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**SINGLE PRODUCT PERIODIC REVIEW INVENTORY CONTROL AND
SUPPLIER SELECTION: OPTIMIZATION VIA SIMULATION APPROACH**

DEPARTMENT OF INDUSTRIAL ENGINEERING

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ABSTRACT

This study describes an Optimization via Simulation (OvS) model developed to analyze a (R, s, S) policy under stochastic environment and lost sales. In this model, Distribution Centers (DCs) are the stores that fulfill customer orders and Suppliers serve the products to supply the DCs replenishment orders. The inventory level of each DC and each Supplier is replenished periodically at one point in time for each period. The goal of this research is to substantially develop a realistic inventory model and to expand research on periodic review system. We also try to point out several important issues: what the optimal values of initial inventory, reorder point and order-up-to level are in (R, s, S) policy for each DC and each Supplier; whether the OvS can successfully integrate the supplier selection and (R, s, S) policy for supply chain environment; how to apply statistical analysis skills to clarify this policy with a greater level of detail. According to the results of statistical analysis including cost components analysis, quantity based analysis, order based analysis, probability based analysis, and lead time based analysis, proposed model help to properly control echelon inventory so that good customer service is maintained. Also, it can be easily applied for the actual situation of the supply chain inventory system and companies may obtain a remarkable amount of saving while increasing the competitive edge.

Keywords: *Supply chain management, Inventory control system, Supplier selection, (R, s, S) policy, Optimization via simulation, Genetic algorithm.*

TEK ÜRÜNLÜ PERİYODİK STOK KONTROLÜ VE TEDARİKÇİ SEÇİMİ: SİMÜLASYON OPTİMİZASYONU YAKLAŞIMI

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ÖZET

Bu çalışmada stokastik çevreyi ve kayıp satışı dikkate alan (R, s, S) politikasını analiz etmek için Simülasyon Optimizasyonu (OvS) modeli oluşturulmaktadır. Bu modelde, Dağıtım Merkezleri (DCler) müşteri siparişlerini karşılayan depolardır ve tedarikçiler ise DClerin yenileme siparişlerini karşılamak için imkan sağlamaktadır. Her DC ve her tedarikçinin stok seviyesi her periyot için belirli bir zaman diliminde periyodik olarak yenilenmektedir. Bu araştırmanın amacı, gerçekçi bir envanter modeli geliştirmek ve periyodik gözden geçirmeye dayalı sistemlerin araştırılmasını genişletmektir. Ayrıca, birkaç önemli konuyu: (R, s, S) politikasında her bir dağıtım merkezi ve her bir tedarikçi için başlangıç stoğu, yeniden sipariş noktası, maksimum sipariş miktarı seviyesinin optimum değerinin ne olduğu; OvS modelinin tedarikçi seçimi ve (R, s, S) politikasıyla birlikte başarıyla tedarik zincirine entegre olup olmadığı; daha detaylı bir analizle bu politikayı incelemek için istatistiksel analizlerin nasıl uygulanması gerektiğini açıklığa kavuşturmaya çalışmaktadır. Maliyet bileşen analizleri, miktar bazında analizler, sipariş bazında analizler, olasılık bazında analizler ve tedarik süresi bazında analizleri de içeren istatistiksel analizlerin sonuçlarına göre, oluşturulan model müşteri hizmetinin iyi bir şekilde devam ettirilebilmesi için uygun stok kontrolünü sağlamaktadır. Ayrıca, bu model tedarik zincirlerinin stok kontrolüne kolayca uygulanabilmekle beraber şirketlerin rekabet gücünü arttırırken kayda değer bir tasarrufta sağlamaktadır.

Anahtar Kelimeler: *Tedarik zinciri yönetimi, Stok kontrol sistemi, Tedarikçi seçimi, (R, s, S) politikası, Simülasyon optimizasyonu, Genetik algoritma.*

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TABLES OF CONTENTS

ABSTRACT	i
ÖZET	ii
ACKNOWLEDGEMENTS	iii
TABLE OF CONTENTS	iv
LIST OF FIGURES	vi
LIST OF TABLES	viii
LIST OF ABBREVIATIONS	ix
CHAPTER 1	
1. INTRODUCTION	1
1.1. Role of Inventory within the Supply Chain	2
1.2. Inventory Control System	5
1.3. Inventory Related Cost.....	7
1.4. Supplier Selection	9
1.5. Research Objectives and Contributions.....	10
1.6. Overview	12
CHAPTER 2	
2. LITERATURE REVIEW	13
2.1. (R, s, S) Inventory Control System and Supplier Selection	13
2.2. Lost Sales	16
2.3. Single Product	17
CHAPTER 3	
3. MATERIAL AND METHODS	19
3.1. Optimization via Simulation	19
3.1.1. Metaheuristics	20
3.1.2. Statistical Methods	21
3.1.2.1. Ranking and selection	21
3.1.2.2. Importance sampling	22
3.1.2.3. Multiple comparison procedures.....	22
3.1.3. Gradient based search	22
3.1.4. Metamodel methods.....	23
3.2. Proposed OvS	23
3.2.1. Optimization phase (Genetic Algorithm)	25
3.2.2. Simulation phase.....	32

3.3. Single Product Inventory Control Problem.....	33
CHAPTER 4	
4. RESULTS AND DISCUSSION.....	41
4.1. Cost Based Analysis	41
4.2. Lead Time Based Analysis for Each Model	66
CHAPTER 5	
5. CONCLUSIONS.....	79
REFERENCES.....	81

LIST OF FIGURES

Figure 3.1. The illustration of the simulation and optimization phase	24
Figure 3.2. Chromosome structure of GA	29
Figure 3.3. Crossover operator of GA.....	31
Figure 3.4. Mutation operator of GA	31
Figure 3.5. General structure of the proposed supply chain.....	36
Figure 4.1. Convergence of the GA towards the best solution in proposed model	41
Figure 4.2. The cost component and probability analysis of the DC1	43
Figure 4.3. The order analysis of the DC1	45
Figure 4.4. The cost component and probability analysis of the DC2	46
Figure 4.5. The order analysis of the DC2	47
Figure 4.6. The cost component and probability analysis of the DC3	49
Figure 4.7. The order analysis of the DC3	50
Figure 4.8. The comparison of total lost sales cost and total lost sales cost during lead time	51
Figure 4.9. The detailed cost component analysis of the Supplier3	52
Figure 4.10. The detailed cost component analysis of the Supplier4	53
Figure 4.11. The detailed cost component analysis of the Supplier5	55
Figure 4.12. Cost analysis of DCs and Suppliers.....	56
Figure 4.13. Evaluation of P1 for DCs	58
Figure 4.14. Evaluation of P1 for Suppliers	59
Figure 4.15. Evaluation of P2 for DCs	59
Figure 4.16. Evaluation of P2 for Suppliers	60
Figure 4.17. Evaluation of NPLO for DCs	60
Figure 4.18. Evaluation of NPLO for Suppliers	61
Figure 4.19. Evaluation of NTLO for DCs	62
Figure 4.20. Evaluation of TLOQ for DCs	62
Figure 4.21. Evaluation of NTMO for DCs	63
Figure 4.22. Evaluation of NTMO for Suppliers	63
Figure 4.23. Evaluation of PLOQ for DCs.....	64
Figure 4.24. Evaluation of PLOQ for Suppliers	64
Figure 4.25. Evaluation of TMOQ for DCs	65
Figure 4.26. Evaluation of TMOQ for Suppliers	65
Figure 4.27. The order met probabilities per replenishment lead time for periodic review	

system	70
Figure 4.28. Lead time analysis for each supply chain member in periodic review	
system	74
Figure 4.29. The average holding unit of supply chain members in periodic review	
system	74

LIST OF TABLES

Table 3.1. Classification of the OvS model	20
Table 3.2. The basic metaheuristics framework.....	21
Table 3.3. The summary of the GA applications in inventory management	26
Table 3.4. The values of parameters of GA	32
Table 3.5. Inventory related costs.....	37
Table 4.1. Average service levels and optimal values of inventory control parameters....	42
Table 4.2. The cost analysis of the DCs	57
Table 4.3. The cost analysis of the Suppliers	57
Table 4.4. The order met probabilities per lead time period for all DCs.....	67
Table 4.5. The lead time period ratio to review period	71
Table 4.6. The average holding unit in DCs and Suppliers	75

LIST OF ABBREVIATIONS

OvS	Optimization via Simulation
GA	Genetic Algorithm
DCs	Distribution Centers
R	Review Period
s	Reorder Point
S	Order-Up-To Level
Q	Order Quantity
(s, Q)	Reorder Point, Order Quantity
(s, S)	Reorder Point, Order-Up-To-Level
(R, S)	Review Period, Order-Up-To-Level
(R, s, S)	Review Period, Reorder Point, Order-Up-To-Level
P1	Order Met Probability per Period
P2	Overall Order Met Probability
TMOQ	Totally Met Order Quantity
TLOQ	Totally Lost Order Quantity
PLOQ	Partially Lost Order Quantity
NTMO	Number of Totally Met Order
NTLO	Number of Totally Lost Order
NPLO	Number of Partially Lost Order

CHAPTER 1

1. INTRODUCTION

Under intense competition, marginal profit is becoming thinner and thinner in recent years and hence companies should improve supply chain management to overcome today's management challenges. Supply chain management includes important decisions related with the management of supply chain assets and products, funds and information flows to maximize total supply chain profitability or minimize total supply chain cost (Chopra and Meindl, 2007). One of the most significant decisions influencing the performance of a supply chain is inventory management because it is pivotal in efficient and effective organization. In addition, it is crucial in the control of products that have to be stored. The main goal of inventory management is balancing the conflicting economics of not wanting to hold too much stock (Adeyemi and Salami, 2010). At this point, the exact determination of optimal inventory is needed because shortage of inventory increases the number of lost sales, while holding excess inventory can result in pointless storage costs. In this case, the determination of the inventory level to be held in supply chain members becomes inevitable so as to achieve goals for the supply chain.

To apply most effective inventory management, the inventory control system should provide enough information to allow managers to make decision on inventory. Hence, many researchers investigate to observe different impacts of the inventory control systems in terms of cost reduction. In this case, determining well-selected set of suppliers makes a strategic difference to an company's ability to ensure continued improvement in control policies. Although there are plenty of researches for the supplier selection model, only limited studies focused on the inventory control policies integrated with supplier selection, especially under stochastic demand and lead times. Also, existing literature on supply chain modeling are generally focused on mathematical modeling. However, mathematical modeling may not meet the expectation due to the high complexity of the problems and only small scale systems are amenable to this model. Also, optimization-based approaches generally require too many assumptions and simplifications to be applicable and effective. On the other hand, simulation based techniques can give reasonable solutions without analytical assumptions and simplifications. Also, simulation has an ability to capture specific features of the real object and to incorporate a greater level of detail (Paul and Chaney, 1998). Simulation provides illustrative insight into certain managerial problems where analytic solutions of the problem are not possible or where the actual environment is

difficult to observe within acceptable time. Simulation seems a remarkable recourse to model and analyze performances for such large-scale cases (Thierry et al., 2008). However, simulation models do not provide the capability of finding the optimum set of decision variables in terms of predefined objective function(s). This is made by optimization models that allow decision makers to find the best possible alternatives. Also, their impact on the system performance can be evaluated using simulation models. Therefore, integrating simulation and optimization into supply chain framework provides decision makers with a comprehensive solution toolbox (Omar et al., 2013) and known as OvS. OvS along with modern computing power is an answer to modeling complex supply chain problem and addressing aforementioned criticisms. OvS can model a system with as much details, realities, and complexities as the modeler wants and is satisfied with; hence, with fast computational resources, OvS could solve any real stochastic complex optimization problem (Kabirian, 2009). In this study, we used OvS model to determine the optimal values of reorder point, order-up-to level and initial inventory in DCs and Suppliers, and properly selecting the set of Suppliers for DCs. Thus, we presented (R, s, S) policy and supplier selection simultaneously in a two echelon supply chain under stochastic environment and lost sales system.

In this chapter, Sections 1.1 presents an overview of supply chain and the role of inventory in supply chain environment. Section 1.2 describes inventory control system. Section 1.3 presents inventory related cost. Section 1.4 describes general supplier selection methodologies. Section 1.5 presents the major contributions of this research and Section 1.6 provides an overview of this thesis.

1.1. Role of Inventory within the Supply Chain

Supply chain can be defined as a sequenced network of business partners which includes manufacturers, distributors, warehouses, retailers, suppliers and even customers themselves (Chopra and Meindl, 2007). Supply chains are the lifeblood of any organizations. To remain competitive, companies must provide high quality, high responsiveness and low cost in today's competitive environment. So they should know that managing supply chain plays a key role to organize total supply chain effectively. However, it includes high level of uncertainty in supply and demand, contradictory objectives, information ambiguity, and a great number of decision variables and constraints (Arisha and Abo-Hamad, 2010). Also, inventory management is a common problem to all organization in any supply chain management system because the cost of inventories accounts for approximately 30% of the value of the product and it directly

affects customer service level in a supply chain and plays a central role in improving supply chain performance.

Determining exact inventory level at each echelon in the supply chain without shortages and excesses while minimizing the total supply chain cost is a main concern for the inventory and supply chain managers. Finding optimal inventory is a key point to provide cost effective system because inventory shortage yields to lost sales, on the other hand excess inventory can cause pointless storage costs. Hence, inventory management at each supply chain member becomes inevitable in order to minimize the cost for the supply chain. Understanding of the whole supply chain perfectly is needed to develop an effective system because every company has different processes and different forms of inventories. Therefore, first of all we need to know why do companies hold inventory? The reasons for holding inventories can be summarized under 5 sub-heading:

1. It enables the company to achieve economies of scale,
2. It regularly balances demand and supply,
3. It provides specialization in manufacturing,
4. It enables protection from uncertainties in demand and order cycle,
5. It behaves as a buffer between critical interfaces within distribution channel (Lambert et al., 1998). These purposes, to a major extent, reflect the environment in which a company operates.

In inventory control, to provide effective system to customers the problem of determining the optimal type of inventory arises. There are many ways to categorize inventories but we recommend six broad decision categories for creating more effective and more responsive supply chains.

1. Cycle stock is the amount of inventory on hand, at any point, results from batches where demand is ordered or produced in batches instead of one unit at a time.
2. Congestion stock is inventory at hand because of products competing for limited capacity (When multiple products share the same production equipment, inventories of these products build up as they wait for the equipment to become available).
3. Safety stock is inventory at hand, on the average, to protection against the uncertainty of supply and the uncertainty of demand in the short run.

4. Anticipation inventory includes stock accumulated in advance of an expected peak in sales. It can also occur because of seasonality of supply.
5. Pipeline (or work-in process) inventory consists of goods in transit between levels of multi-echelon distribution system or between two adjacent workstations in a factory.
6. Decoupling stock is used in multi-echelon supply chains to allow for the separation of decision making at different echelons.

Note that these six functional categories were defined to concentrate attention on the organizational purposes of the inventories, especially with regard to control and manageability rather than on accounting measures (Silver et al., 1998). Defining which one to use depends on the properties of the company. After specifying inventory category, three important issues or problems should be answered in inventory management system.

1. How often the inventory level should be determined?
2. When a replenishment order should be placed?
3. How large the replenishment order quantity should be?

Regarding with the first issue, the less frequently the status is determined, the longer is the period over which the system must protect against unforeseen variation in demand to satisfy customer demand (Silver et al., 1998). On the other hand, if the status is determined more frequently, it may unnecessarily increase the cost of the system. Clearly, answer of this problem specifies the review period (R) which is the time that elapses between two consecutive moments at which we know the stock level. In literature, one of the two basic types of review systems: periodic review or continuous review is used in inventory management. It should be noted that continuous review provides same customer service level and it requires less safety stock but the load is less predictable under continuous review since replenishment decision can be made at practically any moment in time. On the other hand, periodic review provides a reasonable prediction of the workload on the staff involved and it is generally less expensive in terms of reviewing costs and reviewing errors (Silver et al., 1998). Hence, in most cases periodic review is particularly appealing. Regarding with the second problem, reorder point is stated in terms of the inventory level at which a replenishment order ought to be placed for updating the current stock of inventory. Thus, reorder point can be defined as the time of replenishment order. At this point, trade-off between the costs of ordering somewhat early and the costs of providing inadequate customer

service should be found. The answer of the third problem directly depends on the previous two issues and is expressed in terms of what is called 'order quantity'. Details can be found in (Silver et al., 1998). Note that all these questions are also interrelated with customer demands. Hence, demand distribution should be determined carefully. For example, Poisson distribution is generally preferred for slow moving items. On the other hand, the normal and gamma distributions have a better performance for fast moving items.

1.2. Inventory Control System

Existing inventory control systems differ in size and complexity, in the costs associated with operating the system, in the nature of the stochastic processes associated with the system, and the nature of the information available to decision makers at any given point in time. Under intense pressure, supply chain members try to find robust models and to improve replenishment policies in order to tackle with today's inventory management challenges. One of the most critical issues is to decide on the inventory level to be maintained at supply chain members while minimizing the total supply chain cost. At this point, deterministic inventory models such as economic order quantity model can be applied but these models use known and certain customer demand. In real word problems, customer demands are not certain and hence stochastic based inventory models should be used to control dynamic inventory system. In literature, two basic types of inventory control systems: a continuous system and a periodic system are used and numerous numbers of possible alternatives are presented by using this basic system. Note that if constant demand is used, periodic review and continuous review can produce similar results. At this point, differences occur when customer demand is uncertain. Thus, periodic review and continuous review have different advantages under stochastic environment. The most obvious differences between these two systems are operational expense. Continuous review needs considerable manpower and computerized sources to control inventory level accurately. However, periodic review system does not require ongoing transaction control and needs inventory replenishment only when the periodic review date occurs. Periodic review system provides replenishment order predictability since review period is fixed and hence inventory managers can plan inventory level at a minimum cost. In related with product control, continuous review system is best one for fast moving products, while periodic review system is best used for slow moving products. Finally, continuous review provides high levels of customer serviceability by providing timely on-hand balance status and safety stock protection against random variations in

demand (Ross, 2015). Two of the most commonly used continuous review policy are (s, Q) and (s, S) .

In (s, Q) policy, fixed order quantity is placed when the inventory level decreases to the reorder point s or lower. The advantages of the fixed order quantity (s, Q) policy include: that it is quite simple for the stock clerk to understand, that errors are less likely to occur, and that the production requirement for supplier are predictable. The primary disadvantages of an (s, Q) policy is that in its unamended form it may not be able to efficiently cope with the situation in which individual transactions are large; in particular, if the transaction that triggers the replenishment in an (s, Q) policy is large enough, then a replenishment of size Q won't even increase the inventory level above the reorder point (Silver et al., 1998).

In (s, S) policy, the inventory level is closely and continuously controlled, replenishment order is placed to increase the inventory level to the level S whenever this inventory level reaches or drops below the level s . This policy is especially advantageous for critical inventory products such as replacement parts or raw materials and supplies (Taylor III, 2013).

Inventory levels are checked after a fixed review period of time R in periodic review policies. Note that the size of each replenishment order can change depending on the order quantity between successive orders and the resulting inventory at the time of ordering. For retailers, periodic review policies can be simple to implement since they do not require the capability of continuously monitoring inventory. Suppliers may also prefer them due to the regular replenishment orders (Chopra and Meindl, 2007).

(R, S) policy known as a replenishment cycle system, is in common use, especially in companies not using computer control system. Due to the periodic review characteristics, this policy is commonly used to order point systems in terms of coordinating the order replenishments of related products. Also, the (R, S) policy provides a regular opportunity to set the level S , a desirable property if the order quantity is varying with time. The main drawback of the (R, S) policy is that the holding costs are higher than in continuous review policies (Silver et al., 1998).

(R, s, S) policy can be defined as a combination of (s, S) and (R, S) systems. The idea is that every review period R units of time we control the inventory level. At the beginning of each review period, the inventory level is replenished until the order-up-to level (S) whenever it decreases to a value smaller than or equal to the reorder

point(s). If the inventory level is above s , nothing is done until at least the next review period.

To determine the best values of the inventory control parameters, many methods are developed for inventory control policies. Especially, determining reorder point and order-up-to level are major challenges for an inventory control system. Obtaining the optimal values of reorder point and order-up-to level are computationally expensive. That is to say, neither simple procedures nor algorithms are available to give the optimal values of reorder point and order-up-to level in any particular practical situation (Babai et al., 2010). Hence, many of researches have been interested in finding the optimal inventory parameters in traditional inventory control policies using various solution methods. For example, Schneider and Ringuest (1990) developed power approximations to determine the reorder point and the order-up-to level using a specified level of service. Zheng and Federgruen (1991) derived a simple and efficient algorithm to determine optimal (s, S) policies considering a number of new properties of the infinite horizon cost function. In addition, a new upper bound for optimal order-up-to levels and a new lower bound for optimal reorder points are determined. Although the reduction in computation is problem-dependent, Feng and Xiao (2000) show that their proposed method saves more than 30% of computational effort when compared with the study of Zheng and Federgruen (1991). Janssen et al. (1996) proposed three methods to determine the reorder points subject to a service level constraint. Moors and Strijbosch (2002) presented an efficient descriptive method to determine the fill rate for given values of reorder point and order-up-to level under the assumption of gamma distributed demand.

It was deemed crucial to define reorder point and order-up-to level to satisfy objective function (e.g., minimizing total supply chain cost or maximize profit) in either periodic or continuous review control system. Many different viewpoints must be taken into account by considering uncertainty and dynamic nature of the system.

1.3. Inventory Related Cost

Inventory related costs can be grouped under three subheadings: ordering costs, holding (or carrying) costs, and stockout costs. Holding cost can be defined as the cost of holding products in storage. This cost directly depends on the inventory level and changes with the level of inventory. The greater the level of inventory over time, the higher the holding cost. Holding cost consist of many types of cost elements: direct storage costs, such as ventilation, security, illumination; cost of losing the use of funds tied up in inventory; interest on loans used to invest in inventory; depreciation;

obsolescence as markets for products in inventory decrease; product deterioration and spoilage; taxes; breakage; and pilferage (Taylor III, 2013).

Stockout costs, also defined as a shortage cost, occur whenever demand cannot be met due to insufficient level of on hand inventory. Stockout costs are related to inability to satisfy demand. Silver et al. (1998) defined the term stockout as a stockout occasion or event and the number of unit backordered or lost is a measure of the impact of the stockout. If this stockout results in a permanent loss of sales for products demanded but not provided, stockout cost includes the loss of profits. In addition, stockout can cause a loss of goodwill and customer dissatisfaction and that may cause a permanent loss of future sales and customers. Stockout can occur because it is costly to hold inventory in stock. Consequently, stockout cost has an inverse relationship to holding cost; as the inventory level increases, the holding cost increases, while stockout cost decreases (Taylor III, 2013).

Ordering cost is the cost related with inventory replenishment. In literature, ordering cost is generally used as variable ordering costs and/or fixed ordering costs. Variable ordering costs change with the number of replenishment orders made. If the number of the replenishment orders increases, the ordering cost directly increases depending on the ordering number. On the other hand, fixed ordering cost is not affected by the size of the order and is incurred each time the replenishment order is placed. Holding cost generally reacts inversely to ordering costs. When the order size increases, fewer replenishment orders are required, and hence reducing ordering costs. On the other hand, the order size decreases, higher replenishment orders are required, therefore, higher holding cost. Briefly, as the replenishment order size increases, ordering costs decrease and carrying costs increase (Taylor III, 2013).

Although existing literatures related to review systems includes holding, stockout and ordering cost in diverse model formulations, so little is said about costs components. Hence, we divided total supply chain cost into five types of costs:

- 1) Order cost per use (i.e., the one-time cost that is accrued each time any DC/Supplier is used, regardless of the usage duration),
- 2) Average holding cost (i.e., the costs of carrying the products in inventory),
- 3) Order processing cost (i.e., charged proportional to the order processing time which is the length of time between the time when an order for a particular product is placed and when it actually becomes ready to satisfy demand),

4) Lost sales cost (i.e., the costs associated with demands occurring whenever demand cannot be met),

5) Processing cost (i.e., charged proportional to the processing time that is the time needed to prepare products for serving).

Inventory must be kept at the optimal level in each supply chain member to minimize total supply chain cost. The main challenge is neither to bare inventories to the bone to minimize costs nor to have plenty around to meet all customer demands.

1.4. Supplier Selection

In today's competitive environment, how to determine suitable suppliers is one of the most strategic consideration for managers in whole supply chain. It is the process of finding the right set of suppliers for establishing an effective and efficient supply chain. Although many models have been employed for determining suppliers, each model has its own advantages and disadvantages under different situations. One of the most important contributions is made by Boer et al. (2001) where an extensive search is made in the academic literature to support the supplier selection process. The study also covers all phases in the supplier selection process from initial problem definition, over the formulation of criteria, the qualification of potential suppliers, to the final choice among the qualified suppliers. Setak et al. (2012) also reviewed supplier selection considering 170 paper during 2000-2010 and showed their contribution to supply chain environment. After analyzing various studies, the most commonly used methods and criteria are represented. In the light of previous studies, it can be said that since 2008, researchers generally used hybrid methods because the advantages of two or more models can be integrated to solve the problem (Setak et al., 2012).

Although various evaluation criteria are available in literature (e.g. delivery performance, quality), total cost is one of the most common criteria for supplier selection. However, determining total supply chain cost is a complex challenge. Although the remarkable literature on inventory control includes cost components in diverse model formulations, so little is said about the models to be used in evaluating impact of these costs. On the other hand, competitiveness of the supply chain requires accurate information to provide a framework for which cost component should be used to determine suppliers. In general, the dynamic interaction between the suppliers and the supply chain members is not taken into account and hence, supplier selection models are often over-simplified. In this case, OvS can be successfully applied because of providing realistic modeling of supplier selection.

Ding et al. (2003) used key performance indicators for supplier selection. Four key performance indicators including transportation costs, purchasing costs, inventory costs and total backlogged demands are evaluated by a OvS model using a GA to efficiently determine the supplier. In the study, GA's chromosome is made of eight genes in which each gene denotes a supplier and its corresponding transportation link. Actually, four potential suppliers are evaluated with potential transportation links. Also, roulette wheel selection is used to determine chromosomes for the two-point crossover. Crossover rate is set as 0.9 and mutation rate is set as 0.001. In same manner, Ding et al. (2005) solved supplier selection problems using OvS methodology where GA is used for supplier selection decisions, discrete-event model is used for operational performance evaluation. In the study, two segments are used to form the chromosome. First segment denotes the supplier portfolio while second segment represents the parameters for supply chain operational decisions. Roulette wheel selection and two-point crossover operator are used in GA. Also, crossover rate is set as 0.9 and mutation rate is set as 0.01.

Many researchers have shown the importance of supplier selection by displaying the effect that decisions throughout the whole supply chain have, from supplier to final customers. However, despite the growing attention toward the supplier selection, the area of inventory management still seems to lack a clear linkage between inventory control on the one hand and supplier selection aspects on the other hand. Therefore, researchers have continued to develop models including different aspects of the supplier selection and inventory control system.

1.5. Research Objectives and Contributions

In this study, we present inventory control system and supplier selection while simultaneously considering five types of costs (average holding cost, order cost per use, lost sales cost, order processing cost and processing cost). By considering proposed cost function and stochastic parameters, neither simple procedures nor algorithms are available to obtain the optimal values of reorder point and order-up-to level in (R, s, S) policy. Also, existing literature on supply chain modeling is generally focused on mathematical modeling. However, mathematical modeling may not meet the expectation due to the high complexity of the problems and only small scale systems are amenable to this model. Also, optimization-based approaches generally require too many assumptions and simplifications to be applicable and effective. Therefore, although abundant literature is available related with deterministic mathematical models where optimum results are found under some strict assumptions

and simplification, this is not the case for dynamic/stochastic inventory models. A fundamental challenge in stochastic environment is computability and tractability. At this point, OvS can be used with much details, realities, and complexities as the modeler wants in order to solve any real stochastic complex inventory problem. Therefore, most of the current commercial simulation software packages contain the optimization modules. Rather than making statistical estimation, these optimization modules incorporate some search methods to determine the optimal values of input parameters (Wang and Shi, 2013).

Existing literatures related to OvS methods show that most commercial OvS solvers use metaheuristics that have generally been designed and proven to be effective on difficult and deterministic optimization problems (Tsai and Fu, 2014). Especially, GA is applicable to almost any optimization problem, because the operations of selection, crossover, and mutation can be defined in a very generic way that does not depend on specifics of the problem (Banks et al., 2000).

To respond to customer demand, each DC and each Supplier holds inventory and operates under (R, s, S) policy to replenish. In such an inventory control system, determining the optimal replenishment parameters is crucial to minimize total supply chain cost throughout period. Especially, determining reorder point and order-up-to level is major challenges for inventory control system where right amount of inventory must be hold. The reorder point provides sufficient stock to satisfy demand until the next order's arrival. The determination of the order-up-to level allows us to see the maximum inventory level in system. Hence, the optimal values of reorder point and order-up-to level in DCs and Suppliers, and properly selecting the set of Suppliers for DCs are determined by means of OvS. Also, initial inventories of DCs and Suppliers are considered in this study because initial inventory level can influence the efficiency of the inventory control policies. It is necessary to carefully consider the initial inventory level when determining parameters of the supply chain model. When initial inventory level is zero, even a small increase in incoming orders may create a costly outcome. Also, optimum initial inventory level should be determined to prevent all customers/DCs from placing their first order at the same time in (R, s, S) policy. It seems intuitive that OvS provides a significant opportunity to find optimum inventory control parameters because OvS has ability of capturing the advantages of both simulation and optimization based methods simultaneously. Also, OvS is not constrained by analytical assumptions and simplifications. OvS can give reasonable solutions for evaluating different configurations of inventory control system and supplier selection while minimizing the total supply chain cost including inventory related cost.

1.6. Overview

The remainder of this thesis is created as follows. Chapter 2 discusses the relevant contributions from the literature. In particular, three main research areas are reviewed: (1) (R, s, S) inventory control system and supplier selection; (2) lost sales; and (3) single product. Chapter 3 describes the proposed OvS methodology that includes the details of both the optimization phase and the simulation phase. In Chapter 4, a detailed analysis of inventory control systems is given. Finally, Chapter 5 provides concluding remarks for the results obtained in this research.

CHAPTER 2

2. LITERATURE REVIEW

2.1. (R, s, S) Inventory Control System and Supplier Selection

(R, s, S) is a combination of (s, S) and (R, S) policies. The (s, S) policy is the special case where $R=0$, and the (R, S) is the special case where $s=S-1$. Alternatively, one can think of the (R, s, S) policy as a periodic version of the (s, S) policy. Under quite general conditions, the system that minimizes the total of review, replenishment, carrying, and shortage cost will be a member of the (R, s, S) family (Silver et al., 1998). In review period, the inventory level of each echelon in supply chain is replenished until the order-up-to level (S) whenever it is smaller than or equal to the reorder point(s). Once we place an order, a replenishment lead time elapses before the order is available for satisfying customer demands. Therefore, we want to place a replenishment order when the inventory level is still enough to protect us over replenishment lead time. If the order is placed when the inventory level is at exactly reorder point, then a stockout will not occur by the end of the lead time if and only if the total demand during the replenishment lead time is less than reorder point. If demand over the lead time is exactly equal to reorder point, and lead time demand distribution is symmetric, we would expect to stockout in half of all replenishment cycles. If reorder point is higher than the expected lead time demand, we will stockout less often but will carry more inventory (Silver et al., 1998).

In literature, the optimality of (R, s, S) policy is proven assuming linear holding and stockout cost, and fixed ordering costs (Kiesmüller et al., 2011). Moors and Strijbosch (2002) derived exact formula for the average stockout in a replenishment cycle of (R, s, S) policy where stationary gamma demand process and deterministic lead time are used. Hu et al. (2005) presented multi-retailer system with centralised ordering and demand backordered in (R, s, S) policy. Tili et al. (2012) presented a two-echelon inventory control system including an outside supplier, a warehouse and two retailers. In the study, (R, s, S) is used to control inventory level of the warehouse and retailers. Cabrera et al. (2013) analyzed the stochastic capacity constraint under periodic review (R, s, S) that directly affects distribution network design. The best (R, s, S) policy can enable manager to produce a lower holding cost and stockout costs than does another system. However, obtaining the optimal values of the three inventory control parameters is more intense than that for other systems (Silver et al., 1998). In most situations, the effects of two decision variable review period and order-up-to level,

are not independent, that is the best value of review period depends on the order-up-to level value and vice versa. However, it is quite reasonable for practical purposes when dealing with B products to assume that review period has been predetermined without knowledge of the order-up-to level value (Silver et al., 1998). Note that B item is one of the class in ABC classification where items are divided into 3 classes, namely, A (very important), B (moderately), and C (least important). Hence, review period is assumed to be predetermined in this study. Also, neither simple models nor procedures are available to find the optimal reorder point and order-up-to level in any particular practical situation (Babai et al., 2010). Many of the researchers have been interested in finding the optimal inventory parameters in traditional inventory control policies using various solution methods. For example, (Babai et al., 2011) proposed simple a method to determine the order-up-to-level for cost oriented inventory control policy where stochastic lead-times and compound Poisson demand process are used and, unmet demands are backordered. The solution quality is also evaluated for fast and slow moving products in single echelon inventory control system. Silver et al. (2012) presented the selection of the order-up-to level and reorder point in a periodic review inventory control policy where a negative binomial demand is used and management desires two constraints the fill rate and target average time to be met. In the study, constant replenishment lead time is considered and complete backordering is occurred during a stockout situation.

Most literature on inventory control systems showed that different solution methodologies are available to determine optimal parameters of inventory control policy but they do not completely meet the expectations in each inventory control policy. Based on analysis of the previous studies, we conclude that more research is needed to better understand how the lost-sales affect the total supply chain in periodic review setting. At this point, defining the optimal replenishment policy, characterizing its structural properties, and developing robust methods that has ability to solve inventory control problem with supplier selection are very important in lost sales environment. However, not many solution methodologies exist to investigate all these problems simultaneously in two or more echelon inventory system for single product, especially under stochastic demand and lead time. The underlying reason is that many individual decisions that have different degrees of importance are available along a supply chain. Of the diverse operations involved in supply chain, purchasing is one of the most important activities since it provides a major opportunity to decrease total supply chain cost. Supplier selection is a critical task within the purchasing function. Hence, determining the right suppliers is important to the procurement process (Mendoza,

2007). In literature, a number of methods have been created to evaluate and to select the most suitable suppliers in supply chain. One of the most important contributions is made by Boer et al. (2001) illustrated a review of decision methods reported in the previous studies. We also highlight some of key articles to give an insight into this field. Haq and Kannan (2006) considered not only multi echelon inventory control model but also supplier selection in built to order supply chain system using fuzzy analytical hierarchy process and GA. In the study, unlimited supplier capacity and deterministic demand are considered.

Mendoza and Ventura (2010) used mixed integer nonlinear programming model to solve stationary inventory control policy and supplier selection under serial supply chain system where inventory replenished periodically. The objective of the proposed model is to minimize total supply chain cost while coordinating the inventory at the each stage and properly defining the set of suppliers that are the best to meet capacity limits and quality requirements. However, the mathematical model built in that paper was based on a stationary inventory policy with a constant demand. Moreover, the constant lead time and the same order quantity for different suppliers were assumed in the paper. These assumptions could be restrictive in reality, and it may not be appropriate to order the same quantity each time from different suppliers due to the different ordering costs and replenishment lead times.

Guo and Li (2014) investigated inventory control system with supplier selection in a serial supply chain where a central warehouse and N retailers are used to form two echelon system. The supplier selection is assumed to occur in the first stage of the serial supply chain, and is made by considering capacity, ordering cost, unit price, holding and backorder cost. In the study, mixed integer nonlinear programming model is used to define the best policy for the supplier selection and continuous review inventory control in a serial supply chain system under stochastic lead time and stochastic demand. They primarily focus on calculating the expected values of the total ordering size. In the study, all stockouts are considered as backorders and partial replenishment of an order at the warehouse is not allowed.

Keskin et al. (2010) developed OvS approach to improve the supply chain performance by taking into account the total operational cost of logistics, which include not only the inventory control and transportation costs, but also the purchasing costs and fixed management costs. OvS approach is created by means of discrete event simulation and scatter search based metaheuristic optimization method. In the study,

vendor can only be able to meet an order from its interrelated plant if its inventory level is greater than or equal to order quantity and inventory level is continuously reviewed.

2.2. Lost Sales

In literature, many studies related with the inventory control systems assume that unsatisfied demand is backordered. On the other hand, customer behavior analyses demonstrate that most of the unfulfilled demand is lost. Due to the changing competitive environment in the supply chain, customers are not willing to wait anymore and most of the customer demand is considered as lost sales in many practical settings. Nevertheless, so little work has been published about lost sales models. The reason is that lost-sales characteristic is much more complicated to solve and to analyze than the backorder models. The lost sale case shows a completely different stochastic process from the backorder case and it seems much more difficult to treat analytically. Namely, lost sales models cannot have negative inventory level and hence, different types of research approach are required to clarify lost sales systems (Hadley and Whitin, 1963; Bijvank and Vis, 2011).

Kalpakam and Arivarignan (1989) presented the analysis of a single-product inventory control policy in which different types of customers are used to generate unit demands considering exponentially distributed lead times with lost sales. Janakiraman and Roundy (2004) proved some sample-path properties of lost sales in a single-location inventory control system with stochastic demand and periodic review system. In the study, orders do not cross. Considering an additional assumption associated with replenishment lead times, they presented the convexity of the expected discounted sum of lost sales cost and holding cost for cost models in the planning horizon with respect to the order-up-to level.

Sezen (2006) used simulation to analyze the effects of changing the length of review period on two-echelon periodic review system. In the study, normally distributed demand function is produced with deterministic mean and standard deviation. Lead time is shorter than the review period and order splitting is not allowed. Simulation scenarios are created considering the product type and review period length. The results show that performance of the inventory system is interrelated with review period. Also, determining the appropriate review period length is highly dependent on the variability of demand patterns. Xu et al. (2010) presented the optimal system for the finite and infinite horizon problem with lost sales while minimizing the expected discounted cost. Also, lost sales problems are analyzed with Erlang demands.

Annadurai and Uthayakumar (2010) used controllable lead time and illustrated the impacts of increasing logarithmic and power investments to decrease the lost sales rate. The lost sales rate, review period, and lead time are taken as decision variables and basic periodic review system is formulated mathematically with the capital investment.

Bijvank and Johansen (2012) developed and compared lost-sales inventory models with various replenishment systems. Proposed model is developed allowing constant lead time and compound Poisson demand. Also, closed-form expressions are derived to approximate the performance measures of interest for lost-sales inventory control with the pure base-stock policies.

Bijvank and Vis (2012) presented lost sales inventory control policy with service level criterion at a single retailer location. Optimal replenishment and (R, s, S) policies are used considering a single-product inventory control system in discrete time. Also, new approximation procedure is proposed to define the order-up-to level for the (R, s, S) policies under lost sales environment. Based on previous studies we conclude that creating lost-sales inventory models are difficult and require a different type of research approach.

2.3. Single Product

The keeping of inventories represents one of the largest investment made in any form of the business. It is highly desirable to manage the stocks held by a business more effectively than has been the case ever before (Hung, 1985). In literature, researchers are used various numbers and types of variables to create their models. Hence, it is difficult to review all the studies dealing with this subject in a systematic manner. Some of the key articles about single product are summarized to show importance of the inventory in supply chain. Kalymon (1971) presented a single product multi period inventory model and determined the form and bounds of optimal policies for both a finite and infinite planning horizon. In the study, complete backlogging is used, and deterministic delivery lags are permitted. Also, future period's prices are determined by a Markovian stochastic process. Federgruen and Heching (1999) analyzed single product with periodic review model using value iteration method to maximize total expected discounted profit. Excess demand is fully backlogged and independent demands are used in consecutive periods.

Rosenblatt et al. (1998) presented cyclic schedule and determined an acquisition policy for single product to minimize costs that include total periodic

purchasing, inventory carrying, ordering, and supplier management costs. In the study, M suppliers, each with its own cost parameters, are taken into account and the demand is fully met by considering the capacity constraints. Graves (1999) proposed a single-product inventory control system considering a deterministic lead-time and nonstationary demand processes. Li et al. (2008) provided bounds for the order quantity and order threshold in single product periodic review policy under an infinite horizon. The study shows that proposed heuristic gives satisfying results under specified conditions and outperforms many heuristics in the literature for the random yield problem. Halman et al. (2009) presented the first fully polynomial-time approximation for the single product periodic review system considering independent discrete stochastic demands with zero lead time under finite time horizon. Kiesmüller et al. (2011) studied a periodic review single product replenishment policy where three different discrete demand distributions, Poisson, negative binomial, and a discretized version of the gamma distribution are considered. Cheong and White (2013) considered discrete state and action infinite horizon, expected total discounted cost Markov decision process model of a single product. In the study, periodic review system is used with stationary and deterministic demand, lost-sales, and random yield. Zeballos et al. (2013) analyzed single product inventory control system under finite horizon using a simulation with an embedded optimization model. They analyzed the effect of the different sources of financing and determined that short-term debt affect the optimal ordering policy when working capital constraints, payment delays and lead time are taken into account.

CHAPTER 3

3. MATERIAL AND METHODS

3.1. Optimization via Simulation

Dynamic nature of the inventory is the major obstacle for inventory control practitioners and makes most mathematical methods either over simplistic or computationally intractable. To overcome the limitation of existing mathematical methods, OvS can be used due to the capability for handling variability (Ding et al., 2005). OvS methodology include two fundamental tools: (1) An optimization tool is used to determine the optimal result (2) A simulation tool is utilized to evaluate the performance of the candidate solutions. Optimization tool provides the capability of finding the optimum set of decision variables, which are the conditions under which the simulation is run, in terms of predefined objective function(s). The output of the simulation tool is iteratively utilized by the optimization tool to give feedback on searching for the optimal solution (Ding et al., 2005). Therefore, at first the values of decision variables must be set and then simulation is run to estimate the performance of that particular configuration. Basically, techniques for OvS vary greatly depending on the exact problem. We used the total supply chain cost as the objective function to be minimized. In equation (1) objective function is given:

$$\min_{\theta \in \Theta} f(\theta) \quad (1)$$

where θ is the decision parameters including the parameters of the stochastic system of interest, the feasible region $\Theta \subset \mathbb{R}^d$ is the set of possible values of the parameter θ , and the objective function values $f(\theta)$ specify the expected system performance when system parameter values are defined by $\theta \in \Theta$ (Andradóttir, 1998). OvS strategies depend on the nature of f and Θ as seen in Table 3.1. When the feasible set of design parameter vector values Θ is a discrete set, appropriate optimization methods include statistical methods and metaheuristics. If Θ is continuous and f is differentiable, then gradient based methods or metamodels based optimization can be used. White-box methods consist in changing the simulation part by adding routines which provide gradient, subgradient or higher derivatives (Pflug, 1996). On the other hand, black box methods use not more information than normal simulation output. Black box methods are easily implemented. They consist of a simulation module, which is responsible for providing estimates for the objectives function and optimization module, which uses these values to find the minimizer by iteration. The optimization module must use a method, which does not require derivatives (Pflug, 1996).

Table 3.1. Classification of the OvS model.

	OvS			
	Θ discrete set		Θ continuous set, f differentiable	
	$ \Theta $ large of ∞	$ \Theta $ finite, small		
Local/Global Optimization	Global Optimization	Local Optimization	Local Optimization	Local Optimization
Black-Box/White-Box Methods	Black-Box Methods	Black-Box Methods	White-Box Methods	Black-Box Methods
Methods	Metaheuristics	Statistical Methods	Gradient Based Search	Metamodels

3.1.1. Metaheuristics

Metaheuristics are known as one of the most practical method to solve many complex optimization problems. The practical advantages of these methods are their effectiveness and general applicability because many optimization methods have failed to be either efficient or effective. Therefore, metaheuristics are generally preferred over other optimization methods to find the solutions with many local optima and little inherent structure to guide the search (Ólafsson, 2006). In the light of the previous studies, it is said that four metaheuristics (simulated annealing, GA, scatter search and tabu search) have basically been used to create OvS methods (Fu et al., 2005).

In metaheuristic methods, obtaining an initial set of solution(s) is considered as a first step. Then, initial solution(s) are improved by certain principles. At this point, the structure of the search includes many common elements across various methods. In each step, a solution (or a set of solutions) θ_k , which specifies the current state of the algorithm is found by search algorithm. Note that simulated annealing and tabu search are solution-to-solution search methods. Thus, θ_k is a single solution or point $\theta_k \in \Theta$ in some solution space Θ . On the other hand, GA and scatter search are set-based, that is, θ_k represents a set of solutions $\theta_k \subseteq \Theta$ in each step. However, the basic structure of the search is same for solution to solution and set-based methods.

Given a neighborhood $N(\theta_k)$ of the solution (set), a candidate solution (set) $\{\theta_k\} \subset N(\theta_k)$ is selected and evaluated. Thus, the performances of the candidate

solution(s) are calculated or estimated. Then, they are compared with the performance of θ_k and occasionally with each other. Considering this evaluation, the candidate can be either accepted ($\theta_{k+1} = \theta^c$) or rejected ($\theta_{k+1} = \theta_k$). Basic metaheuristics framework can be defined as follows:

Table 3.2. The basic metaheuristics framework.

Obtain an initial solution (set) θ_0 and set $k=0$.
Repeat:
Identify the neighborhood $N(\theta_k)$ of the current solution(s).
Select candidate solution(s) $\{\theta^c\} \subset N(\theta_k)$ from the neighborhood.
Accept the candidate(s) and set $\theta_{k+1} = \theta^c$ or reject it and set $\theta_{k+1} = \theta_k$.
Increment $k=k+1$.
Until stopping criterion is satisfied.

Note that this framework is applicable for numerous metaheuristics (Ólafsson, 2006).

3.1.2. Statistical methods

To find the optimal solution, all possible combinations can be evaluated if the number of possible solutions is low. On the other hand, stochastic problems have appeared in real-world environment and one replication alone may not be enough to precisely evaluate the performance of each solution. Hence, the number of replications for each solution is required to determine the optimal solution (Figueira and Almada-Lobo, 2014). Statistical methods, which include the well-known ranking and selection, importance sampling, and multiple comparison procedure, focus on this aspect.

3.1.2.1. Ranking and selection

The concept of ranking and selection methods that can be classified into indifference-zone ranking and subset selection was firstly presented by defining a problem where the aim is to determine the best population. Typically, a certain number of observations are collected from each population and the best population is selected using statistics. It should be noted that the best population may not be selected because the observations are taken as a realizations of random variables. The major drawback of ranking and selection methods is its permanent requirement for common and known variance among populations. When a system that does not physically exist is being modeled, the system output's variance is generally not known. Also, existing

system may not allow the researchers to know its output's variance due to the practical infeasibility of data collection or potentially high cost. Moreover, providing common output variance across different system designs can be difficult although the variance is known (Swisher et al., 2003).

3.1.2.2. Importance sampling

Importance sampling is a very powerful simulation tool that has been used in evaluating low probability error events. The basic principle of importance sampling is that of making the low probability events occur more frequently by modifying the probability density function of the input random process, so that the simulation of these events can be made without needing a very large number of samples. Meanwhile, the unbiasedness of the estimate of the error probability is obtained as a result of the proper weighting of these events. In the previous considerations of importance sampling approaches, the probability density function of the input random variables is improved by means of increasing the variance of the input random variables. An optimization that minimizes the simulation estimation variance with respect to the input variance is performed (Lu and Yao, 1988).

3.1.2.3. Multiple comparison procedures

Multiple comparison procedures treat the comparison problem as an inference problem on the performance parameters of interest. Multiple comparison procedures account for the error that occurs when making simultaneous inferences about differences in performance among the systems (Goldsman and Nelson, 1994). Multiple comparison procedures signify the use of certain pairwise comparisons to make inferences in the form of confidence intervals (Fu, 1994). The main aim of multiple comparison procedure is to quantify the differences between systems' performance. It is seen that the aim of multiple comparison procedure is completely different from ranking and selection because the aim of ranking and selection is to make a decision (Lu and Yao, 1988).

3.1.3. Gradient based search

Gradient based search to simulation optimization find an appropriate gradient for the simulation model to use as a move direction in an improving search. The key factor to an effective gradient based search in simulation optimization is the quality of the gradient estimator (Medal, 2008). Basic gradient based search methods are finite differences, perturbation analysis, likelihood ratio method, and frequency domain experimentation.

Finite differences are defined as a crudest method of estimating the gradient. There can be a need for multiple observations for each derivative to provide a more reliable estimate of the derivatives (Azadivar, 1992).

Perturbation analysis considers what would have happened if various parameters were different, that is, the effect of a parameter change on the performance measure is of interest while the experiment is evolving (Farenhorst-Yuan, 2010).

Likelihood ratio is also known as the score function. In this method, the gradient of the expected value of an output variable with respect to an input variable is defined as the expected value of a function of a) input parameters, and b) simulation parameters (Carson and Maria, 1997).

In frequency domain experimentation, determined input parameters are oscillated sinusoidally at different frequencies during one long simulation run (Carson and Maria, 1997).

Finite differences and frequency domain experimentation methods change the input and analyze the resulting output, while likelihood ratio and perturbation analysis contain an "add-on" to the simulator itself that includes additional accumulations and calculations. Nonetheless, the underlying simulator is not changed, and hence likelihood ratio and perturbation analysis can also be applied for on-line gradient estimation and optimization (Fu, 1994).

3.1.4. Metamodel methods

Two general methods are used for metamodel-based OvS: global metamodel fit and iterated local metamodels. In global metamodel fit method, the entire region of interest (in terms of θ) is discovered, and the experimental results are employed to fit a global approximation. Then, iterative process is used to explore the global approximation in the process of optimization. For local fitting strategies, the fitting and optimization steps alternate: as the optimization search moves, new local regions of space are discovered, and new metamodel approximations are fitted (Barton, 2009).

3.2. Proposed OvS

Most of the current commercial simulation software packages contain the optimization modules and metaheuristics are the most commonly used methods embedded in simulation software. When combining the metaheuristics with simulation models, the latter can be seen as a black box, i.e., some input parameters are given to the black box, then the simulation models will give some feedbacks or responses,

which can be used to guide the search process in metaheuristics (Wang and Shi, 2013). An excellent survey of the use of metaheuristics for OvS was presented by Ólafsson (2006). GA is one prominent example, but others such as simulated annealing, tabu search and many variations are available. Analyses of previous studies show that GA is a challenging alternative method to cope with noisy outputs and complex systems especially in combinatorial optimization problems.

In the study, simulation models are created by using Simio (Version: 7.121.12363) that allows users to enter input values and to run multiple replications for evaluating the system performance. Processor is Intel® Core™ i5-3470 CPU @ 3.20 GHz and system type is 64 bit operating system.

GA is developed to assign new values for selected decision variables (i.e., generating candidate solutions). In each cycle, simulation output is returned to the GA as the most recent fitness function to be evaluated, and GA once more tries to find better decision variables to increase model performance.

Detailed structures of the proposed OvS method can be found in following two subtitles: the optimization phase (GA) and the simulation phase. In optimization phase, GA is used to optimize inventory control parameters and supplier selection. In the simulation phase, performances of candidate solutions are evaluated.

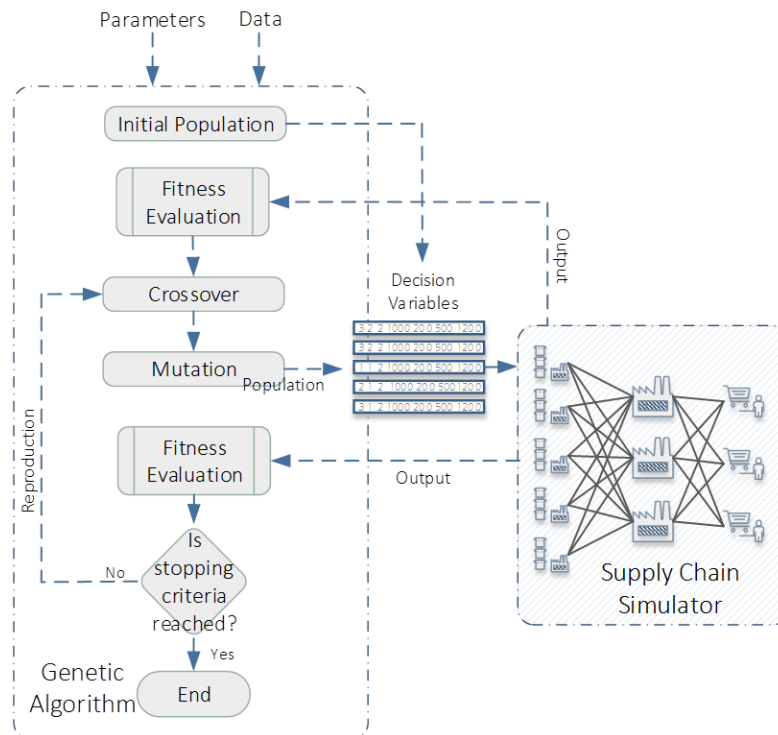


Figure 3.1. The illustration of the simulation and optimization phase.

3.2.1. Optimization phase (Genetic Algorithm)

In this phase, it is very important that an optimization algorithm should provide the capability of finding optimal or near-optimal solutions in the early stages of the search process (Wang and Shi, 2013). In literature, many different solution methodologies such as population-based, single-solution based and set-based are available as metaheuristic methods but population based GA can be considered as the most commonly used method. GA is an optimization method, originally motivated by the Darwinian principle of evolution through (genetic) selection. It uses a highly abstract version of evolutionary processes to improve solutions (McCall, 2005).

The population to population approach provides a multiple directional search and tries to make the search escape from the local optima. Also, information related with objective function is only used to guide them through the solution space in GA. For this reason, it requires less mathematical requirements about the problems. Unlike many other optimization methods, GA can be successfully used to solve any optimization problem, even if the problem is of a stochastic nature. GA provides the maximum “black-box” approach. For example, preliminary considerations related with the goal function or initial values of the control parameters need not to be taken. This feature is important in the simulation models where prior knowledge of the simulation models behavior may not exist (Paul and Chaney, 1998). Hence, many authors have employed GA to solve complicated inventory problems (Table 3.3). In literature, a number of distinct components are available to construct GA and this is considered as a particular strength since standard components can be re-used, with trivial adaptation in many different GA (McCall, 2005). In GA, solution space is searched by building and evolving a population of solutions. The evolution is carried out by means of producing new solutions from two or more solutions in current population. The main advantage of GA over those based on sampling the neighborhood of a single solution (e.g., tabu search and simulated annealing) is that it may explore a larger area of solution space with smaller number of objective function evaluations (Zeng and Yang, 2009).

To explain general GA methodology in OvS, we assumed that there are k possible solutions to the OvS problem and $X = \{x_1, x_2, \dots, x_k\}$ denote the solutions, where the i th solution $x_i = \{x_{i1}, x_{i2}, \dots, x_{im}\}$ provides specific setting for the m decision variables. The simulation output at solution x_i is denoted by $Y(x_i)$; this could be the output of a single replication, or the average of several replications. At each iteration that is also known as a generation GA operates on a “population” of p solutions. Denote the population of solution on the j th iteration as $P(j) = \{x_1(j), x_2(j), \dots, x_p(j)\}$.

Table 3.3. The summary of the GA applications in inventory management.

Author	Chromosome representation	Initialization	Fitness Function	Crossover	Mutation
Hollier et al. (2005)	Maximum issue quantity, critical inventory position, reorder point, order-up-to level	Random generation	The expected annual inventory cost minimization	Randomly by using crossover rate and the crossover rate is set as 0.8	Randomly by using mutation rate and the mutation rate is set as 0.08
Daniel and Rajendran (2005)	Base-stock levels	Random generation	The total supply chain costs minimization	The single point crossover operator and varying crossover rate	The gene-wise mutation and varying mutation rate
Nachiappan and Jawahar (2007)	Sales quantity	Random generation	The channel profit maximization	The simple single-point crossover and the crossover rate is set as 0.6	Randomly by using mutation rate and the mutation rate is set as 0.03
Taleizadeh et al. (2009a)	The inventory levels of the products	Random generation	The multiple objective functions	The single-point crossover and varying crossover rate	Randomly by using mutation rate and varying mutation rate

Table 3.3. (Continued)

Taleizadeh et al. (2009b)	The order quantities of the products	Random generation	The profit maximization and service rate maximization	The single-point crossover operator and varying crossover rate	Randomly by using mutation rate and varying mutation rate
Paul and Rajendran (2011)	The set of base-stock levels and review periods	Random generation and heuristic procedure	The total supply chain costs minimization	The gene-wise crossover operator and single point crossover operator, and the crossover rate is fixed as 1	The gene-wise mutation and varying mutation rate
Moin et al. (2011)	The number of suppliers and the number of periods	Random generation	The total costs minimization	The modified uniform crossover and crossover rate is fixed as 0.7	Randomly by using mutation rate and the mutation rate is set as 0.1
Yang et al. (2012)	The number of retailers, the number of products and the number of planning period	Random generation	The total costs minimization	The single point crossover and the crossover rate is set as 0.5	Randomly by using mutation rate and the mutation rate is set as 0.1

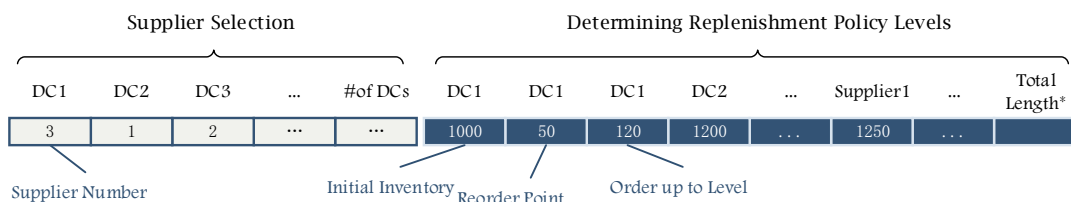
Table 3.3. (Continued)

Lee et al. (2013)	The replenishment strategy	Random generation	The total costs minimization	The standard two-cut-point crossover operator and the crossover rate is set as 0.75	Randomly by using mutation rate and the mutation rate is set as 0.009
Amaruchkul and Auwatanamongkol (2013)	The reorder point and the order-up-to level	Random generation	The expected total inventory cost minimization	The crossover with a probability equal to a predefined crossover rate and the crossover rate is set as 0.8	Mutation rate is set as 0.05
Gorji et al. (2014)	The situation of ordering or not ordering a product to a supplier in each period	Random generation	The total profit maximization	The one-point crossover operator and the crossover rate is set as 0.98	Randomly by using mutation rate and the mutation rate is set as 0.01

There may be multiple copies of the same solution in $P(j)$, and $P(j)$ may contain solutions that were discovered on previous iterations. From iteration to iteration, this population evolves in such a way that good solutions tend to survive and give birth to new and hopefully better solutions, while inferior solutions tend to be removed from the population (Banks et al., 2000). The basic GA is given here (Banks et al., 2000; Beasley et al., 1993):

Step 1. The GA starts with an initial population that consists of a set of individuals corresponds to a set of solutions. The details about initial population formation can be found in (Maaranen et al., 2007) that basically answer to the question whether the initial population plays a role in the performance of GA and if so, how it should be generated.

In this study, the iteration counter is firstly set as a $j = 0$, and an initial population of p solutions $P(0) = \{x_1(0), x_2(0), \dots, x_p(0)\}$ is selected. GA randomly generates an initial population of chromosomes. In GA, potential solution of the problem is defined as a set of parameters that are joined together to create a chromosome. The chromosome structure of the considered problem is depicted in Figure 3.2. First part of the chromosome represents supplier selection for DCs. Length of the supplier selection part is equal to the number of DCs. The second part of the chromosome represents determination of the initial inventory, reorder point and order-up-to level of each DC and each Supplier, respectively.



* Total Length = Number of DCs x 3 (i.e., Initial inventory, Reorder Point, and Order-up-to Level) + Number of Suppliers x 3 (i.e., Initial inventory, Reorder Point, and Order-up-to Level)

Figure 3.2. Chromosome structure of GA.

Step 2. The simulation experiments are run to obtain performance estimates $Y(x)$ for all p solutions $x(j)$ in $P(j)$. Thus, the fitness value of each alternative solution is automatically taken from simulation model to form a new generation in GA. The fitness evaluation operation of GA calculates the fitness value of each individual according to the objective function that minimizes total supply chain cost. Fitness value of chromosome k , f_k , is computed by using the objective function value as given below:

$$f_k = \frac{1}{TSCC_k} \quad (2)$$

Here $TSCC_k$ is the objective function value of the k th chromosome. After calculating fitness value, the plan for selecting chromosomes to create the next generation is displayed by selection strategy. Selection operator leads GA to select chromosomes from the population as parents to use in crossover. There exist many selection schemes for GA and each has a different characteristics. Ideal selection operator should be simple to code and efficient for both nonparallel and parallel architectures. Also, it ought to adjust the selection pressure to adapt to different domains. In recent years, tournament selection is substantially being used as GA selection since it satisfies all of the above criteria. Thus, tournament selection is simple to code and is efficient for both nonparallel and parallel architectures. Furthermore, it could adjust the selection pressure in order to tune selection performance for different domains. The selection pressure is increased (decreased) by simply increasing (decreasing) the tournament size. Briefly, all of these factors increase the usage of tournament selection as a selection strategy for GA (Miller and Goldberg, 1995). Hence, the tournament selection is used in this study as it is simpler and produces reasonably good results. It randomly picks two chromosomes from the population and selects higher fitness value as a parent.

Step 3. A population of p solutions is selected from those in $P(j)$ in such a way that those with smaller $Y(x)$ values are more likely, but not certain, to be selected. This population of solutions is denoted as $P(j + 1)$.

Step 4. The solutions are recombined in $P(j + 1)$ via crossover and mutation. Crossover generates new solutions by selecting individuals from mating pool (population after reproduction stage) and exchanging their parts. It is emphasized in literature that crossover is the most important procedure in GA to obtain new high quality solutions. It should be noted that the performance of the GA decreases when the number of crossover points increases. Adding additional crossover points disrupts the building blocks. Therefore, most of the researchers preferred single point crossovers (Figure 3.3). In single point crossover, two individuals are taken and their chromosome strings are randomly cut to produce two "head" segments and two "tail" segments. Then, the tail segments are swapped over to create two new full length chromosomes. Crossover proceeds in three steps.

1. A pair of two individual strings is selected randomly for the mating.
2. A cross site is selected randomly on the string length.

3. At the last step, position values are changed between the two strings following the cross site (Sivanandam and Deepa, 2008). It should be noted that crossover is generally not applied for all pairs of individuals selected for mating. In literature, crossover rate is typically applied between 0.6 and 1.0 and it is taken as 0.8 in this study. The crossover operator is illustrated in Figure 3.3.

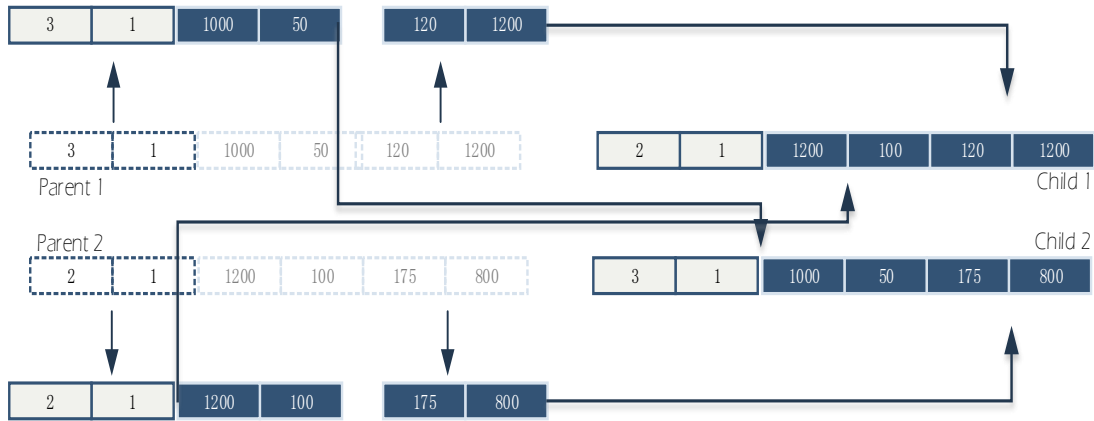


Figure 3.3. Crossover operator of GA.

After applying crossover, mutation is randomly performed with a small rate. Mutation is a random search and protect against premature convergence to local maxima. Mutation rate is very important. If it is too low, danger of premature convergence is occurred. On the other hand, too high mutation rate causes losing a lot of valuable genetic information and directly decreases the performance of the algorithm.

Mutation generally works on a single chromosome and produces another chromosomes through exchange of the values of two string positions or modification of the value of a string position to prolong the diversity of population. Many forms of mutation exist in nature and the details can be found in (Falco et al., 2002). In this study, we set mutation rate as 0.05. In this way, a small amount of random search is provided. Mutation operator is illustrated in Figure 3.4.

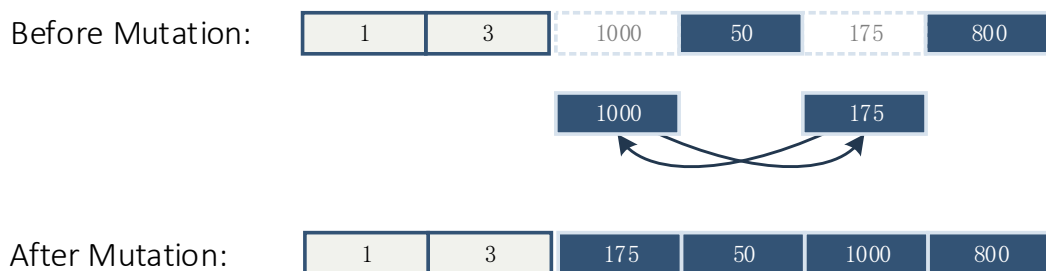


Figure 3.4. Mutation operator of GA.

Step 5. Finally, we set $j = j + 1$ and go to Step 2. The GA is terminated after a specified number of iterations. At termination, the solution x^* that has the smallest $Y(x)$ value in the last population is chosen as the best. The values of parameters of GA are given in Table 3.4.

Table 3.4. The values of parameters of GA.

Parameters of GA	Values
Population Size	50
Number of Iterations	150
Crossover Rate	0.8
Mutation Rate	0.05

3.2.2. Simulation phase

Existing mathematical methods could not use all variables with stochastic properties within whole supply chain; hence these methods can only present the optimal values for partial supply chains. It is not possible to handle all the dynamically changing supply chain variables using mathematical methods. At this point, simulation is known as the most effective method for dealing with stochastic variables existing within whole supply chain. In addition, it can work for the global optimization of planning an whole supply chain with finding local optimum values within each component (Lee et al., 2002). The outcomes for different alternatives are evaluated via simulation and therefore, unnecessary errors and costs are minimized. In simulation, numerical and logical models based on real-world problems are created and various scenarios are imitated by means of computers to solve problems. Computer simulation technology ensures an efficient tool to make a plan for analyzing, solving, and evaluating many different alternatives. Hence, it is especially important for complex problems with high risks or that are impossible for real-world testing (Kuo and Yang, 2011). There are great differences between existing inventory systems. They change according to the size and complexity; the types of products, the cost elements related with operating the system, and in the nature of the information available to decision makers at any given point in time (Hadley and Whitin, 1963). In this case, simulation seems a remarkable recourse to model and analyze the performance for inventory control systems. Simulation has an ability to capture specific features of the real object and to incorporate a greater level of detail (Paul and Chaney, 1998). Also, researchers can easily change the simulation model parameters and tries to analyze the proposed

system performance under different sets of parameters. In simulation phase, defining control parameters is very important because it directly affects system performance.

In this study, DCs and Suppliers adopt the (R, s, S) inventory policy and simulation starts with initial inventory at DCs and Suppliers because the initial conditions of a simulation are crucial aspects of simulation modeling. In review period, the inventory level of each DC and each Supplier is replenished until the order-up-to level whenever it decreases to a value smaller than or equal to the reorder point. The chances of lost sales are directly proportional to value of the inventory control parameters. The higher the inventory levels in supply chain, the lower the chance of lost sales. However, customer order quantity can be lower than inventory level in specified review period and hence excess holding cost can be incurred. Managers should decide how inventory level should be built up to meet not only the customer demand, but also other factors such as cost minimization. In this respect, simulation provides an illustrative insight into the problem where the actual environment is difficult to observe within acceptable time.

3.3. Single Product Inventory Control Problem

In this study, DCs are the stores that fulfill customer orders and Suppliers serve the products to supply the DCs replenishment orders. Thus, our supply chain conjures up images of single product from Suppliers to DCs and DCs to customers along a chain. Inventory levels of DCs and Suppliers are all inspected at every R time units where R is a fixed constant and assumed to be 5 days. However, only this value is considered to be constant and assumed to be the same for all Suppliers and DCs placed in the supply chain. Each DC and each Supplier has their own initial inventory, reorder point, and order-up-to level values, separately. The lower and upper bound value of the initial inventory is considered to be 800 and 2000 for each DC and each Supplier, respectively. The lower and upper bound value of the reorder point is considered to be 50 and 200 for each DC and each Supplier, respectively. The lower and upper bound value of the order-up-to level is considered to be 200 and 750 for each DC and each Supplier, respectively. The distribution of the customer order quantity at the DCs has a Poisson distribution with a rate parameter of 50. Also, we assumed that average customer arrival at each DC is 1 per day. Each DC replenishment order may vary depending on the order quantity between successive orders and the resulting inventory at the time of ordering. The DC replenishment lead time is assumed to be stochastic. Each DC requires a triangular processing time with endpoints (1, 3) and mode at 2 minutes to reflect the processing of the product into the

stores and on the shelves. DCs receive orders (i.e., each DC will receive orders from customers over time) and need order processing time to process them. The order processing time that is uniformly distributed on the interval [2, 5] hours is the length of time between the time when an order for a particular product is placed and when it actually becomes ready to satisfy demand. In this respect, order processing time should be thought as the time spent processing order before it is filled (i.e., some routine paperworks and arrangements). Also, transportation times (i.e., from Suppliers to DCs) are uniformly distributed on the interval [1.25, 3] days. Thus, DC's replenishment lead time includes order processing time at Suppliers, transportation time from Supplier to DCs, and processing time at DCs. It should be noted that inventory level continues to decrease over the duration of the lead time since the order placed at a review period will not be received until the end of the lead time; hence the inventory level will continue to decrease until the lead time expires. DCs can take many number of customer orders within a review period. Note that the cumulative demand over period n denoted by D_{in} (i denotes DC in the system, $i=1,2,3,\dots,I$ and n is the set of periods where an order is placed) and calculated as follow:

$$D_{in} = \sum_{t=1}^n D_{it} \quad (3)$$

where t denotes any time over period n ($1 < t \leq n$) and D_{it} represents customer demand at time t for DC_i . If D_{it} is lower than the current inventory level of DC_i (X_{it}), demand is fully satisfied. If D_{it} quantity exceeds X_{it} , possible order fulfillment takes place. Unmet customer order quantity at time t ($X_{it}^- = X_{it} - D_{it}$) is lost. At the beginning of each review period, the inventory level of each DC is replenished until the order-up-to level (S) whenever it decreases to a value smaller than or equal to the reorder point(s). In this system, the interval time between review periods is fixed but DCs replenishment order quantity can vary according to customer orders.

$$Q_{in} = \begin{cases} S - X_{in} & \text{if } X_{in} \leq s \\ 0 & \text{if } X_{in} > s \end{cases} \quad (4)$$

where X_{in} is the inventory level of each DC at review period. Q_{in} denotes the replenishment order quantity for each DC and is replenished only from its predetermined Supplier.

To satisfy the DC replenishment order, the firm should select the most suitable Supplier $j, j \in J$ (j denotes number of Suppliers in the system, $j=1,2,3,\dots, J$). It is worth remembering that DCs face stochastic customer demands for a single product and the Suppliers receive only the replenishment orders from each DC as follows:

$$D_{jt} = \sum_{i=1}^I Q_{in} \quad (5)$$

where D_{jt} represents replenishment order quantity of DCs at time t for Supplier j . Then, the cumulative demand over period n (D_{jn}) calculated as follow:

$$D_{jn} = \sum_{t=1}^n D_{jt} \quad (6)$$

D_{jn} directly depends on the supplier selection because each replenishment order of the DC is only fulfilled from selected Supplier. For example, suppose that Supplier1 is selected for DC_1 and DC_3 over period n . The replenishment order quantity of the DC_1 is 50 units and replenishment order quantity of the DC_3 is 60 units. Replenishment orders of other DCs for Supplier1 are assumed to be zero. Thus, Supplier1 receives 110 units (D_{1n}) over period n . The DC's replenishment orders are satisfied if the current inventory level of Supplier j (X_{jt}) is greater than or equal to the DC's replenishment order quantity. If Supplier does not have enough inventories to fulfill order, possible order fulfillment takes place depending upon X_{jt} . Excess DC's replenishment order quantity is lost ($X_{jt}^- = D_{jt} - X_{jt}$). At the beginning of each review period, the inventory level of each Supplier is replenished until the order-up-to level whenever it decreases to a value smaller than or equal to the reorder point. If inventory level is higher than the reorder point, we do not place any order for Supplier j at review period.

$$Q_{jn} = \begin{cases} S - X_{jn} & \text{if } X_{jn} \leq s \\ 0 & \text{if } X_{jn} > s \end{cases} \quad (7)$$

where X_{jn} is the inventory level of each Supplier at review period n . Q_{jn} denotes the replenishment order quantity for each Supplier and is replenished from unlimited sources. The Suppliers' replenishment lead times are also assumed to be stochastic and includes processing time and order processing time. Processing time to prepare products (i.e., the processing of the product into the stores and on the shelves) for serving DCs is assumed to be a random variable that has triangular distribution with endpoints (3, 7) and mode at 5 minutes at each Supplier. Suppliers receive orders (i.e., Suppliers can only receive orders from DCs at each review periods according to their inventory positions) and need order processing time to process them.

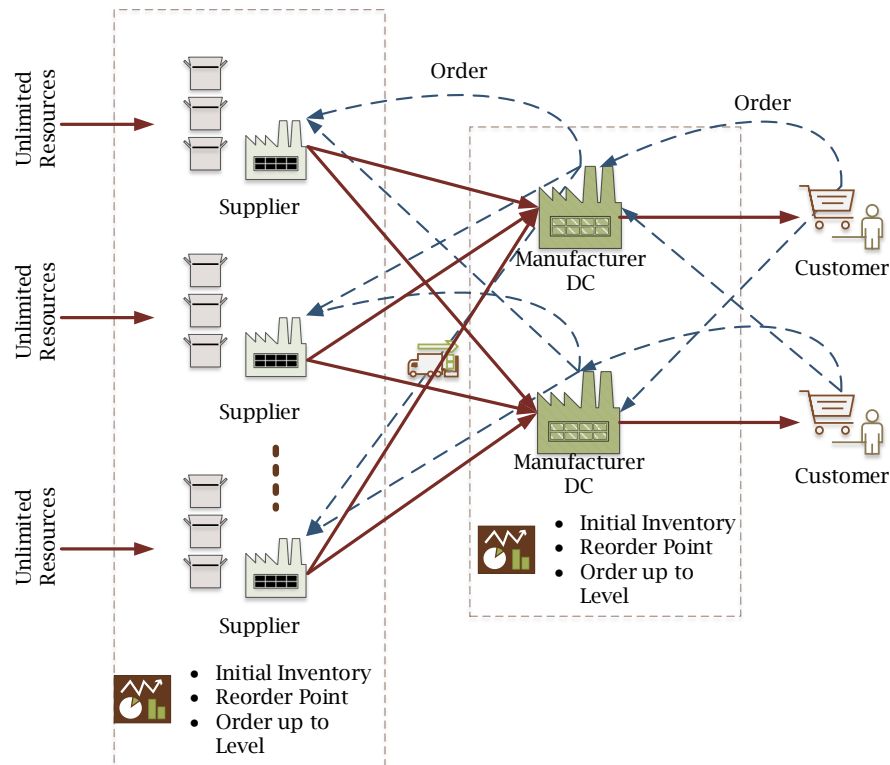


Figure 3.5. General structure of the proposed supply chain.

As for the DCs, the order processing time that is uniformly distributed on the interval $[2, 5]$ hours is the length of time between the time when an order for a particular product is placed and when it actually becomes ready to satisfy demand. In this respect, order processing time should be thought as the time spent processing order before it is filled (i.e., some routine paperworks and arrangements). Note that, transportation time is not considered for Suppliers during the replenishment lead time. Also, there is always enough time for receiving an order before the next review period because replenishment lead time will always be shorter than the review period. It should be noted that inventory level continues to decrease over the duration of the lead time since the order placed at a review period will not be received until the end of the lead time; therefore the inventory level will continue to decrease until the lead time expires. Suppliers can take just one order for each DC but can accept orders from more than one DC at a time within a review period. The general structure of the considered supply chain is given in Figure 3.5. Three different sources of customers place orders on DCs. The three chain DCs can utilize five different Suppliers for a particular item. Both DCs and Suppliers use similar inventory models (i.e., (R, s, S)) to replenish their inventory positions to satisfy demands from customers and DCs, respectively. To estimate the performance of a given system design average holding

cost, lost sales cost, fixed and variable ordering costs are specified as seen in Table 3.5.

Table 3.5. Inventory related costs.

Suppliers	DCs
Average Holding Cost (h_j): Uniform (2,5)	Average Holding Cost (h_i): Uniform (2,5)
Lost Sales Cost (k_j): Uniform (80, 100)	Lost Sales Cost (k_i): Uniform (80, 100)
Processing Cost (p_j): Uniform (50, 75)	Processing Cost (p_i): Uniform (5,10)
Order Cost Per Use (c_j): Uniform (50,100)	Order Cost Per Use (c_i): Uniform (50,100)
Order Processing Cost Rate: Uniform (2,5)	Order Processing Cost Rate: Uniform (2,5)
Cost Per Use: Uniform (100,150)	Cost Per Use: Uniform (10,20)

Any non-negative inventory level is charged a holding cost ($h_i X_{in}^+$) proportional to the remaining inventory quantity over period n . A lost sales cost $k_i X_{in}^-$ is charged proportional to the unmet customer order quantity at DC_i over period n . $p_i P_i$ is charged proportional to the processing time to use any DC for processing activity. Order cost per use, c_i is the cost charged, or accrued, to the cost of any order that is placed at any DC irrespective of the time spent in there. Order processing cost, O_i includes order processing cost rate, which is proportional the order processing time, which is the length of time between the time when an order for a particular product is placed and when it actually becomes ready to satisfy demand, and cost per use, which is the one-time cost that is accrued each time any DC is used, regardless of the usage duration. Thus, we formulated total supply chain cost for DCs over periods ($TSCC_{in}$) as follows:

$$TSCC_{in} = h_i X_{in}^+ + I\{X_{in} \leq s\} (k_i X_{in}^- + p_i P_i + c_i + O_i) \quad (8)$$

where, $I\{\cdot\}$ specify indicator function of the set. Similarly, total supply chain cost for Suppliers over periods ($TSCC_{jn}$) is calculated. Any non-negative inventory level at Supplier j is charged a holding cost ($h_j X_{jn}^+$) proportional to the remaining inventory quantity over period n . A lost sales cost $k_j X_{jn}^-$ is charged proportional to the unmet order quantity at Supplier j over period n . $p_j P_j$ is charged proportional to the processing time to use any Supplier for processing activity. Order cost per use, c_j is the cost charged, or accrued, to the cost of any order that is placed at any Supplier irrespective of the time spent in there. Order processing cost, O_j includes order processing cost

rate, which is proportional the order processing time that should be thought as the time spent processing order before it is filled (i.e., some routine paperworks and arrangements), and cost per use which is the one-time cost that is accrued each time any Supplier is used, regardless of the usage duration. Thus, we formulated $TSCC_{jn}$ as follows:

$$TSCC_{jn} = h_j X_{jn}^+ + I\{X_{jn} \leq s\}(k_j X_{jn}^- + p_j P_j + c_j + O_j) \quad (9)$$

Finally, total cost of each DC and each Supplier are summed up to calculate total supply chain cost over periods ($TSCC_n$) as follows:

$$\sum_{n=1}^{Periods\ Considered} (TSCC_n) = \sum_{n=1}^{Periods\ Considered} \left(\sum_{i=1}^I TSCC_{in} + \sum_{j=1}^J TSCC_{jn} \right) \quad (10)$$

In this study, proposed method aims at minimizing $TSCC_n$. It is also worth noting that optimization of all inventory control parameters of both Suppliers and DCs and the most suitable Supplier selection is performed simultaneously.

The proposed OvS model assumptions are determined as follows:

- 1) Single product flows through the two echelon supply chain.
- 2) DCs and Suppliers operate under the (R, s, S) policy where R is fixed (i.e., 5 days).
- 3) Inventory order policy parameters that are initial inventory, order-up-to level, reorder point for a given DC and Supplier remain the same across the entire finite time horizon.
- 4) Poisson demand process and stochastic lead time are used.
- 5) Each customer order is supplied only by a single predetermined DC and each DC replenishment order is supplied only by a single Supplier which is determined after the optimization phase among the candidate Suppliers. Each Supplier replenishes its inventory from unlimited sources.
- 6) If the demand quantity exceeds the current inventory level, possible order fulfillment takes place and unmet demand is lost.
- 7) There is always enough time for receiving an order before the next review period because replenishment lead time both for DCs and Suppliers is shorter than the review period.
- 8) Only transportation times between Suppliers and DCs are considered.

9) Simulation model is run for one year.

10) Inventory levels are not allowed to be negative.

To analyze proposed OvS model with a greater level of detail, descriptive statistics including cost component analysis (average holding cost, order cost per use, lost sales cost, order processing cost and processing cost), probability based analysis per each period (P1 and P2), quantity based analysis per each period (TMOQ, TLOQ, and PLOQ), order based analysis per each period (NTMO, NTLO, and NPLO) and lead time based analysis per each replenishment lead time (order met probabilities, average holding unit, and length of the lead time) are given in following chapter.

CHAPTER 4

4. RESULTS AND DISCUSSION

The supply chain considered in the current study is a single product two echelon supply chain consisting of Suppliers which is the source of supply for DCs which are source of supply for customer demands. To provide effective solution methodology for these supply chain system, we presented OvS model minimizing $TSCC_n$. The proposed OvS model has the ability of capturing the advantages of both simulation and optimization based method where GA is used and the convergence of the search process for (R, s, S) settings are plotted in Figure 4.1.

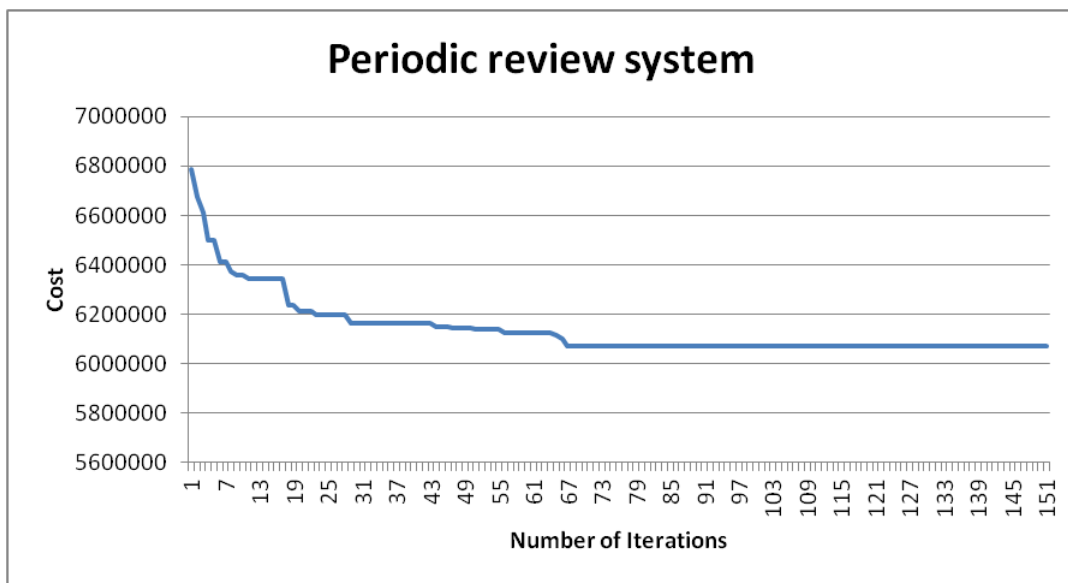


Figure 4.1. Convergence of the GA towards the best solution in proposed model.

4.1. Cost based analysis

OvS model determined the best possible values of the initial inventory, reorder point, and order-up-to level for each DC and each Supplier while minimizing cost related fitness function. One of the repercussions of this convergence is that if the inventory control parameters defined effectively, then the total supply chain cost could be automatically improved. Besides considering inventory control parameters, the most suitable supplier is determined for each DC. Supplier3, Supplier4, and Supplier5 are selected to satisfy DCs replenishment order in proposed model. Also, overall average service levels are summarized for each DC and each Supplier in Table 4.1. Taking a glance at overall average service levels of Suppliers reveals that there seems no problem with Suppliers. Note that average service level specifies the ratio of current inventory level in each DC/Supplier to number of units ordered by the customers/DCs over total number of incoming orders and can be calculated as follow:

$$\text{Average service level} = \frac{\sum_{a=0}^{\text{Per Arrival}} \min\left(1, \frac{\text{Current Inventory Level}}{\text{Incoming Order Quantity}}\right)}{\text{Total Number of Incoming Orders}} \quad (11)$$

Table 4.1. Average service levels and optimal values of inventory control parameters.

Supply Chain Component	Initial Inventory	Reorder Point (s)	Order-Up-To Level (S)	Average Service Level
DC1	1897	82	656	0.789633
DC2	1897	82	503	0.69926
DC3	1985	82	503	0.704517
Supplier1	-	-	-	-
Supplier2	-	-	-	-
Supplier3	1880	144	679	0.996853
Supplier4	936	193	576	0.993674
Supplier5	1667	193	652	0.993619

With optimal inventory control parameters, DCs and Suppliers fulfill a strategic role of achieving the supply chain objectives of lower costs. In this respect, key to the managing of DCs and Suppliers lie in the evaluation of the optimal cost model for any given structure. Thus, information on where cost components are incurred and whether the cost components are rising or falling is required. In this study, we used total supply chain cost including five different cost components (average holding cost, order cost per use, lost sales cost, order processing cost and processing cost). To substantially analyze a realistic inventory model, a detailed descriptive statistics including cost component analysis per each period, probability based analysis per each period (P1 and P2), quantity based analysis per each period (TMOQ, TLOQ, and PLOQ), order based analysis per each period (NTMO, NTLO, and NPLO) and lead time based analysis per each replenishment lead time (order met probabilities, average holding unit, and length of the lead time) are given. To the best of our knowledge, there is no study is available about (R, s, S) policies including such a detailed analysis.

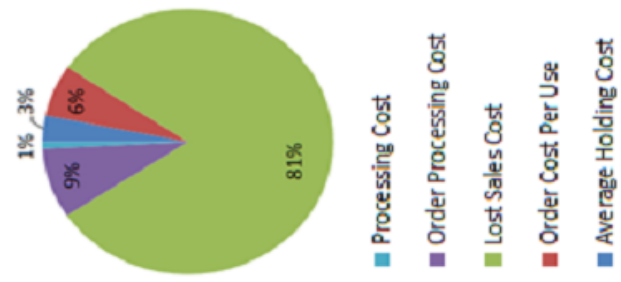
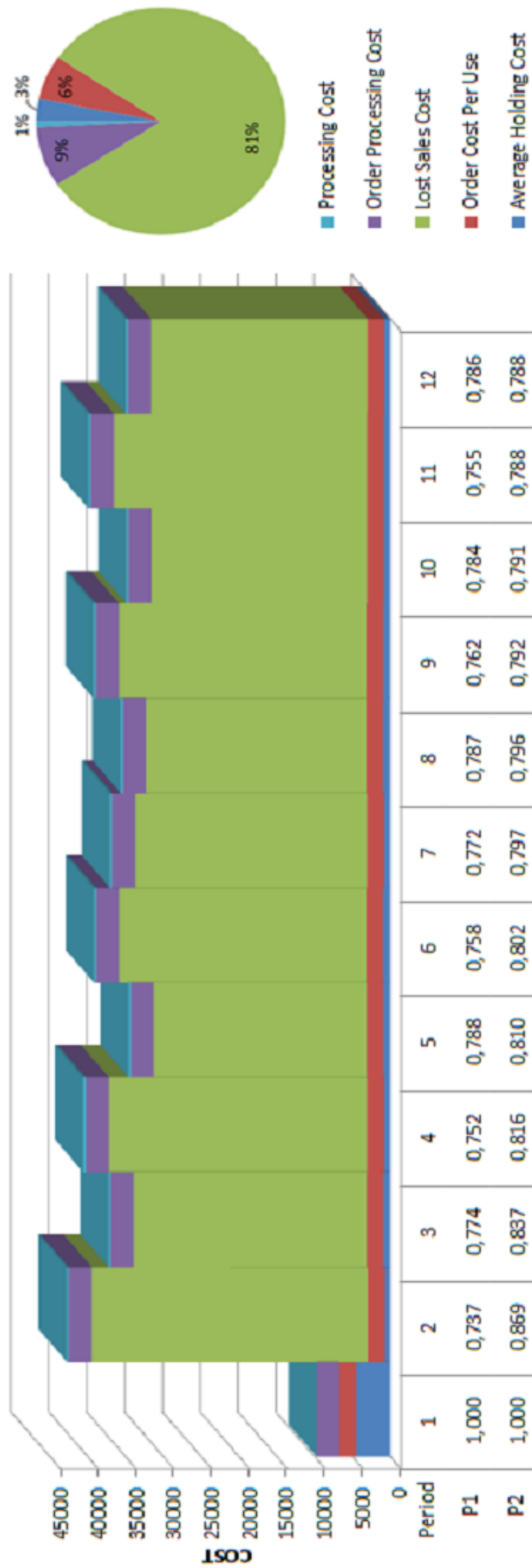


Figure 4.2. The cost component and probability analysis of the DC1.

The majorities of the studies in the literature are briefly analyzed the cost, demand and lead time behavior in supply chain. For example, Movahed and Zhang (2015) analyzed demand and lead time uncertainties and provided an effective guide for decision-makers to find the optimal value of inventory policy parameters. An important remark to the conclusions drawn previous studies is that such a detailed statistical analysis of (R, s, S) policies was not taken into account and calculating such statistics can only be possible through simulation based models such as OvS models.

The analysis of cost components showed that the largest share in Figure 4.2 for DC1 is the lost sales cost (81%). Except for the first period the values of cost components can be said to be uniformly distributed across the periods with DC1. The reason for period 1's being an exception is DCs' having adequate levels of initial inventories at that period. P1 for both Suppliers and DCs are calculated by using equation (12).

$$\int_{n-1}^n \min\left(1, \frac{\text{Current Inventory Level}}{\text{Incoming Order Quantity}}\right) dt \quad (12)$$

Calculating such a statistic allows one to obtain hidden but valuable information about the dynamics of the supply chain which is ignored most of the time. Also, P2 for both Suppliers and DCs are calculated by using equation (13) for comparison purposes.

$$\int_0^n \min\left(1, \frac{\text{Current Inventory Level}}{\text{Incoming Order Quantity}}\right) dt \quad (13)$$

Note that P1 and P2 values should be close to 1 across the periods for all supply chain members to have the potential to meet all incoming orders over time. It is noticeable that except for the first period the value of P1 and P2 uniformly distributed across the periods with all DCs. Note that, at period 1 all incoming orders are met (i.e., P1 is 1) for all DCs due to having adequate levels of initial inventories at that period. But, this is not the case for DC1 at period 2 where P1 is 0.737 (i.e., All incoming orders are met 73.7 percent of the time over period 2 or incoming orders are met with 0.737 probability). Finally, P2 value is 0.869 for DC1 at period 2. In other words, 86.9 percent of the time (i.e., over two months) all incoming orders at DC1 are met. Likewise, the same value can be interpreted as all incoming orders at DC1 within the first two months are met with 0.869 probability.

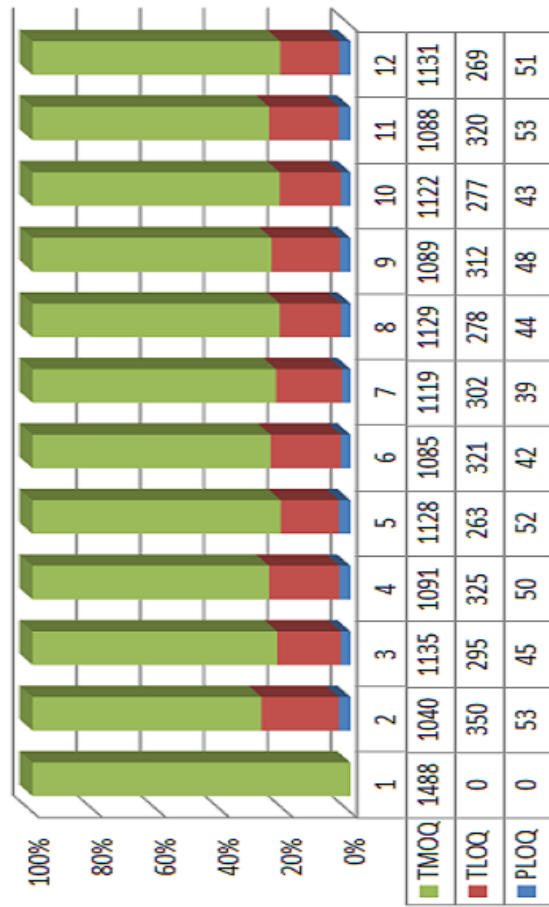
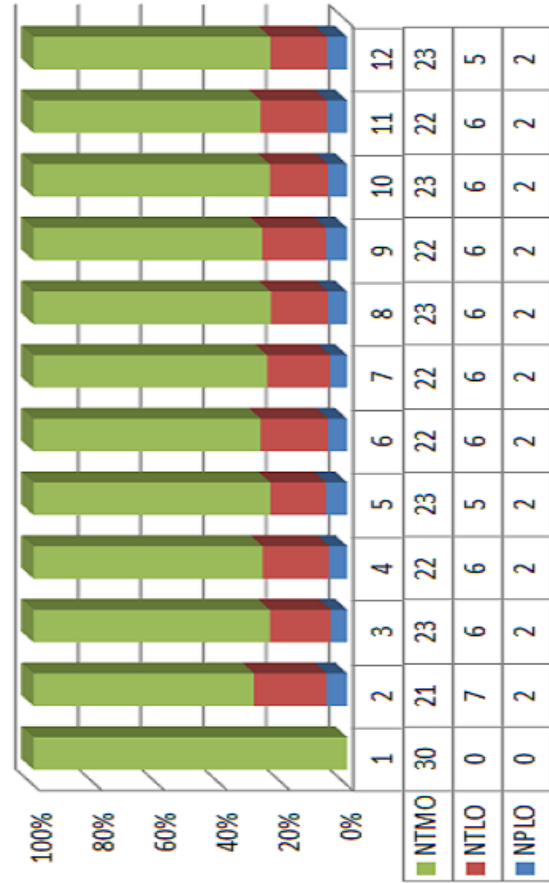


Figure 4.3. The order analysis of the DC1.

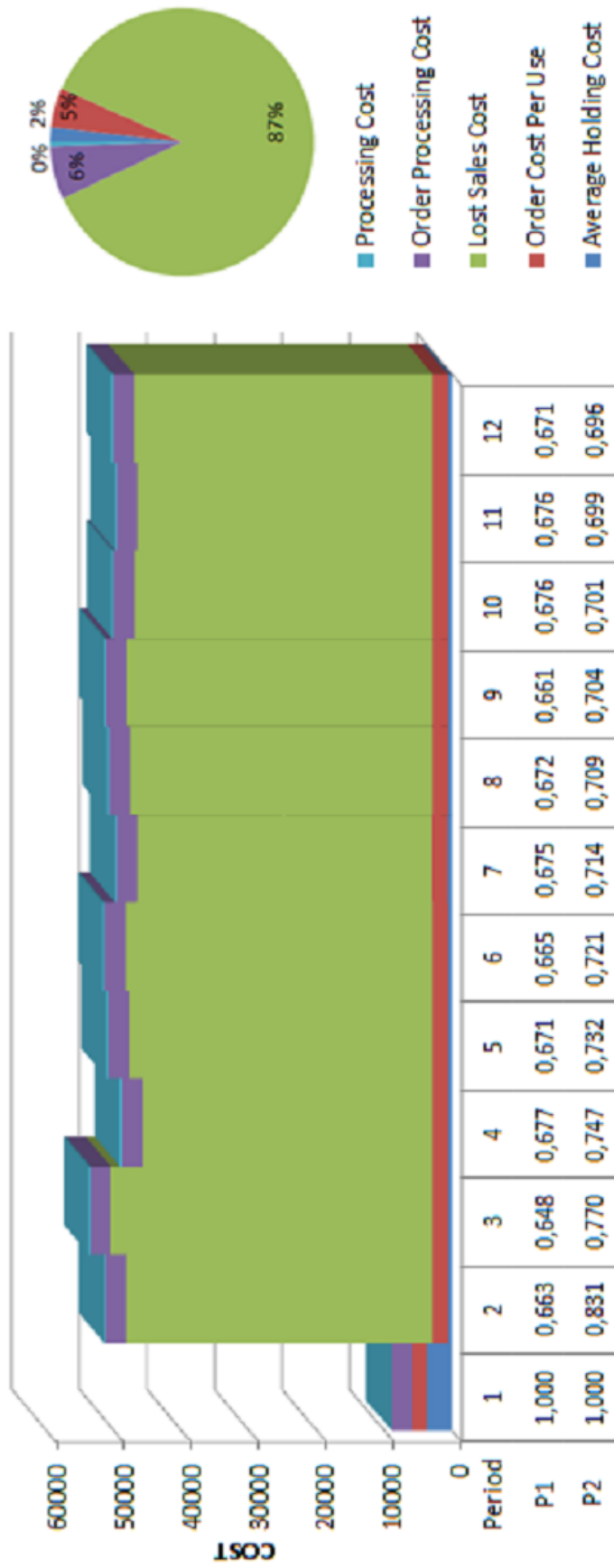


Figure 4.4. The cost component and probability analysis of the DC2.

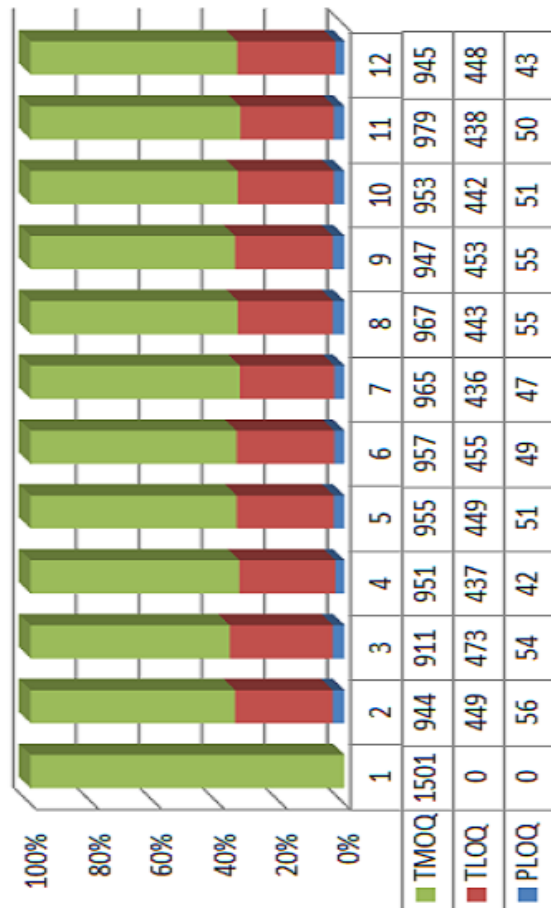
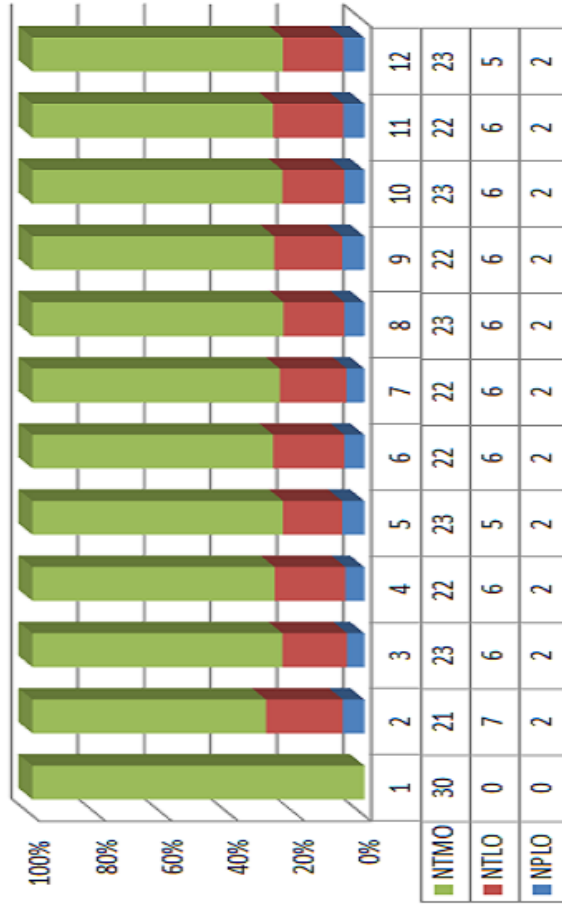


Figure 4.5. The order analysis of the DC2.

Comparing P2 with P1 provides very useful information for decision makers. It is apparently seen that it can be quite misleading to consider just P2 values since it is being a biased indicator due to its taking account of initial conditions. Note that P1 values are calculated just for each period and thus can be seen just a fine tuned version of P2 values. Being much more realistic indicators P1 values should be relied on while making decisions.

Figure 4.3 summarizes analysis of number of orders together with order quantities. Except for the first period the values of TMOQ uniformly distributed across the periods with DC1. Similar conclusions can be drawn related to TLOQ, PLOQ, NTMO, NTLO, and NPLO. Note that, at period 1 there is no totally lost and/or partially lost orders with DC1 due to adequate levels of initial inventories.

The analysis of cost components showed that the largest share in Figure 4.4 is the lost sales cost (87%) whose value is higher than DC1. Except for the first period the values of cost components can be said to be uniformly distributed across the periods with DC2.

Similar conclusions can be drawn related to TMOQ, TLOQ, PLOQ, NTMO, NTLO, and NPLO in Figure 4.5. Except for the first period the value of this statistics uniformly distributed across the periods for DC2. It is seen that DC1 and DC2 have some difference in cost and order analysis. The source of these variations may be due to stochastic order processing times, stochastic transportation times, or other stochastic parameters. The strongest candidate among these is stochastic customer order quantity.

The analysis of cost components showed that the largest share in Figure 4.6 for DC3 is the lost sales cost (86%) whose value is slightly higher than DC1 and lower than DC2. The values of P1, P2, TMOQ, TLOQ, PLOQ, NTMO, NTLO, and NPLO are uniformly distributed across the periods for DC3 except for the first period. It is apparently seen that the value of each cost component exhibits substantially different cost structures in accordance with the periodic review system at each DC. From Figure 4.7, the value of P1 and P2 across the periods for DC1 is higher than those of DC2 and DC3 except for the first period. Having the same customer order arrival rates this result seems a bit cumbersome for the DCs' managers. Then the source of variation may be due to stochastic environment. The strongest candidate is the level of inventory control parameters.

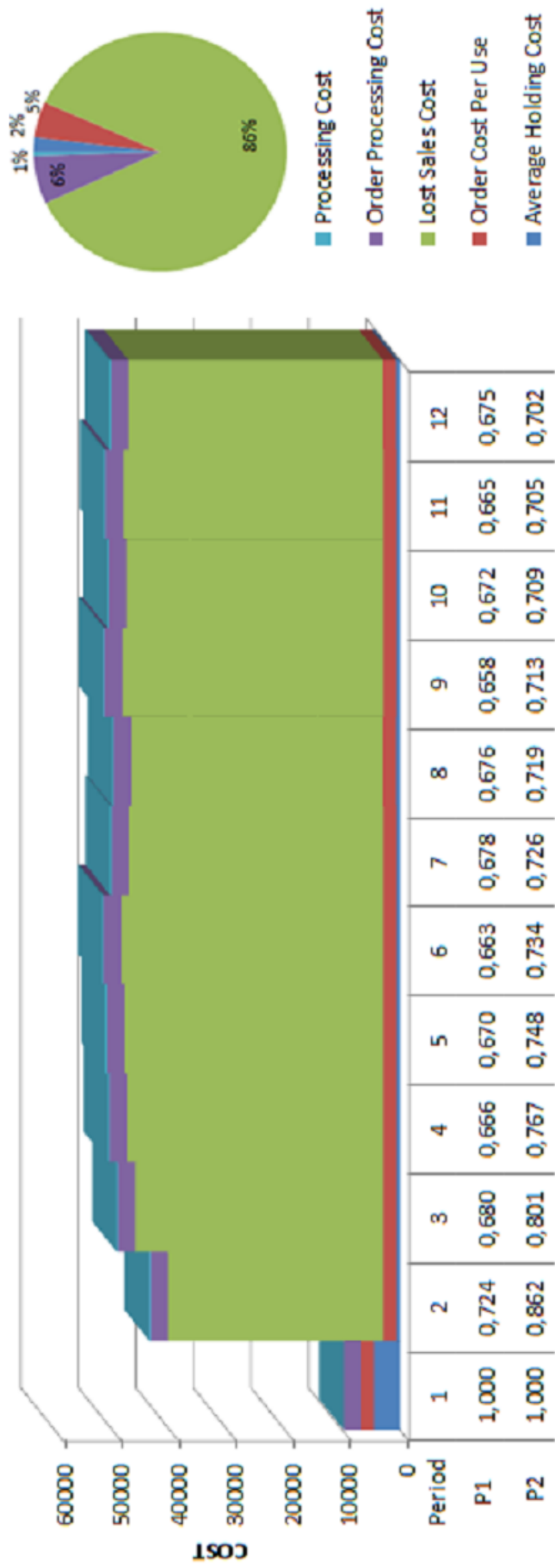


Figure 4.6. The cost component and probability analysis of the DC3.

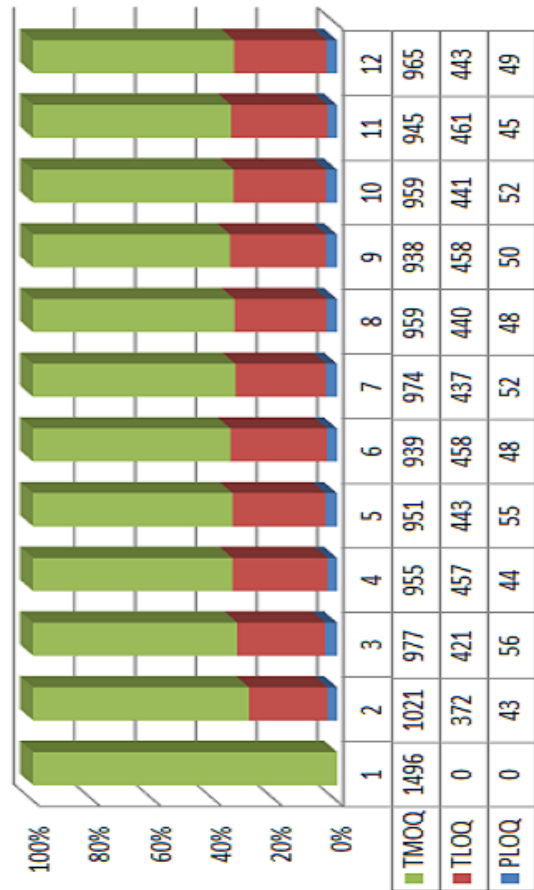
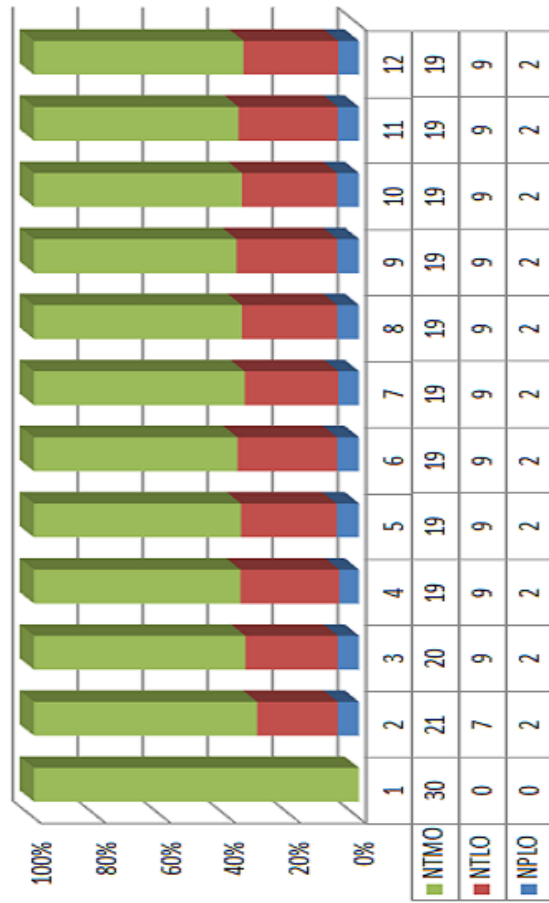


Figure 4.7. The order analysis of the DC3.

From Table 4.1, initial inventory levels are seen to be very close each other and also reorder point levels are all the same for all DCs. But, DC1's order-up-to level (i.e., 656) is higher than those of DC2 and DC3. Note that, DC2 and DC3 have the same level of order-up-to level (i.e., 503) which justifies our forecast. TMOQ per period with DC1 is higher than those of DC2 and DC3. Again the reason for this good statistic with DC1 originates from DC1's having a higher level of order-up-to level than those of the others. It is noticeable that except for the first period the values of TMOQ uniformly distributed across the periods with all DCs, being higher with DC1 for each period than those of the others. Similar conclusions can be drawn related to TLOQ, PLOQ, NTMO, NTLO, and NPLO.

The analysis of periodic review system showed that the largest share in the pie chart for all DCs is the lost sales cost. It should be noted that even the minimum one is accounted for 81% of the total DC cost (i.e., the total lost sales cost with DC1). Thus, shortage is the most strategic issue despite various cost types involved in DCs. It is well known that competition among DCs has become fiercer and fiercer in recent years. Hence, if lost sales cost could be reduced effectively, total supply chain cost for DCs may not be changed but at worst customer satisfaction will be improved.

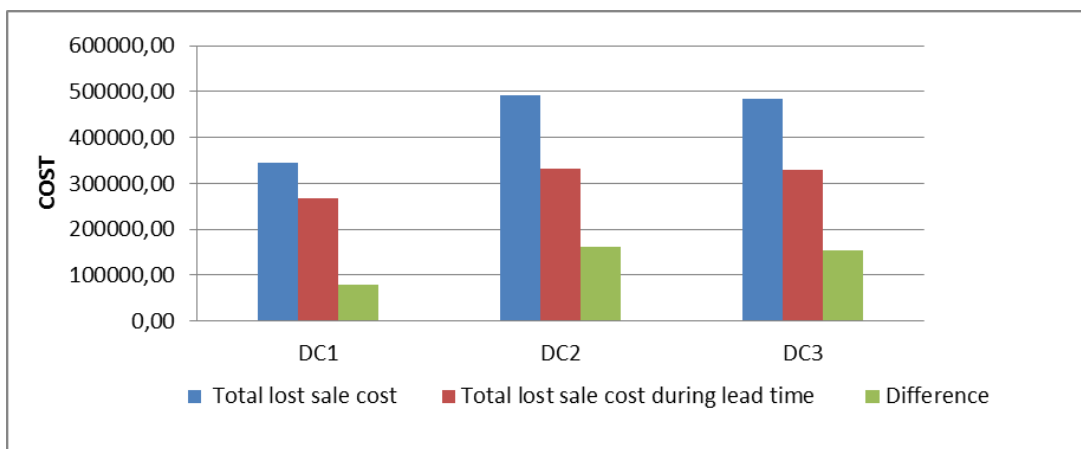


Figure 4.8. The comparison of total lost sales cost and total lost sales cost during lead time.

It is seen in Figure 4.8 that the high proportion of the lost sales cost occurs during replenishment lead time periods. At this point, the longer the length of lead time, the higher the proportion of lost sales would be. Remember that, the length of the review period is the single deterministic component and is considered to be 5 days for all DCs and Suppliers.

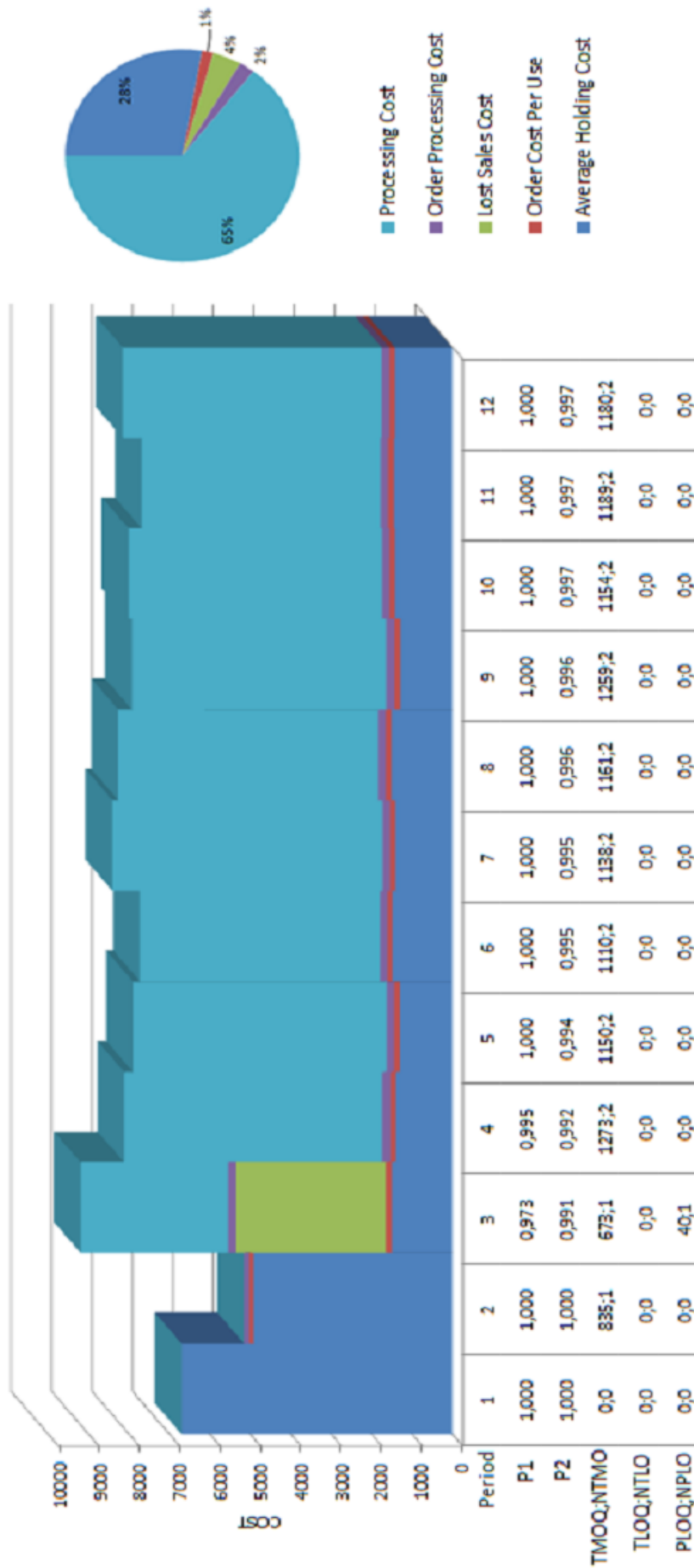


Figure 4.9. The detailed cost component analysis of the Supplier3.

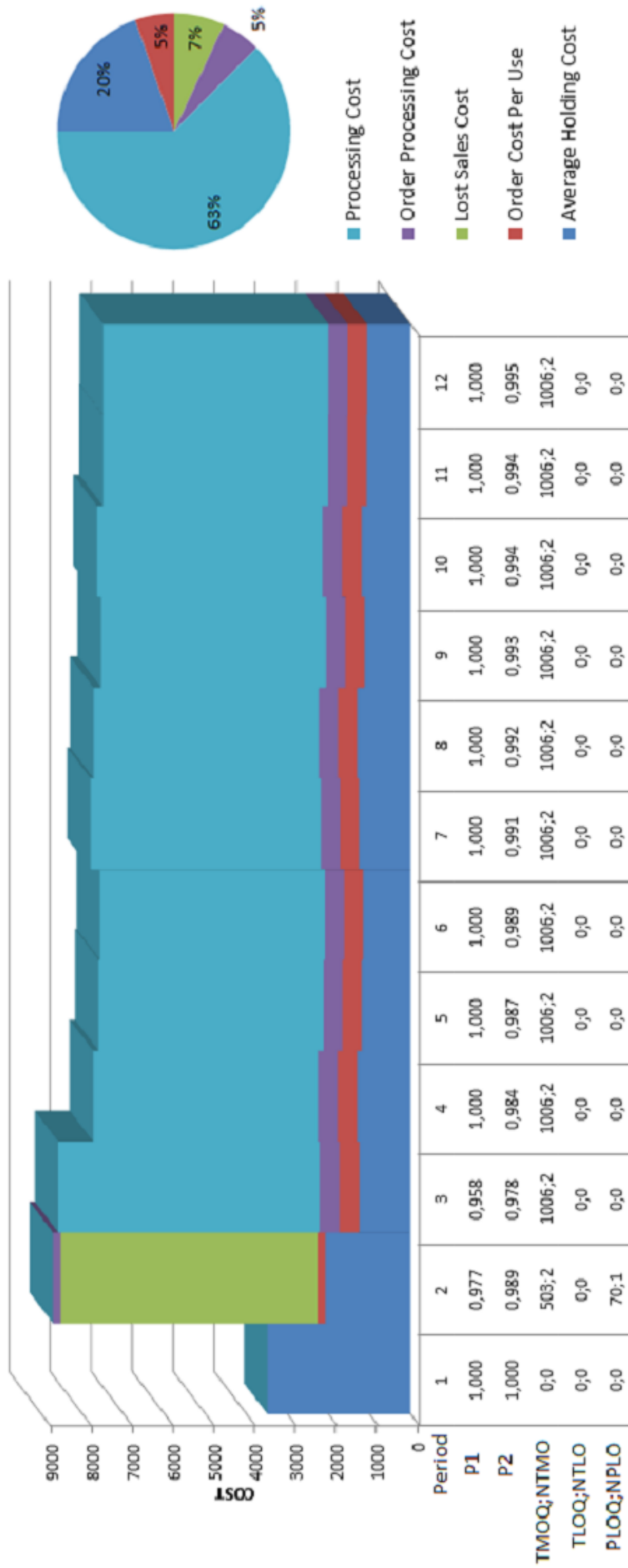


Figure 4.10. The detailed cost component analysis of the Supplier4.

Contrary to DCs, Suppliers lost sales costs are extremely lower since they have shorter lead-times (Suppliers' lead times do not include transportation time). After evaluating DCs, we give a detailed analysis about Suppliers. Suppliers with periodic review system have no totally lost sales. Note that Supplier1 and Supplier2 are not preferred by DCs with periodic review system. It is apparently seen in Figure 4.9 that processing cost is the most strategic issue despite various cost types involved in Supplier3. Note that share of the lost sales cost is dramatically lower than DCs. On the other hand, share of the average holding cost particularly increases with respect to DCs. Figure 4.9 also summarizes analysis of number of orders, order quantities, P1 and P2 for Supplier3. It is noticeable that after period 4 the values of TMOQ can be said to be uniformly distributed across the periods among Suppliers. TLOQ and NTLO are all zero across the periods. Note that, although PLOQ and NPLO are generally zero across the periods with Supplier3, DC replenishment orders are partially met in period 3. However, unmet order quantity is negligible which is justified by the higher values of both P1 across the periods and P2 over all periods. Also, it should be noted that the value of P1 and P2 uniformly distributed across the periods for Supplier3.

The analysis of cost components showed that the largest share in Figure 4.10 for Supplier4 is the processing cost. Except for the first, second and third period the values of cost components can be said to be uniformly distributed across the periods with Supplier4. Similar conclusions can be drawn related to TMOQ, TLOQ, PLOQ, NTMO, NTLO, and NPLO. It is noticeable that after period 2 the values of TMOQ can be said to be uniformly distributed across the periods among Supplier4. TLOQ and NTLO are all zero across the periods. Note that, although PLOQ and NPLO are generally zero across the periods with Supplier4, in period 2 DC replenishment orders have been unmet. However, unmet order quantity is negligible which is justified by the higher values of both P1 across the periods and P2 over all periods. Also, the value of P1 and P2 are uniformly distributed across the periods for Supplier4. It is seen in Figure 4.11 Supplier5 is slightly different from Supplier3 and Supplier4. Number of partially lost order is higher than others. Except for the first, second, third, fifth and eighth period the values of cost components can be said to be uniformly distributed across the periods with Supplier5. TLOQ and NTLO are all zero across the periods. Note that, although PLOQ and NPLO are generally zero across the periods with Supplier5, in period 3, 5 and 8 DC replenishment orders are partially met.

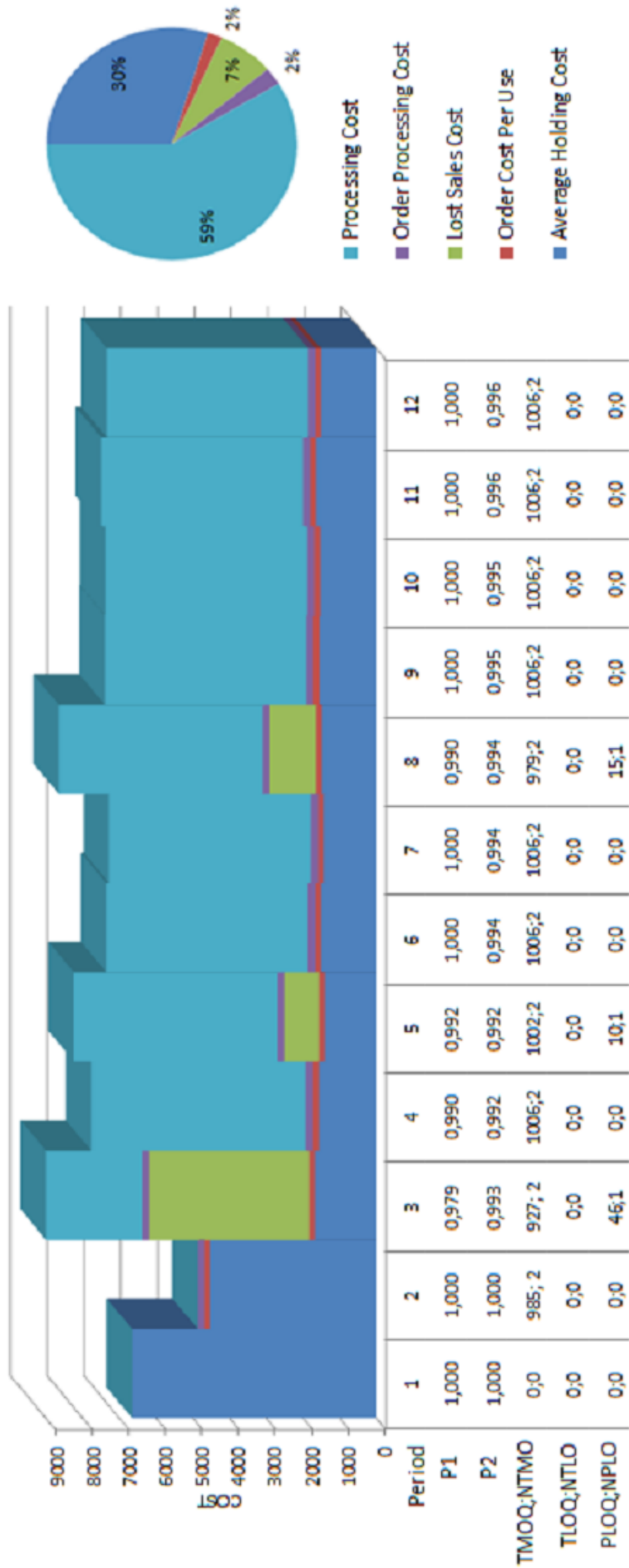


Figure 4.11. The detailed cost component analysis of the Supplier5.

It is noticeable that after period 3 the values of TMOQ can be said to be uniformly distributed across the periods among Supplier5. It is apparently seen that the largest share in the pie chart for all Suppliers is the processing cost. The minimum one is accounted for about 59% of the total supply chain cost for Suppliers with proposed model. Note that share of the lost sales cost in the pie chart is dramatically lower than DCs. On the other hand, share of the average holding cost particularly increases with respect to DCs. After period 4, the value of TMOQ across the periods for Supplier3 is higher than those of Supplier4 and Supplier5. The reason for this slight difference may be because of stochastic order processing times, stochastic transportation times, and levels of inventory control parameters. The strongest candidate among these is the level of inventory control parameters. From Table 4.1, Supplier3 has a higher level of initial inventory and order-up-to level than those of the others but its reorder point is lowest with proposed model.

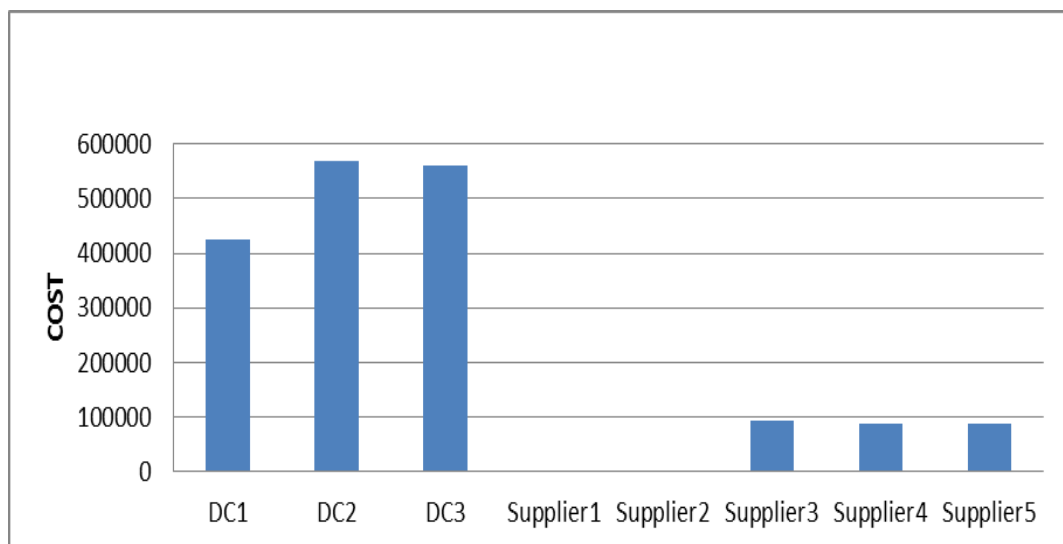


Figure 4.12. Cost analysis of DCs and Suppliers.

It is clearly seen in Figure 4.12, total cost for DCs is extremely higher than Suppliers. This results show that creating review system for DCs is more critical than Suppliers since incorrect selection can be more costly for DCs. After general analysis of supply chain member, we also analyzed each cost component for the whole supply chain as given in Table 4.2-4.3.

The success of DCs and Suppliers clearly depends on the extent of cost savings and the customer service level. To achieve significant savings, companies should integrate inventory control and supplier selection instead of treating them separately. This could be achieved through the use of OvS based models. In this study, we have presented an answer to the question of how periodic review system is become

more appropriate in lost sales inventory systems while considering total supply chain cost.

Table 4.2. The cost analysis of the DCs.

	Average Holding Cost	Order Cost Per Use	Lost Sales Cost	Order Processing Cost	Processing Cost
DC1	13669	26875.7	345373	36460.1	3457.4
DC2	10111	26962.9	492530	36302.3	3075.6
DC3	11022	27005.4	483175	36501	3077
Total Supply Chain Cost for DCs	34802	80844	1321078	109263.4	9610

Table 4.3. The cost analysis of the Suppliers.

	Average Holding Cost	Order Cost Per Use	Lost Sales Cost	Order Processing Cost	Processing Cost
Supplier3	25831	1470	3709	2021.9	60261
Supplier4	17523	4891.6	6261.46	4891.6	55887
Supplier5	26513	1673.9	6533	2189	52454
Total Supply Chain Cost for Suppliers	69867	8035.5	16503.5	9102.5	168602

To present a convenient way to visually compare all supply chain member on five statistics, we also used box plot that includes the minimum and maximum range values, the upper (75th) and lower quartiles (25th), and the median (50th). The 25th and 75th percentiles are given as a box centered about the 50th percentile (median). The median is the middle observation in a ranked dataset and is a measure of the central tendency of the data. An advantage of the median is its resistance against outlying values for $3 \geq n$, where n is the number of observations. The major purpose of

this graph is to permit an appropriate way to visually compare all supply chain member on these five statistics at the same time. The manager can look for differences between members and then conduct further investigations to establish plausible explanations for differences. Note that outliers are represented by “*” and the line connected supply chain member shows the mean that is directly affected by an extreme outlying observation. Whereas the mean can be skewed by an extreme outlying observation, the median is unaffected and therefore remains robust.

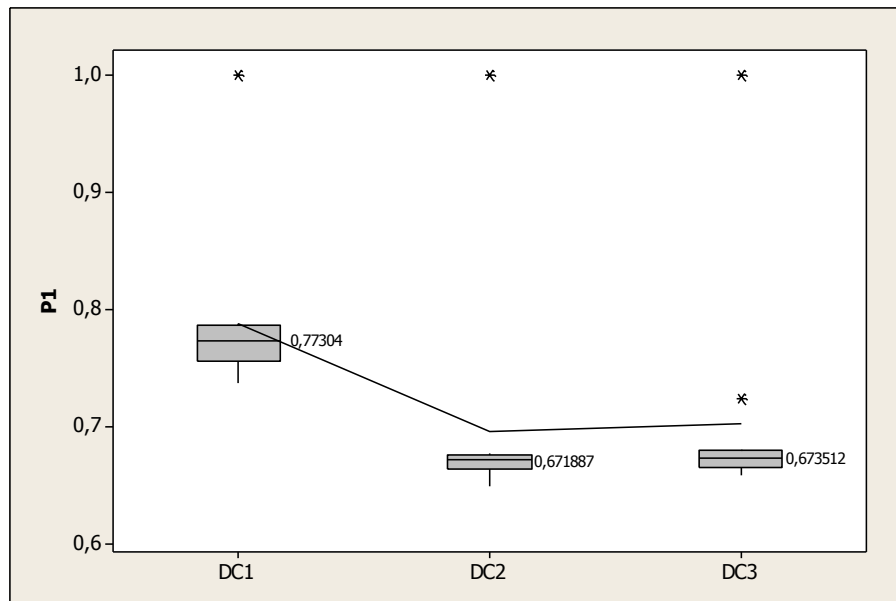


Figure 4.13. Evaluation of P1 for DCs.

The value of P1 for DC1 is higher than those of DC2 and DC3 (Figure 4.13). This result shows that DC1 can satisfy customer order with higher probability in each period. Note that P1 value should be close to 1 across the periods for all supply chain members to have the potential to meet all incoming orders over time.

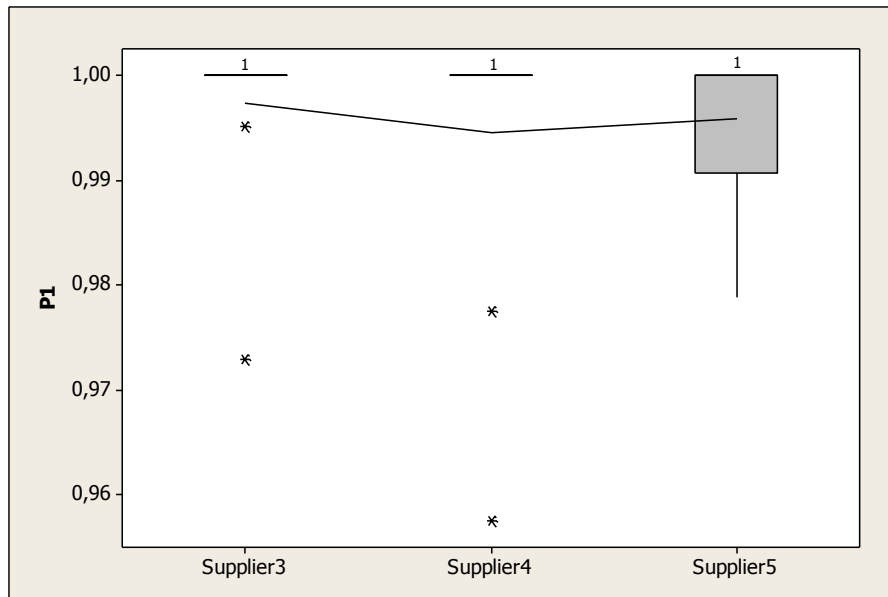


Figure 4.14. Evaluation of P1 for Suppliers.

The value of P1 for Supplier3 and Supplier4 is approximately same but Supplier5 is a bit different from other Suppliers (Figure 4.14). It is seen that Supplier5' box length that shows the variability of P1 is higher and hence Supplier3 and Supplier4 are better than Supplier5 when box plot is taken into account.

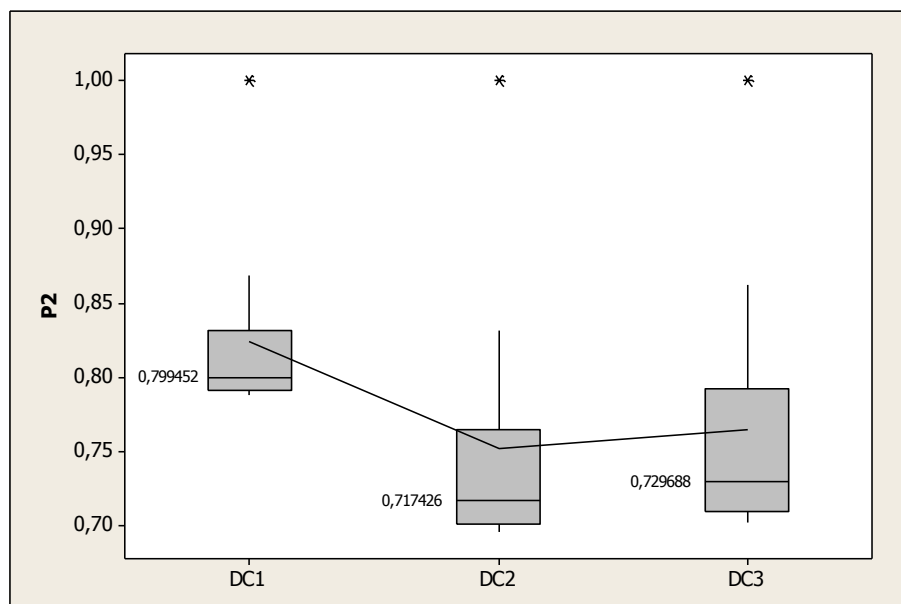


Figure 4.15. Evaluation of P2 for DCs.

The value of P2 for DC1 is higher than those of DC2 and DC3 (Figure 4.15). This result show that DC1 can satisfy customer order with higher probability over periods. Note that P2 values should be close to 1 across the periods for all supply chain members to have the potential to meet all incoming orders over time.

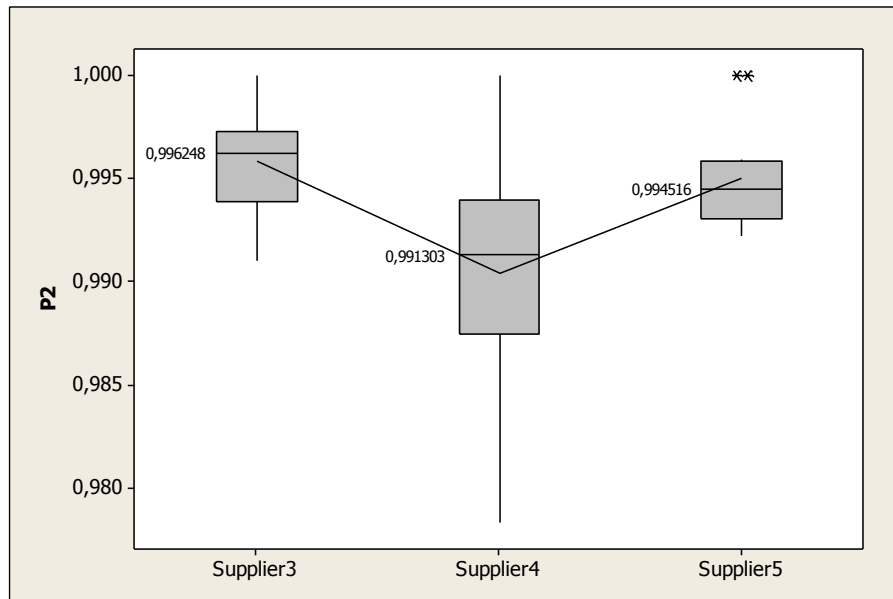


Figure 4.16. Evaluation of P2 for Suppliers.

In Figure 4.16, it is noticeable that the value of P2 for Suppliers is different from P1 value. The variability of P2 is higher than P1. According to Figure 4.16, Supplier3 is better than other Suppliers. The values of P2 for Supplier4 have a higher variability and are also lower than others. Comparing P2 with P1 gives very valuable information for managers. It is clearly seen that it can be quite misleading to consider just P2 values because it is being a biased indicator due to its taking account of initial conditions.

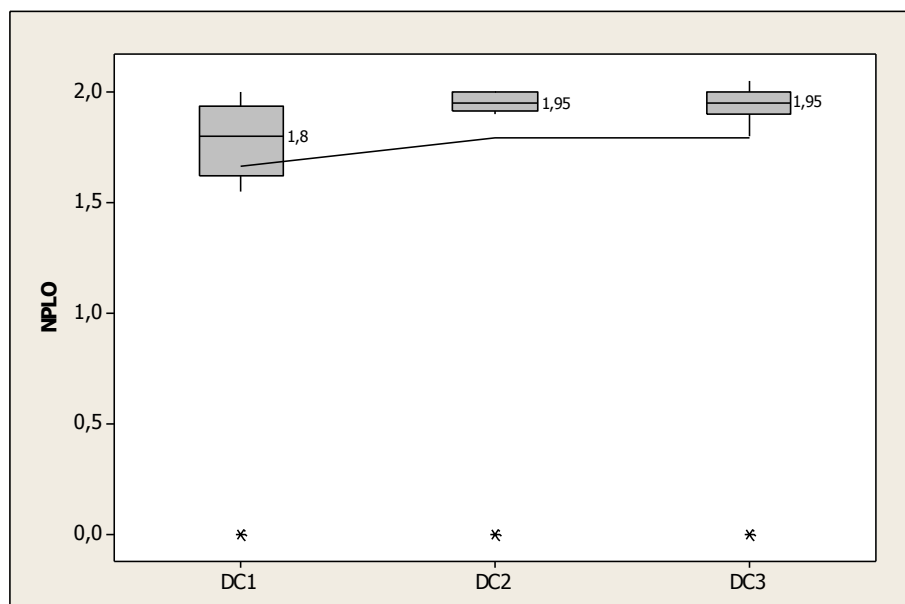


Figure 4.17. Evaluation of NPLO for DCs.

From Figure 4.17, the box plots indicate that there is no difference between DC2 and DC3. In fact, it is clearly visible that the boxes and the median values are on

the same level. On the other hand, median value of DC1 is lower than other DCs and also its NPLO variability is higher when box length is taken into account.

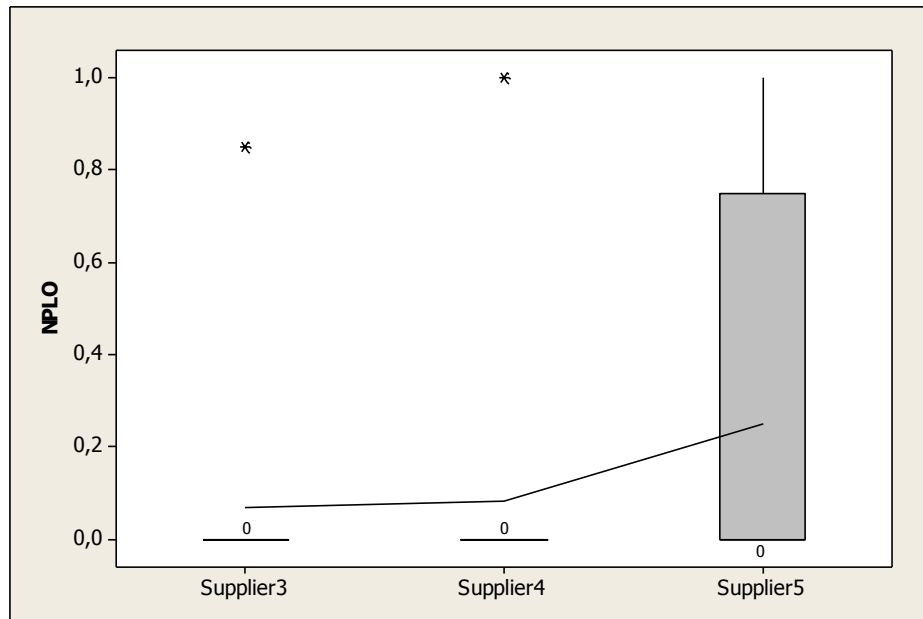


Figure 4.18. Evaluation of NPLO for Suppliers.

The box plots indicate that there is no difference between Supplier3 and Supplier4 (Figure 4.18). In fact, it is clearly visible that the median values are zero. Supplier5 has a different structure although median is zero. NPLO for Supplier5 has a great variability due to wide range of box length. Therefore, Supplier3 and Supplier4 have better performance than Supplier5 when NPLO is taken into account.

Due to the increased competition in the supply chain environment, customers are not willing to wait anymore and most of the customer demand is considered to be lost in many practical settings. Therefore, characterizing supply chain members' structural properties, and evaluating proposed method are very important in lost sales environment. In this study, the values of NTLO (Figure 4.19) and TLOQ (Figure 4.20) for DC1 are lower than those of DC2 and DC3. Hence, customer satisfaction is higher than DC2 and DC3 since the customer satisfaction could be highly increased by reducing lost sales. Note that Suppliers have no NTLO and TLOQ.

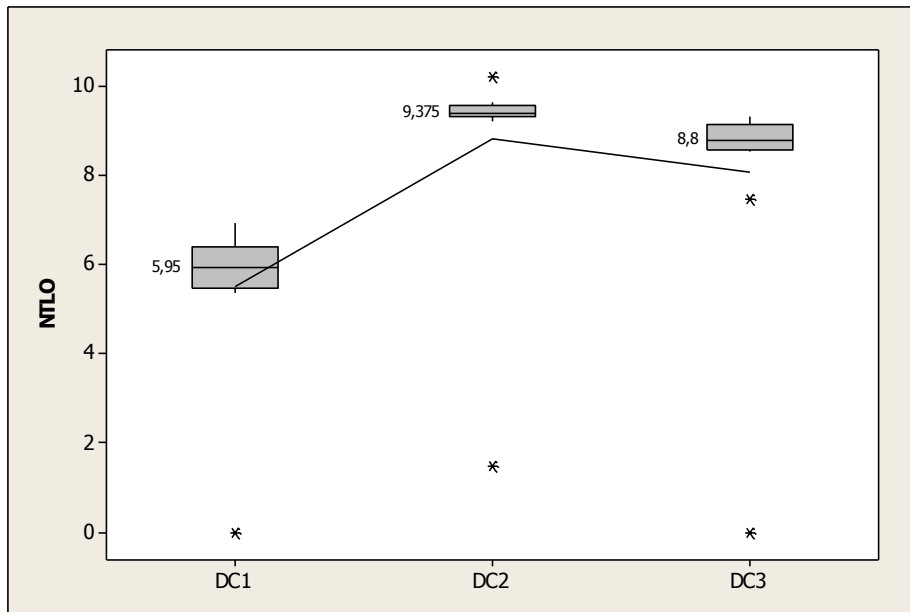


Figure 4.19. Evaluation of NTLO for DCs.

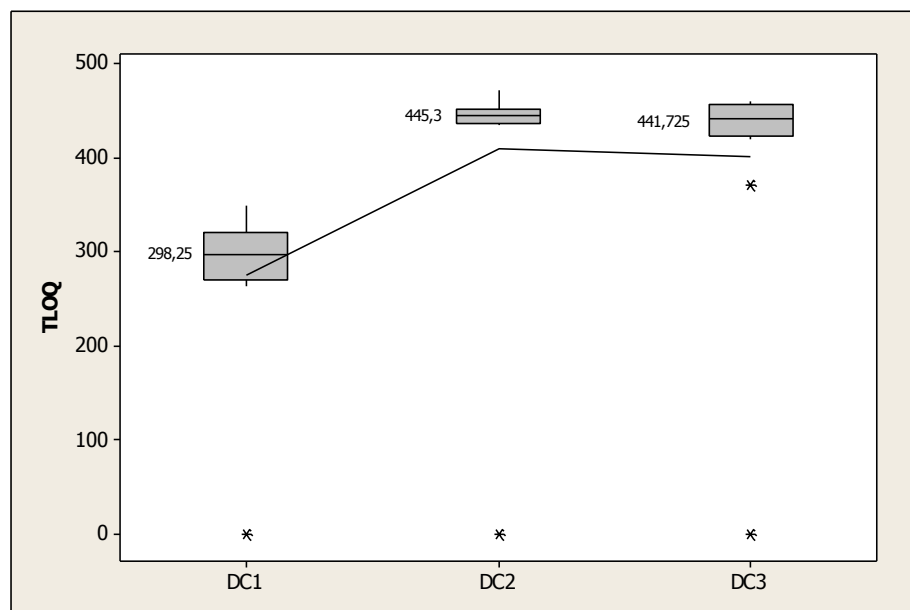


Figure 4.20. Evaluation of TLOQ for DCs.

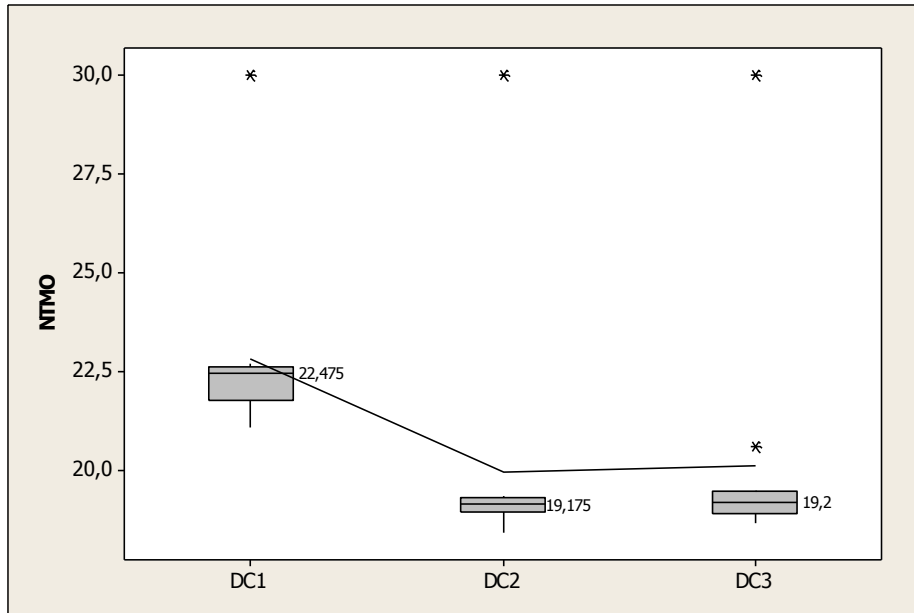


Figure 4.21. Evaluation of NTMO for DCs.

There is no observable difference between DC2 and DC3 as seen in Figure 4.21. The value of NTMO for DC1 is higher than those of DC2 and DC3.

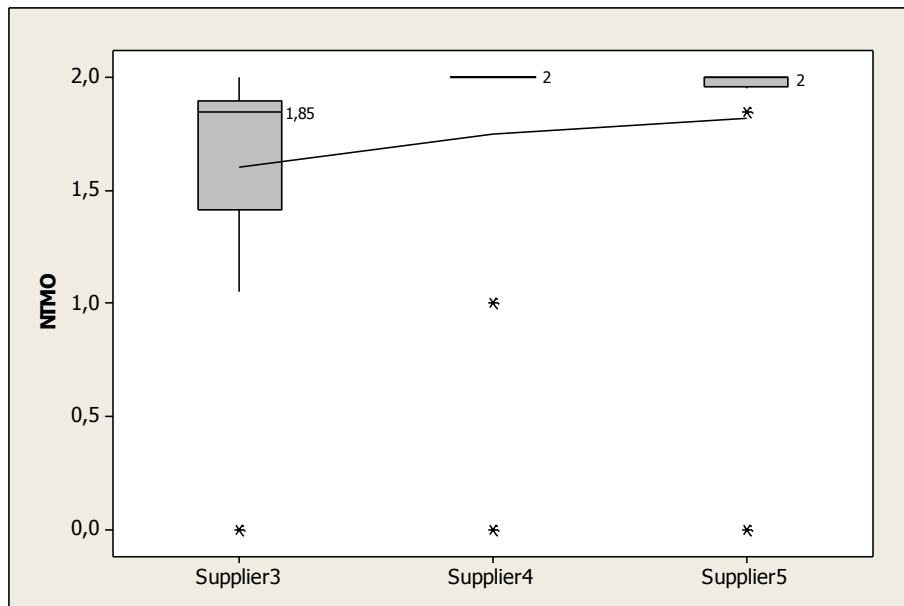


Figure 4.22. Evaluation of NTMO for Suppliers.

The box plots indicate that there are some differences between Suppliers (Figure 4.22). In fact, it is clearly visible that the median values are equal to 2 for Supplier4 and Supplier5 but Supplier5 has some variability. The median value for Supplier3 is lower than other Suppliers. Also, it has a great variability due to wide range of box length.

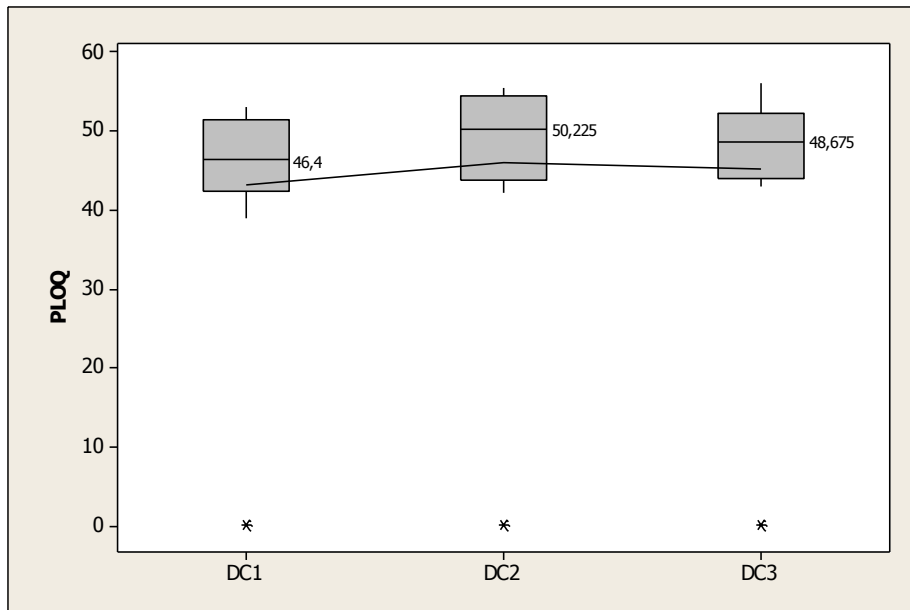


Figure 4.23. Evaluation of PLOQ for DCs.

Although there is no observable difference between DCs, the median value of PLOQ for DC2 is higher than those of DC1 and DC3 (Figure 4.23).

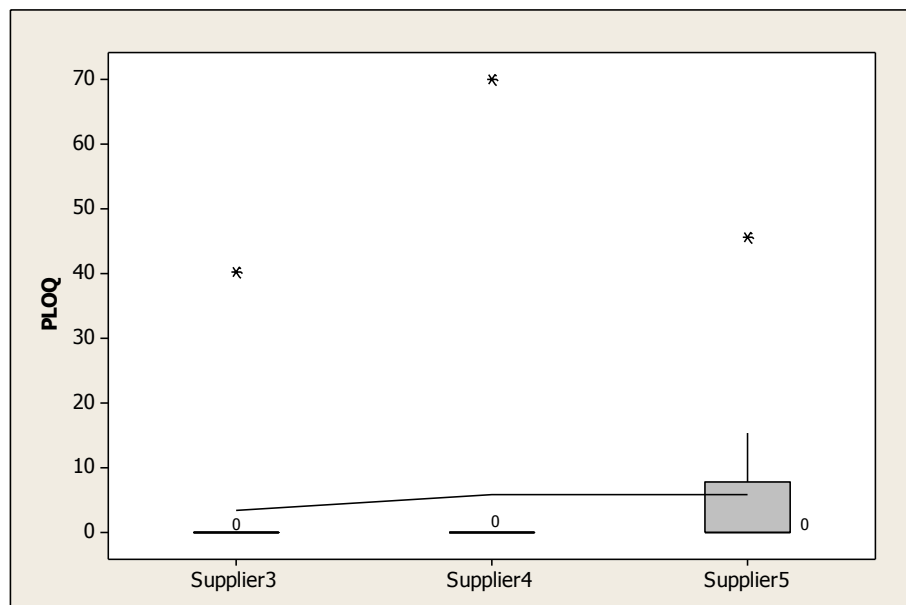


Figure 4.24. Evaluation of PLOQ for Suppliers.

As seen in Figure 4.24 there is no observable difference between Suppliers considering median. Note that, Supplier5 has some variability and box length shows the variability of PLOQ.

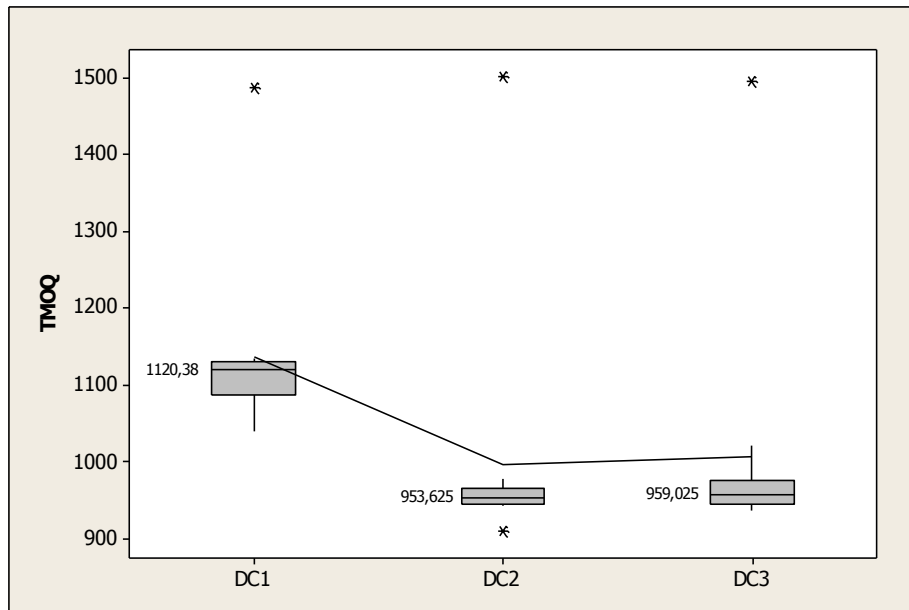


Figure 4.25. Evaluation of TMOQ for DCs.

The value of TMOQ for DC1 is higher than those of DC2 and DC3 (Figure 4.25). Higher TMOQ means high level of customer satisfaction. Similar things can be said with regard to the value of TMOQ for Suppliers as seen in Figure 4.26. Note that, box length of Supplier3 shows the variability of TMOQ.

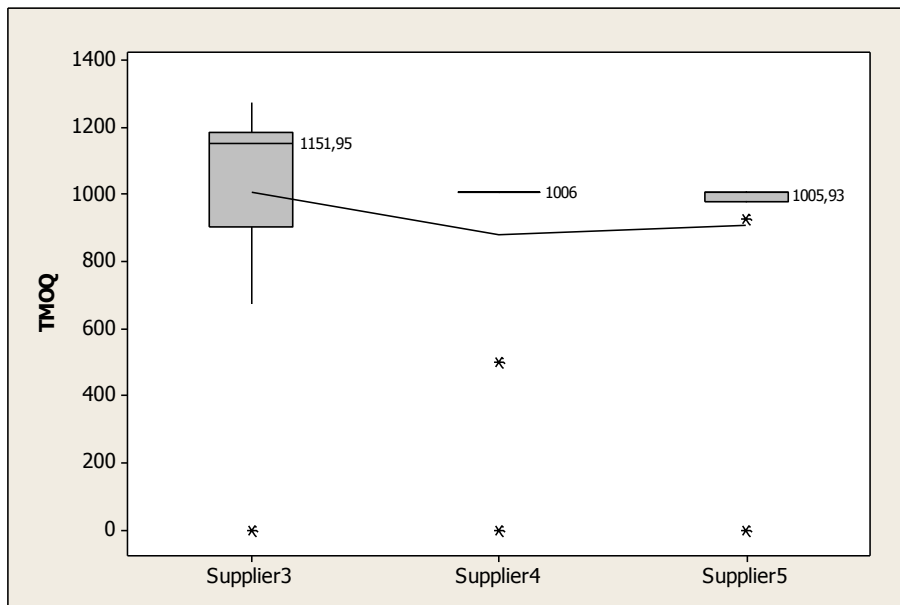


Figure 4.26. Evaluation of TMOQ for Suppliers.

In conclusion, supply chain members have some differences. The source of variation may be due to stochastic order processing times, stochastic transportation times, and levels of inventory control parameters. The strongest candidate among

these is the level of inventory control parameters. To remain competitive, companies must analyze all supply chain member and this study can help them to understand how to apply statistical analysis skills to clarify these policies with a greater level of detail.

4.2. Lead time based analysis for each model

The purpose of this section is to show the lead time related statistics more in depth to provide more useful information. Hence, statistical analysis extended by calculating order met probabilities per lead time period which is one of the most significant statistics. The overall goal of such a detailed analysis is to extract dynamics of the system considered and transform it into an understandable structure for managerial decision making. Moreover, taking into account the stochastic lead times further is increased the importance of this statistic. Order met probability per lead time period is calculated by using equation (14).

$$\int_n^{\text{end of lead time}} \min\left(1, \frac{\text{Current Inventory Level}}{\text{Incoming Order Quantity}}\right) dt \quad (14)$$

It should be emphasized that calculating such a statistic can only be possible through simulation which reinforces once again the power of simulation. Note that there could be no replenishment orders for some periods. Still, these statistics are collected for periods with replenishment orders. To the best of our knowledge such a valuable statistic never ever held before while analyzing such systems. Note that order met probabilities per lead time for Suppliers are always 1 or close to 1 in all periods. It should be noted that the simulation is run over one year period. Since review period length is five days (i.e., inventory is reviewed at every five days at both DCs and Suppliers) actually a total of 73 lead time per period will be come true for all DCs and all Suppliers. Note that, at some periods there will be no replenishment orders for both DCs and Suppliers and denoted as “-” in following tables. Also, order met probabilities per lead time period within some review periods will be zero for some DCs and Suppliers.

From Table 4.4, it is clearly seen that order met probabilities per lead time period are very low for almost all DCs. The best order met probability per lead time period is at most 20.14% (row 9) which means that 79.86% of incoming orders lost during 9th lead time period.

Table 4.4. The order met probabilities per lead time period for all DCs.

	Periodic Review System			Periodic Review System		
	DC1	DC2	DC3	DC1	DC2	DC3
1	-	-	-	0,0346	0,0150	0
2	-	-	-	0,0729	0	0
3	-	-	-	0,0639	-	0
4	-	-	-	0,0066	0	0
5	-	-	-	0,0457	0	0
6	-	-	-	0,1036	-	0
7	-	-	-	0,1222	0	0,0235
8	-	-	-	0,0283	0	0
9	0,0491	0,0507	0,2014	0,0670	-	0
10	-	-	-	0,0364	0	0
11	-	-	0,0420	0,0115	0	0
12	0,1159	0	0	0,0945	-	0
13	0	-	0,0289	0,1129	0	0
14	-	0,0811	0	0,0259	0,0014	0
15	0,0593	0	0,0416	0,0591	-	0

Table 4.4. (Continued)

16	0,1635	-	-	53	0,0719	0	0
17	0	0	0,0018	54	0,0315	0	0
18	0,0576	0	0	55	0,0273	-	0
19	0,0279	-	0	56	0,1572	0	0
20	0,0010	0	0	57	0,0536	0	0
21	0,0332	0	0	58	0,0262	-	0
22	0,1125	-	0	59	0,1000	0	0
23	0,0173	0	0	60	0,0522	0,0011	0
24	0,0672	0	0	61	0	-	0
25	0,0368	-	0	62	0,0510	0	0
26	0,0645	0	0,0310	63	0,1052	0	0,0006
27	0,0746	0	0	64	0,0176	-	0
28	0,0931	-	0,0273	65	0,1351	0	0
29	0,0209	0	0	66	0,0667	0	0
30	0,1269	0,0049	0,0004	67	0,0123	-	0
31	0,0283	-	0	68	0,0595	0	0
32	0,0375	0	0	69	0,0977	0	0
33	0,0471	0	0	70	0,0131	-	0
34	0,0947	-	0	71	0,1293	0	0

Table 4.4. (Continued)

35	0	0	0	0	72	0,1098	0	0
36	0,0583	0	0,0004	73	0,0107	0	0	
37	0,0578	-	0					

Of course, these values are not self-explanatory and dependent on the length of the lead time period and average inventory holding unit during the length of lead time. Thus, evaluating order met probabilities along with the length of lead time period and average inventory holding unit during the length of lead time will make it much more comprehensible.

It is clear that longer lead time periods together with lower average inventory holding unit will result in lower order met probabilities during lead time period. But, longer lead time periods together with higher average inventory holding unit will result in higher order met probabilities during lead time period. Note that, average inventory holding unit depends particularly on the level of inventory at the beginning of the lead time period. But, it also depends on the length of the lead time period (see equation (14)). In this respect, Table 4.4 are all supplemental tables and should be evaluated together to increase comprehensibility. From row 30 of Table 4.4 it is seen that order met probabilities per lead time period for all DC1, DC2, and DC3 are 12.69%, 0.49%, and 0.04%. In other words, 12.69% percent of the lead time period incoming orders are met by DC1 or during lead time period 12.69% percent of the incoming orders are met by DC1. In addition to this, we used box plot to present lead time based analysis in a detailed way.

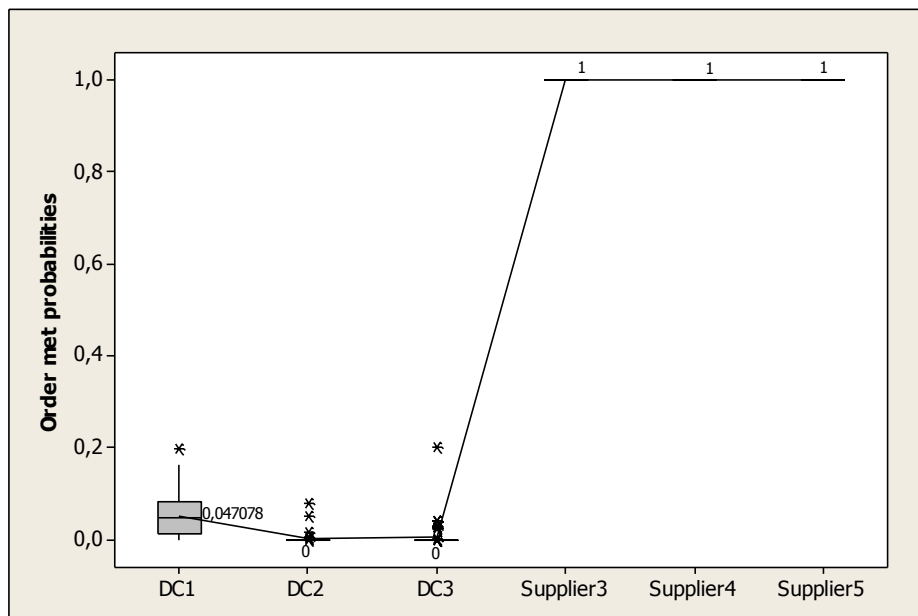


Figure 4.27. The order met probabilities per replenishment lead time for periodic review system.

Table 4.5. The lead time period ratio to review period.

	DC1	DC2	DC3	Supplier3	Supplier4	Supplier5	DC1	DC2	DC3	Supplier3	Supplier4	Supplier5
1	-	-	-	-	-	-	38	0,0581	0,1601	0,1013	0,2223	-
2	-	-	-	-	-	-	39	0,2017	0,4430	0,4666	0,0421	0,0855
3	-	-	-	-	-	-	40	0,2510	-	0,0218	0,1284	0,2620
4	-	-	-	-	-	-	41	0,1946	0,1504	0,0841	0,1762	-
5	-	-	-	-	-	-	42	0,1308	0,4461	0,4736	0,1363	0,0872
6	-	-	-	-	-	-	43	0,2621	-	0,0347	0,0867	0,2628
7	-	-	-	-	-	-	44	0,1826	0,1521	0,0953	0,1947	-
8	-	-	-	-	-	-	45	0,0857	0,4398	0,4354	0,1252	0,0875
9	0,6130	0,5564	0,5356	-	-	-	46	0,2866	-	0,0342	0,0658	0,2616
10	-	-	-	-	-	-	47	0,1764	0,1234	0,1075	0,1971	-
11	-	-	0,0432	-	-	-	48	0,0829	0,4461	0,4170	0,1567	0,0879
12	0,1885	0,5564	0,5525	-	-	-	49	0,2148	-	0,0578	0,0669	0,2614
13	0,4345	-	0,0231	-	0,4003	-	50	0,3172	0,1474	0,0865	0,1520	-
14	-	0,1080	0,0220	-	-	-	51	0,0825	0,4722	0,4782	0,2177	0,0874
15	0,1955	0,4806	0,5845	-	0,0624	-	52	0,1487	-	0,0639	0,0655	0,2620
16	0,3168	-	-	0,1393	0,2800	0,2938	53	0,2863	0,1650	0,0980	0,0851	-
17	0,1150	0,1169	0,0408	0,2358	-	-	54	0,1984	0,4313	0,4667	0,2209	0,0875
18	0,1227	0,4847	0,5260	0,0944	0,0681	0,0174	55	0,0956	-	0,0624	0,1104	0,2617
												0,2628

Table 4.5. (Continued)

19	0,3670	-	0,0266	0,0853	0,2794	0,3012	56	0,2709	0,1386	0,0921	0,0658	-	0,0172
20	0,1254	0,1177	0,0980	0,2718	-	-	57	0,1329	0,4602	0,4311	0,1904	0,0869	0,0350
21	0,1345	0,4710	0,4922	0,0906	0,0696	0,0349	58	0,1499	-	0,0614	0,1090	0,2624	0,2616
22	0,2025	-	0,0215	0,0878	0,2781	0,2798	59	0,3036	0,1576	0,0836	0,1112	-	0,0175
23	0,2020	0,1170	0,0882	0,1279	-	-	60	0,1924	0,4825	0,4634	0,1736	0,0882	0,0349
24	0,2152	0,4980	0,4442	0,1564	0,0697	0,0348	61	0,0234	-	0,0588	0,1312	0,2627	0,2618
25	0,2031	-	0,0265	0,1511	0,2797	0,2798	62	0,3248	0,1492	0,0913	0,0226	-	0,0175
26	0,1283	0,1180	0,1039	0,1328	-	-	63	0,2474	0,4433	0,4528	0,2220	0,0872	0,0349
27	0,3220	0,4937	0,4204	0,0842	0,0699	0,0349	64	0,0681	-	0,0476	0,1722	0,2620	0,2612
28	0,1614	-	0,0443	0,2197	0,2792	0,2627	65	0,2606	0,1237	0,1003	0,0429	-	0,0176
29	0,1603	0,1233	0,0940	0,1046	-	0,0228	66	0,2717	0,4248	0,4537	0,1675	0,0867	0,0350
30	0,2173	0,5185	0,4814	0,1122	0,0699	0,0349	67	0,0619	-	0,0510	0,1986	0,2624	0,2620
31	0,2020	-	0,0351	0,1466	0,2792	0,2794	68	0,2578	0,1327	0,0662	0,0442	-	0,0174
32	0,0794	0,0922	0,0912	0,1564	-	-	69	0,2833	0,4391	0,4637	0,1738	0,0871	0,0350
33	0,2827	0,4581	0,4538	0,0650	0,0698	0,0346	70	0,0737	-	0,0495	0,1943	0,2615	0,2615
34	0,1897	-	0,0361	0,2004	0,2802	0,2792	71	0,2660	0,1411	0,0794	0,0441	-	0,0174
35	0,0891	0,1255	0,0943	0,1262	-	-	72	0,2844	0,4363	0,4832	0,1911	0,0875	0,0348
36	0,2031	0,5073	0,4912	0,0684	0,0699	0,0348	73	0,0625	-	0,0537	0,1714	0,2613	0,2627
37	0,3286	-	0,0328	0,1537	0,2804	0,2794							

From Figure 4.27, it is clearly seen that order met probabilities per lead time period are very low for almost all DCs in periodic review system. However, order met probabilities per lead time for all Suppliers in periodic review system are always 1 or close to 1 in all periods.

Note that outliers are represented by “*” and the line connected supply chain member in Figure 4.27 shows the mean that is directly affected by an extreme outlying observation.

Table 4.5 simply summarizes the ratio between the length of lead time period and the length of review period (i.e., percentages of lead time periods over the review periods). According to row 12 of Table 4.5 it can be said that lead time of DC1 comprised 18.85 percent of review period 12 (i.e., $5 \times 0.1885 = 0.9425$ days). Likewise, lead time of DC2 and DC3 comprised 55.6 and 55.3 percent of review period 12 (i.e., $5 \times 0.5564 = 2.782$ days and $5 \times 0.5525 = 2.7625$ days, respectively), respectively.

Consequently, the minimum percentage of lead time period for DCs comprise 2.18% of related review period and the maximum percentage of lead time period comprise 61.3% of related review period. Also, the minimum percentage of lead time period for Suppliers comprise 1.72% of related review period and the maximum percentage of lead time period comprise 40.03% of related review period. Such a large gap between minimum and maximum values shows the importance of taking stochastic behavior of the system into account.

In Figure 4.28, box length shows the variability of length of lead time and the line across the box presents where the lead times are centered. It is seen that each member is different from each other in periodic review system due to stochastic environment.

Increased levels of inventory parameters will definitely improves not only average holding unit levels over lead time but also order met probabilities over lead time both at DCs and Suppliers at the expense of increased total cost. Figure 4.29 summarizes the average holding unit that is hold at DCs and Suppliers during the replenishment lead time in periodic review system. The box length gives an indication of the average holding unit variability and the line across the box shows where the average holding unit is centered.

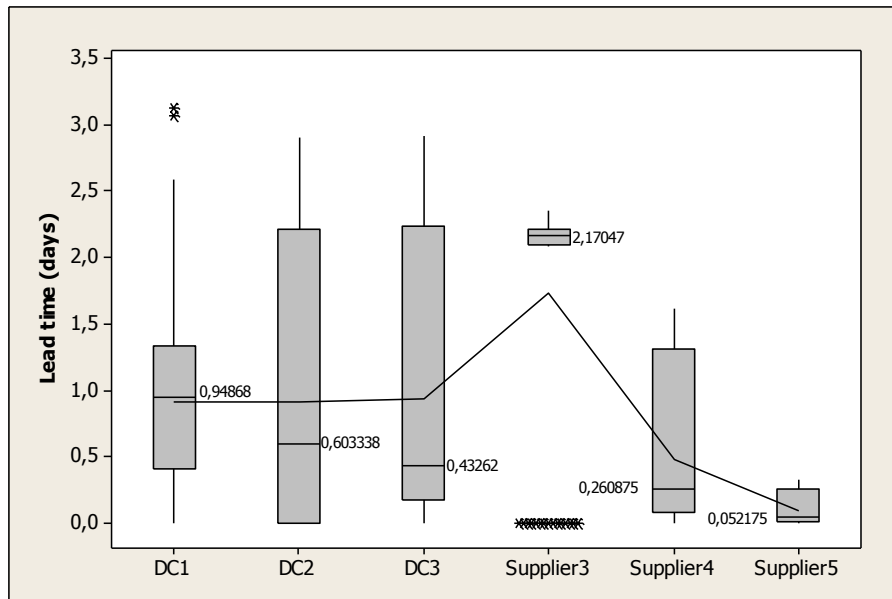


Figure 4.28. Lead time analysis for each supply chain member in periodic review system.

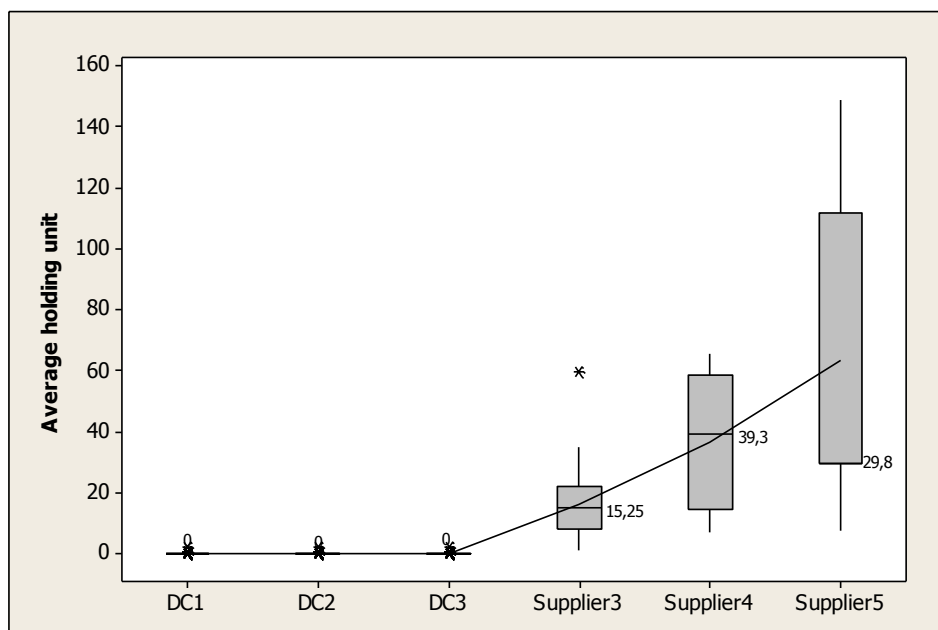


Figure 4.29. The average holding unit of supply chain members in periodic review system.

Table 4.6 summarizes the average holding unit that is hold at both DCs and Suppliers during the lead time periods. It should be noted that DCs average holding unit over lead time period are all close to zero. The main reason for this situation arises from the fact that even maximum amount of order-up-to level cannot handle incoming orders to the DCs.

Table 4.6. The average holding unit in DCs and Suppliers.

	DC1	DC2	DC3	Supplier3	Supplier4	Supplier5	DC1	DC2	DC3	Supplier3	Supplier4	Supplier5
1	-	-	-	-	-	-	38	0	0	0	20	-
2	-	-	-	-	-	-	39	1	0	0	7	30
3	-	-	-	-	-	-	40	1	-	0	19	58
4	-	-	-	-	-	-	41	0	0	0	18	-
5	-	-	-	-	-	-	42	1	0	0	8	15
6	-	-	-	-	-	-	43	1	-	0	11	58
7	-	-	-	-	-	-	44	2	0	0	24	-
8	-	-	-	-	-	-	45	1	0	0	24	15
9	0	0	2	-	-	-	46	1	-	0	7	58
10	-	-	-	-	-	-	47	0	0	0	22	-
11	-	-	0	-	-	-	48	0	0	0	13	15
12	2	0	0	-	-	-	49	2	-	0	6	58
13	0	-	1	-	0	-	50	2	0	0	19	-
14	-	1	0	-	-	-	51	0	0	0	26	15
15	1	0	1	-	20	-	52	1	-	0	7	58
16	3	-	-	3	62	131	53	1	0	0	13	-
17	0	0	0	0	-	-	54	0	0	0	22	15
18	1	0	0	0	11	30	55	0	-	0	12	58
19	0	-	0	13	62	119	56	2	0	0	7	-
20	0	0	0	16	-	-	57	1	0	0	31	15

Table 4.6. (Continued)													
21	0	0	0	5	11	30	58	0	-	0	13	58	112
22	2	-	0	10	62	119	59	2	0	0	10	-	7
23	0	0	0	24	-	-	60	1	0	0	29	15	30
24	1	0	0	9	11	30	61	0	-	0	15	59	112
25	0	-	0	20	62	119	62	1	0	0	1	-	7
26	1	0	1	12	-	-	63	2	0	0	21	15	30
27	1	0	0	15	11	30	64	0	-	0	24	58	112
28	1	-	0	24	62	112	65	2	0	0	6	-	7
29	0	0	0	20	-	0	66	1	0	0	31	15	30
30	2	0	0	9	11	30	67	0	-	0	20	58	112
31	0	-	0	27	62	119	68	1	0	0	5	-	7
32	1	0	0	13	-	-	69	2	0	0	20	15	30
33	1	0	0	8	11	30	70	0	-	0	25	58	112
34	1	-	0	17	62	119	71	2	0	0	5	-	7
35	0	0	0	22	-	-	72	1	0	0	30	7	7
36	1	0	0	3	11	30	73	0	-	0	27	66	112
37	1	-	0	16	62	119							

The results of the study show that indeed proposed model has significant effects on the optimal policy values in DCs. Balancing the total average holding cost with the total lost sales cost, also balances P1 and P2 among the DCs. It is clear that proposed model allows managers to have the same level of total supply chain costs in DCs while increasing customer satisfaction by decreasing number of totally lost orders and the number of partially lost orders. Looking at individual cost components in OvS model, we observe that the decrease in the lost sales costs are offset by the increase in average holding costs. This is a counterintuitive result that highlights the importance of inventory decisions in supply chain.

CHAPTER 5

5. CONCLUSIONS

Inventory control systems are challenging in the case of modeling because managing inventories is typically difficult in a stochastic and/or dynamic environment. Providing optimal inventory control system is a crucial foundation for achieving both strategically and tactically success in inventory management. On the other hand, modeling of inventory control system in a stochastic and/or dynamic environment needs too much computational effort to solve and sometimes they are not solvable in reasonable time. Also, existing models are analytically solvable only under simplifying assumptions and approximations due to inability of the representing stochastic and/or dynamic environments. Hence, many researchers have dedicated themselves to search more robust model. At this point, OvS can be used with much details, realities, and complexities as the modeler wants in order to solve any real inventory control systems. Therefore, we used OvS model to optimize inventory levels considering (R, s, S) inventory control system and supplier selection in a two echelon supply chain with lost sales system. Our proposed OvS approach for solving the considered problem can be explicitly considered as a complementary tool for determining the reorder point, order-up-to-level, and initial inventory while ensuring cost based objective function with lost sales system. Although many researchers have dedicated themselves to search more robust model involving stochastic behaviors existing in real-world problems, they do not report such an extensive analysis for (R, s, S) policies. To understand better the scope of periodic review systems and opportunities associated with inventory management, we give a detailed analysis of inventory control system including cost component analysis (average holding cost, order cost per use, lost sales cost, order processing cost and processing cost), probability based analysis per each period (P1 and P2), quantity based analysis per each period (TMOQ, TLOQ, and PLOQ), order based analysis per each period (NTMO, NTLO, and NPLO) and lead time based analysis per each replenishment lead time (order met probabilities, average holding unit, and length of the lead time) for proposed OvS models, which are remarkable model for inventory control systems in determining the best inventory control parameters. Extensive statistical analyses also yield third important results.

(1) Supplier selection is important in inventory control system. OvS model integrates the supplier selection and inventory control system to make a supply chain member more flexible and responsive to customer requests.

(2) Looking at each cost component in OvS model, we observe that the decrease in the lost sales costs are offset by the increase in average holding costs. Also, if the periodic review system could be applied effectively, total supply chain cost could be automatically improved in lost sales system.

(3) The ratio between the lost sales cost and total supply chain cost in DCs is dependent on the length of replenishment lead time through the amount of shortages.

In conclusion, increasing diversity in customer expectations can be easily satisfied using our proposed model since it has ability to ensure right level of responsiveness at the lowest possible cost in each DC and each Supplier. It shall also be of great value not only to readers who desire to extend their research avenues into this exiting area, but also to those who have already investigated this topic, but in isolation or with limited scope.

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