silver E.A. (1987) "Analysis of a Two-echelon Inventory Control System with Complete Redistribution", *Management Science*, Vol. 33, pp. 215-27.

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*, vol. 15, pp. 16-26.

Joshi, R.K. (2009) *International Business*, Oxford University Press.

Jösson, H., Silver, E.A. (1987) "Analysis of a two-echelon inventory control system with complete redistribution", *Management Science*, vol. 33, pp. 215–227.

Kamath, K.R. and Pakkala, T.P.M. (2002) "A Bayesian approach to a dynamic inventory model under an unknown demand distribution", *Computers & Operations Research*, vol. 29, pp. 403-422.

Karmarkar, U.S. (1987) "The multi-location multi-period inventory problem: Bounds and approximations", *Management Science*, vol. 33, pp. 86-94.

Karmarkar, U.S. and Patel, N.R. (1977) "The one-period N-location distribution problem", *Naval Research Logistics*, vol. 24, pp. 559–575.

Kranenburg, A.A. (2006). “Spare parts inventory control under system availability Constraints”, Ph.D. Dissertation, Eindhoven University of Technology.

King, R.T.F.A., Radha, B. and Rughooputh, H.C.S. (2004) “A fuzzy logic controlled genetic algorithm for optimal electrical distribution network reconfiguration,” *Proceedings of 2004 IEEE International Conference on Networking, Sensing and Control*, Taipei, Taiwan, Mar. 21 – 23, pp. 577 – 582.

Köchel, P., Kunze, S. and Nieländer, U. (2003) “Optimal control of a distributed service system with moving resources: Application to the fleet sizing and allocation problem”, *International Journal of Production Economics*, vol. 81-82, pp. 443-459.

Koster, René de, Le-Duc, Tho and Roodbergen, Kees Jan (2007) “Design and control of warehouse order picking: A literature review”, *European Journal of Operational Research*, vol. 182, issue 2, pp. 481-501.

Krishnan, K. and Rao, V. (1965) “Inventory control in N warehouses”, *Journal of Industrial Engineering*, vol. XVI, pp. 212–215.

Kuo C. and Reitsch, A. (1995) “Neural networks vs. conventional methods of forecasting,” *J. Business Forecast. Meth. Syst.*, vol. 14, no. 4, pp. 17–22.

Lambert, D., Stock J. and Elbron, L. (1998) *Fundamentals of Logistics Management*, Irwin McGraw-Hill, Irvin.

Lambert, D.M. and Cooper, M.C. (2000) “Issues in supply chain management”, *Industrial Marketing Management*, vol. 29, pp. 65-83.

Lamothe, J., Hadj-Hamou, K. and Aldanondo, M. (2006) “An optimization model for selecting a product family and designing its supply chain,” *European Journal of Operational Research*, vol. 169, no. 3, pp. 1030 – 1047.

Lee, H.L. (1987) “A multi-echelon inventory model for repairable items with emergency lateral trans-shipments”, *Management Science,* vol. 33, pp. 1302–1316.

Lee, H.L. and Billington, C. (1992) “Managing supply chain inventory: pitfalls and opportunities”, *Sloan Management Review*, vol. 33, pp. 65-73.

Lee, W. I. (2010). “The development of a qualitative dynamic attribute value model for healthcare institutes”. *Iranian Journal of Public Health,* Vol. 39, No. 4, pp. 15–25.

Lee, W. I., Chen, C.W., Chen, T. H. and Chen, C. Y. (2010). “The relationship between consumer orientation, service value, medical care service quality and patient satisfaction: The case of a medical center in Southern Taiwan". *African Journal of Business Management*, Vol. 4, No. 3, pp. 448–458.

Lee, Ying-Lien, Hwang, Sheue-Ling and Wang, Eric Min-Yang (2006) "An integrated framework for continuous improvement on user satisfaction of information systems," *Industrial Management and Data Systems*, vol. 106, pp.581-595.

Lee, Y. H., Jung, J. W. and Jeon, Y. S. (2007) "An effective lateral transshipment policy to improve service level in the supply chain," *International Journal of Production Economics*, vol. 106, no. 1, pp. 115 – 126.

Lertpalangsunti, N., Chan, C.W., Mason, R. and Tontiwachwuthikul, P. (1999) "A toolset for construction of hybrid intelligent forecasting systems: application of water demand prediction," *Artificial Intelligence in Engineering*, vol. 13, pp. 21-42.

Leslie, K., Vokurka, R. and Lummus, R. (2003) "A conceptual model of supply chain flexibility," *Industrial Management and Data Systems*, vol. 103, pp.446-456.

Leung, H.C. (1995) "Neural networks in supply chain management," *Proceedings of IEEE International Conference on Engineering Management*, pp. 347-352.

Lu, X.W., Song J.S., and Regan, A. (2006) "Inventory planning with forecast updates: approximate solutions and cost error bounds", *Operations Research,* vol. 54, pp. 1079-1097.

Lummus, R. R. and Vokurka, R. J. (1999) "Defining supply chain management: a historical perspective and practical guidelines", *Industrial Management & Data System,* vol. 99, pp. 11-17.

Mahmoud, E., DeRoeck, R., Brown, R. G. and Rice, G. (1992). "Bridging the gap between theory and practice in forecasting". *International Journal of Forecasting*, Vol. 8, pp. 251–267.

Makridakis, S.,Wheelwright, S. C. and McGee,V. E. (1989). Forecasting methods for management (5th ed.). New York: Wiley.

Marshall, J.E., Gorecki, H., Korytowski, A., and Walton, K. (1992) *Time-Delay Systems: Stability and Performance Criteria with Applications*, New York: Ellis Horwood.

McCarthy,T. M.,Davis,D. F., Golicic, S. L. and Mentzer, J.T. (2006). "The evolution of sales forecasting management: A 20-year longitudinal study of forecasting practices". *Journal of Forecasting*, Vol. 25, pp. 303–324.

Melachrinoudis, E., and Min, H. (2002) “The Dynamic Relocation and Phase-Out of a Hybrid, Two-Echelon Plant/Warehousing Facility: A Multiple Objective Approach”, *European Journal of Operational Research*, vol. 123, pp. 1-15.

Mentzer, J.T. (2001) *Supply Chain Management*, Thousand Oaks, Calif: Sage Publications.

Minner, S. and Silver, E.A. (2005) “Evaluation of two simple extreme trans-shipment strategies”, *International Journal of Production Economics*, vol. 93-94, pp. 1-11.

Mohebbi, E. (2006) “A production-inventory model with randomly changing environmental conditions”, *European Journal of Operational Research*, vol. 174, pp. 539-552.

Nakamura, T., Judd, K., Mees, A. and Small, M. (2006) “A comparative study of information criteria for model selection,” *International Journal of Bifurcation and Chaos,* vol. 16, pp. 445-464.

Narasimhan, R. and Das, A. (1999) “Manufacturing agility and supply chain management practices”, *Production and Inventory Management Journal*, vol. 40, pp. 4-10.

Nagy, Gábor and Salhi, Saïd. (2007) “Location-routing: Issues, models and methods”, *European Journal of Operational Research*, vol. 177, issue 2, pp. 649-672.

Niculescu, S.I., Verriest, E.I., Dugard, L., and Dion, J.M. (1997) “Stability and Robust Stability of Time-Delay Systems: A Guided Tour”, In Dugard, L., and Verriest, E.I. (Eds), *Stability and Control of Time-Delay Systems*, London: Springer-Verlag, pp. 1-71.

Oliver, R.K. and Webber, M.D. (1982) *Supply Chain Management: Logistics Catches Up With Strategy, Logistics: The Strategic Issues*, London: Chapman and Hall.

Ozen, T. and Garibaldi J.M. (2011) “Effect of Type-2 Fuzzy Membership Function Shape on Modelling Variation in Human Decision Making”, *Proceedings of IEEE International Conference on Fuzzy Systems*, pp. 210-220.

Pegels, C.C. and Jelmert, A.E. (1970) “An Evaluation of Blood-Inventory Policies: A Markov Chain Application”, *Operations Research*, vol. 18, pp. 1087-1098.

Peng, Z. Z. (1997) *Mathematical Model and the Modeling Method*, Dalian, China, Dalian Maritime University Press.

Prasad, S., Babbar, S. (2000) “International operations management research”, *Journal of Operations Management*, vol. 18, pp. 209–247.

Renaud, J., Laporte, G. and Boctor, F. F. (1996) “A tabu search heuristic for the multi-depot vehicle routing problem,” *Computers & Operations Research*, vol.

23, no. 3, pp. 229 – 235.

Rissanen, J. (1989) *Stochastic complexity in statistical inquiry*, World Scientific, Singapore.

Robinson, L.W. (1990) “Optimal and approximate policies in multi-period, multi-location inventory models with trans-shipments”, *Operations Research*, vol. 38, pp. 278–295.

Rosenshine M. and Obee D. (1976). “Analysis of a standing order inventory system with emergency orders”, *Operations Research*, vol. 24, no. 6, pp. 1143-1155.

Ross, D. F. (1998), *Competing through supply chain management*, New York: Chapman & Hall.

Rudi, N., S. Kapur, and D. Pyke. (2001) “A two-location in-ventory model with trans-shipment and local decision making”, *Management Science*, vol. 47, pp. 1668-1680.

Sabel, C., Herrigel, G., Kazis, R. and Deeg, R. (1987) “How to keep mature industries innovative”, *Technology Review*, vol. 90, pp. 26-35.

Salvador, F., Forza, C., Rungtusanatham, M. and Choi, T. Y. (2001) “Supply chain interactions and time-related performances: An operations management perspective", *International Journal of Operations & Production Management*, vol. 21, pp. 461-475.

Slack, N. (1991) *The Manufacturing Advantage*, London: Business Books.

Scarf, H. (1959) "Bayes solution of the statistical inventory problem", *Annals of Mathematical Statistics*, vol. 30, pp. 490-508.

Scarf, H. (1960) "Some remarks on Bayes solution to the inventory problem", *Naval Research Logistics*, vol. 7, pp. 591-596.

Sethi, S.P. and Cheng, F. (1997) "Optimality of (s, S) policies in inventory models with Markovian demand", *Operations Research*, vol. 45, pp. 931-939.

Sethi, S.P., Yan, H.M., and Zhang, H.Q. (2003) "Inventory models with fixed costs, forecast updates and two delivery modes", *Operations Research*, vol. 51, pp. 321-328.

Shih, B. Y. and Chung, Y. S. (2008). "The development of a CFM hybrid artificial sale forecasting model". *International Journal of Electronic Business Management*, Vol. 6, No. 3, pp. 227–236.

Simchi-Levi, D., Kaminsky, P., and Simchi-Levi, E. (2003) *Designing and Managing the Supply Chain: Concepts, Strategies, and Case Studies*, New York: McGraw-Hill.

Small M. and Tse, C.K. (2002) "Minimum description length neural networks for time series prediction," *Physical Review* E, vol. 66, pp. 066701.

Small M. and Tse, C.K. (2003) "Detecting determinism in time series: the method of surrogate data," *IEEE Trans. on Circuits and System-I*, Vol. 50, pp. 663-672.

Simon, H.A. (1952) "On the Application of Servomechanism Theory in the Study of Production Control", *Econometrica*, vol. 20, pp. 247-268.

Song, J.S. and Zipkin, P. (1993) "Inventory control in a fluctuating demand environment", *Operations Research*, vol. 41, pp. 351-370.

Stevens, G.S. (1989) "Integrating the supply chain", *International Journal of Physical Distribution and Logistics Management*, vol. 19, pp. 3-8.

Supply Chain Council (2004) http://www.supply-chain.org.

Tan, K. C., Kannan, V. R. and Handfield, R. B. (1998) "Supply chain management: supplier performance and firm performance", *International Journal of Purchasing and Materials Management*, vol. 3, pp. 2-9.

Tan, K. C. (2001) "A framework of supply chain management literature", *European Journal of Purchasing & Supply Management*, vol. 7, pp. 39-48.

Tagaras, G. (1989) "Effects of pooling on the optimization and service levels of two-location inventory systems", *IIE Transactions*, vol. 21, pp. 250–257.

Tagaras, G. and M. Cohen. (1992) "Pooling in two-location inventory systems with non-negligible replenishment lead times”, *Management Science*, vol. 38, pp. 1067-1083.

Tagaras, G. (1999) “Pooling in Multi-Location Periodic Inventory Distribution Systems”, *Omega*, vol. 27, pp. 39-59.

Terwiesch, T., Ren, Z.J., Ho, T.H. and Cohen, M.A. (2005) “An empirical analysis of forecast sharing in the semiconductor equipment supply chain,” *Management Science,* vol. 51, no. 2, pp. 208-220.

Theiler, J., Eubank, S., Longtin, A., Galdrikian, B. and Farmer, J. D. (1992) “Testing for nonlinearly in time series: The method of surrogate data,” *Phys. D*, vol. 58, pp. 77-94.

Thomas, D.J. (1999) “Why your supply chain doesn’t work”, *Logistics Management and Distribution Report*, vol. 38, pp. 42-44.

Thomas, D. J. and Griffin, P. M. (1996) “Coordinated supply chain management”, *European Journal of Operational Research*, vol. 94, pp. 1-15.

Thomassey, S., Happiette, M. and Castelain, J.M. (2005) “A global forecasting support system adapted to textile distribution,” *International Journal of Production Economics*, vol. 96, pp. 81-95.

Thomassey, S. and Happiette, M. (2007). “A neural clustering and classification system for sales forecasting of new apparel items". *Applied Soft Computing*, Vol. 7, No. 3, pp. 1177–1187.

Thomassey, S. and Fiordaliso, A. (2006) "A hybrid sales forecasting system based on clustering and decision trees," *Decision Support Systems*, vol. 42, pp. 408– 421.

Toffner-Clausen, S. (1996) *System Identification and Robust Control: A Case Study Approach*, New York: Springer.

Treharne, J.T. and Sox, C.R. (2002) "Adaptive inventory control for non-stationary demand and partial information", *Management Science*, vol. 48, pp. 607-624.

Türkyilmaz, Ali and Özkan, Coskun (2007) "Development of a customer satisfaction index model: An application to the Turkish mobile phone sector," *Industrial Management and Data Systems*, vol. 107, pp.672-687.

Umeda, S. and Zhang, F. (2006) "Supply chain simulation: generic models and application examples", *Production Planning and Control*, vol. 17, pp. 155-166.

Vassilopoulos, A. P., Georgopoulos, E. F. and Dionysopoulos, V. (2007) "Artificial neural networks in spectrum fatigue life prediction of composite materials", *International Journal of Fatigue*, Vol.29, No.1, pp. 20-29.

Velten, K., Reinicke, R. and Friedrich, K. (2000) "Wear volume prediction with artificial neural networks", *Tribology International*, Vol.33, No.10, pp. 731–736.

Waters, D. (2003) *Logistics: An Introduction to Supply Chain Management*, New York: Palgrave Macmillan.

Weber, C. E. (2004) "More on complementarily and substitutability in the trans-shipment problem", *European Journal of Operational Research*, vol. 156, pp. 213-222.

Weigend, A. S., Rumelhart, D. E. and Huberman, B. A. (1991). "Generalization by weight-elimination with application to forecasting". *Advance Neural Information Processing Systems*, Vol. 3, pp. 875–882.

Winklhofer, H. and Diamantopoulos, A. (2003). "A model of export sales forecasting behavior and performance: Development and testing". *International Journal of Forecasting*, Vol. 19, No. 2, pp. 271–285.

Wong W., Cattrysse D. and D. Van Oudheusden. (2005) "Inventory pooling of repairable spare parts with non-zero lateral transshipment time and delayed lateral transshipments", *European Journal of Operational Research*. vol. 165, pp. 207-218.

Yang, J. and Qin Z.Q. (2007) "Capacitated production control with virtual lateral trans-shipments", *Operations Research*, vol. 55, pp. 1104-1119.

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, pp. 51-57.

Yalet. Herer, Michal Tzur and Enver Yucesan (2006) "The Multilocation Transshipment Problem", *IIE Transactions, Vol.* 38, pp. 185–200.

Yoo, H. and Pimmel, R.L. (1999) "Short-term load forecasting using a selfsupervised adaptative neural network," *IEEE Transactions on Power Systems*, vol. 14, pp. 779– 784.

Young, Hae Lee, Jung, Woo Jung and Young, Sang Jeon (2007) "An effective lateral transshipment policy to improve service level in the supply chain", *International Journal of Production Economics*, vol. 106, issue 1, pp. 115-126.

Yu, D.J., Small, M., Harrison R.G. and Diks, C. (2000) "Efficient implementation of the Gaussian kernel algorithm in estimating invariants and noise level from noisy time series data," *Phys. Rev.* E, Vol. 61, pp. 3750 – 3756.

Zhang, G.P. (2003) "Time series forecasting using a hybrid ARIMA and neural network model," *Neurocomputing*, vol. 50, pp.159–175.

Zhang, X. (2004) "Evolution of ARMA demand in supply chains", *Manufacturing & Service Operations Management*, vol. 6, pp. 195-198.

Zhao, Y., Sun, J.F. and Small, M. (2008) “Evidence consistent with deterministic chaos in human cardiac data: surrogate and nonlinear dynamical modeling,” *Inter. Jour. Bifur. Chaos*, Vol. 18, No. 2, pp. 141-160.

Zhao Y. and Small, M. (2006) “Minimum description length criterion for modeling of chaotic attractors with multilayer perceptron networks,” *IEEE Trans. Circ. Syst. I*, Vol. 53, No. 3, pp. 722-732.

Zomaya, A. Y. (2001) “Natural and simulated annealing,” *IEEE Computing in Science & Engineering*, vol. 3, no. 6, pp. 97 – 99.

Appendix A: The workflow in the Intelligent Supply Chain System (ISCS)

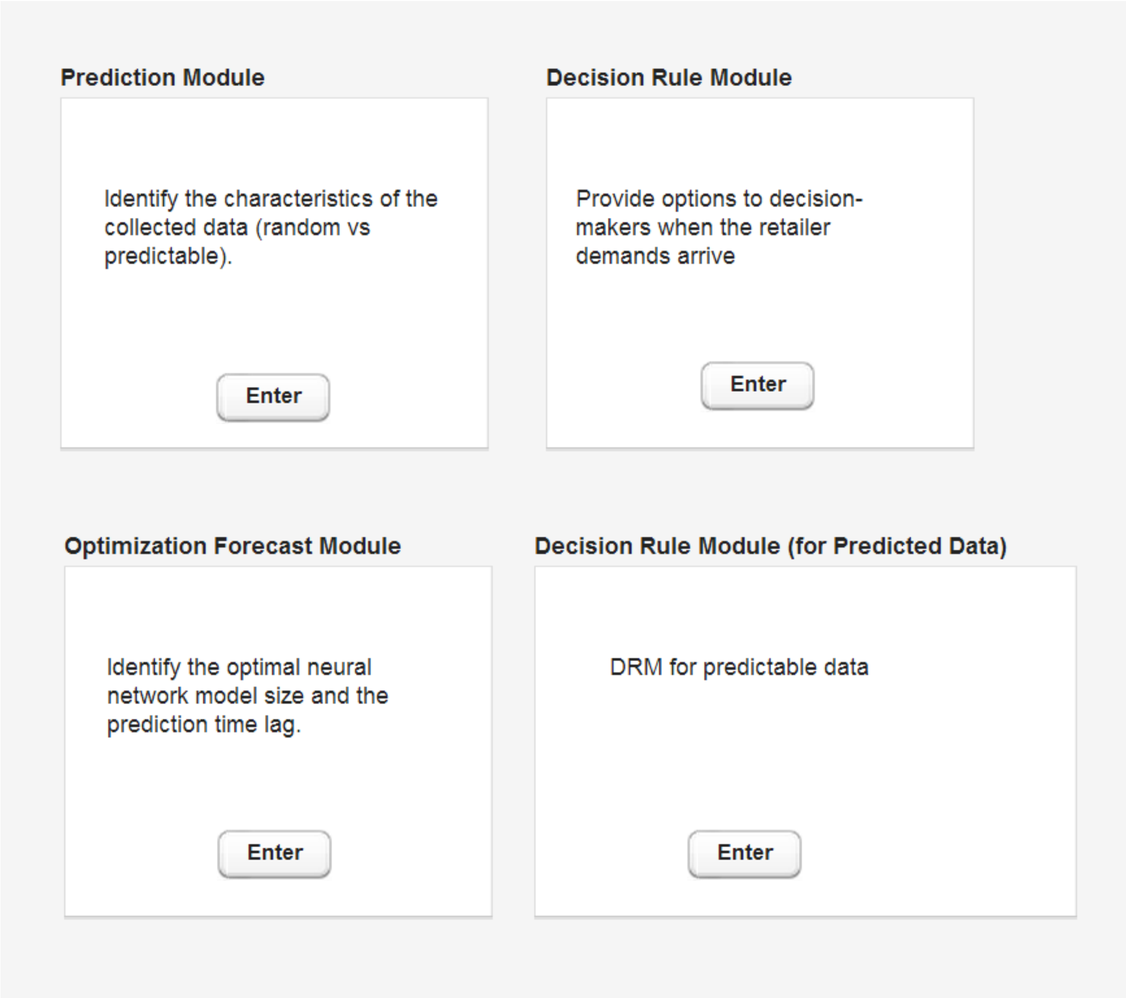
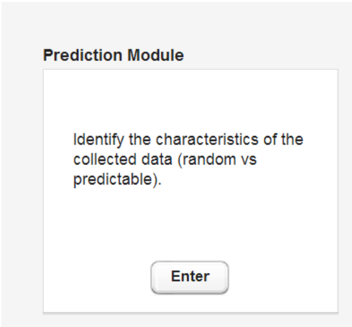
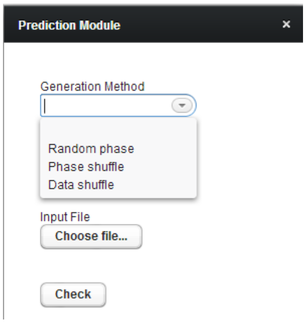
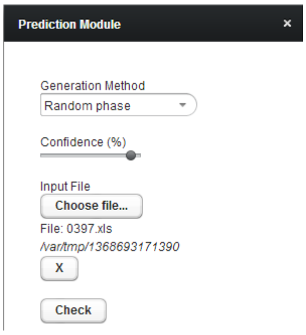
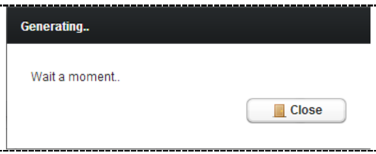
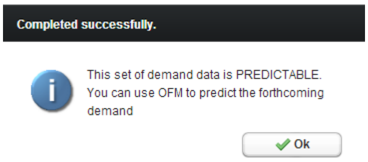
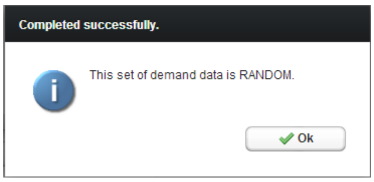


Figure A: The main menu of the prototype

Prediction Module – Predictability evaluation of demand data

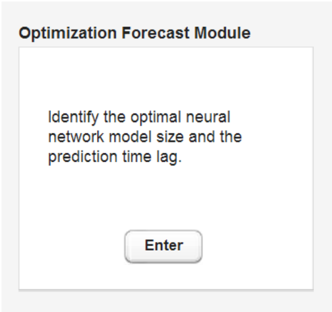
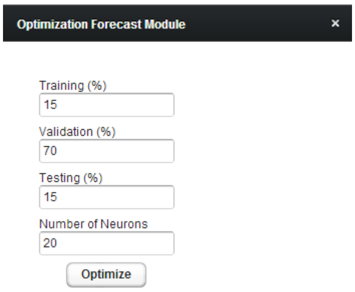
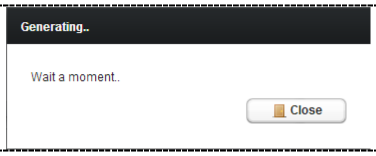
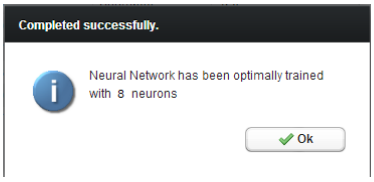
<table>
<tr><td>
</td><td>1. Click the <u>Enter</u> button to initiate the Prediction Module.</td></tr>
<tr><td>
</td><td>2. Select the <u>Generation Method</u>.
(e.g. Random phase)</td></tr>
<tr><td>
</td><td>3. Adjust the <u>Confidence (%)</u>.
4. Upload the <u>historical data</u> for analysis.
(e.g. excel file)
5. Click Check to start the evaluation..</td></tr>
<tr><td>
</td><td>6. Wait for the evaluation result.</td></tr>
<tr><td>


</td><td>Scenario 1 – PREDICTABLE
(go to Optimization Forecast Module)

Scenario 2 – RANDOM
(go to Decision Rule Module)</td></tr>
</table>

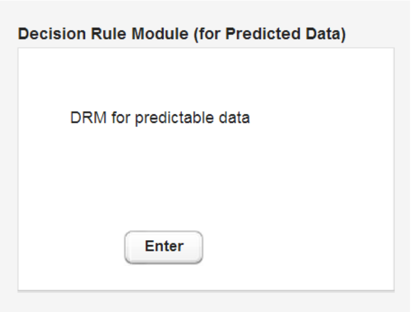
*In the case study (chapter 6), the result of predictability analysis indicated that, Product 0397 (Chinese soft drinks) was considered as predictable, while the Product 1582 (Chinese noodles) was considered as stochastic.

Optimization Forecast Module – Forecast analysis

<table>
<tr>
<td>
</td>
<td>1. Click the <u>Enter</u> button to initiate the Optimization Forecast Module.</td>
</tr>
<tr>
<td>
</td>
<td>2. Default values for <u>Training</u>, <u>Validation</u>, <u>Testing</u> and <u>Number of Neurons</u> should be listed. (Change the values if necessary)
3. Click Optimize to start the process.</td>
</tr>
<tr>
<td>
</td>
<td>4. Wait until the process is completed.</td>
</tr>
<tr>
<td>
</td>
<td>5. An dialogue box should appear to indicate the neural network has been optimally trained with a specific number of neurons.</td>
</tr>
</table>

*In the case study (chapter 6), the result of optimization forecast indicated that, for Product 0397 (Chinese soft drinks), the neural network was optimally trained with 8 neurons.

Decision Rule Module (for Predicted Data) – Scenario 1



1. Click the <u>Enter</u> button to initiate the **Decision Rule Module (for Predicted Data)**.

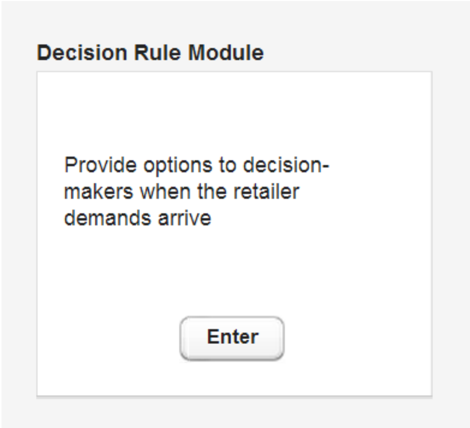
DATE	PREDICTED DEMAND	EXPECTED DEMAND	DEMAND	TRANSHIPMENT	SUPPLY COST	DECISION
2010-01-06	420	480	+60	---	---	
2010-01-13	420	300	-120	Available	1140	
2010-01-20	250	520	+270	---	---	
2010-01-27	150	200	+50	---	---	
2010-02-03	305	180	-125	Not Available	1187.5	
2010-02-10	310	100	-210	Available	1995	
2010-02-17	500	220	-280	Not Available	2660	

2. The predicted data would be retrieved from the **Optimization Forecast Module**.
   - System would list the <u>Predicted demand</u>, <u>Expected demand</u> and <u>their difference</u>.
   - System would also check <u>if transshipment is available</u>.
   - System would also calculate the necessary <u>purchase cost</u> based on demand difference.

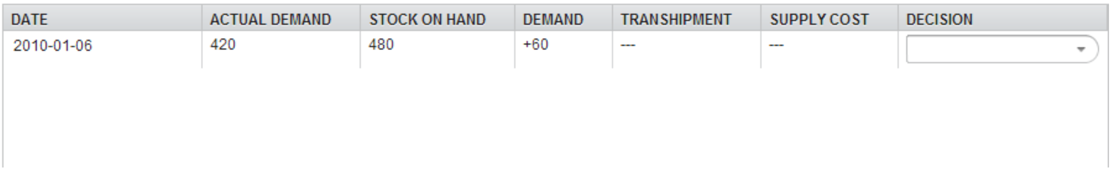
DATE	PREDICTED DEMAND	EXPECTED DEMAND	DEMAND	TRANSHIPMENT	SUPPLY COST	DECISION
2010-01-06	420	480	+60	---	---	
2010-01-13	420	300	-120	Available	1140	Transitment Purchase Order
2010-01-20	250	520	+270	---	---	
2010-01-27	150	200	+50	---	---	
2010-02-03	305	180	-125	Not Available	1187.5	
2010-02-10	310	100	-210	Available	1995	
2010-02-17	500	220	-280	Not Available	2660	

3. User can select either to place a <u>Transshipment order</u> for stock redistribution, or place a <u>Purchase order</u> to bring up the stock level.

Decision Rule Module – Scenario 2



1. Click the Enter button to initiate the **Decision Rule Module**.



2. System would list the Actual demand, Stock on hand and their difference.
3. System would also check if transshipment is available.
4. System would also calculate the necessary purchase cost based on demand difference.

5. User can select either to place a Transshipment order for stock redistribution, or place a Purchase order to bring up the stock level.