Characterizing Stochastic and Dynamic Forward/Closed-Loop Supply Chains by using Simulation Optimization

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ABSTRACT

CHARACTERIZING STOCHASTIC AND DYNAMIC FORWARD/CLOSED-LOOP SUPPLY CHAINS BY USING SIMULATION OPTIMIZATION

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A supply chain network, due to its nonlinear, stochastic, time-dependent nature, and presence of complex interactions between supply chain members, can become quite challenging to optimize and requires a more complex model. At this point, simulation optimization gains a better understanding of the complex and messy phenomenon of supply chain problems. In this thesis, two types of supply chain problem are solved by using simulation optimization. The first one is a forward supply chain problem (FSCP), and the second one is a closed-loop supply chain problem (CLSCP). Simulation optimization consists of two-phase, namely (1) optimization phase, and (2) simulation phase. Optimization phase tries to find out answers for both strategic and operational decisions. Inventory control system parameters and strategic decisions (selecting a supplier, opening a plant etc.) are determined by using genetic algorithm. Then, determined decision variables are evaluated by using simulation model. Moreover, extensive statistical analysis is given to enhance the understanding of system behavior. Computational results showed that not only cost functions but also other performance measures (average service levels etc.) can be improved by using simulation optimization. Proposed simulation optimization provides a remarkable contribution to the uncertain, dynamic and complex real-world supply chain problems.

Keywords: supply chain, closed loop supply chain, simulation optimization, genetic algorithm, inventory control system

ÖZET

STOKASTİK VE DİNAMİK İLERİ/KAPALI ÇEVRİM TEDARİK ZİNCİRİNİN SİMÜLASYON OPTİMİZASYONU KULLANILARAK KARAKTERİZE EDİLMESİ

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Tedarik zinciri ağını, doğrusal olmayan, stokastik, zaman bağımlı doğası ve tedarik zinciri üyeleri arasındaki karmaşık yapısından dolayı optimize etmek oldukça zor olabilir ve daha kapsamlı modeller gerekir. Bu noktada simülasyon optimizasyonu tedarik zincirinin kompleks ve karmaşık olgusunda daha iyi anlayış kazandırır. Bu tezde, iki tip tedarik zinciri problemi simulasyon optimizasyonu kullanarak çözüldü. Problemlerden ilki ileri tedarik zinciri ağ problemi, ikincisi ise kapalı çevrim tedarik zinciri problemidir. Simülasyon optimizasyonu iki aşamadan oluşmaktadır: (1) optimizasyon aşaması, ve (2) simülasyon aşaması. Optimizasyon aşaması stratejik ve operasyonel kararlara cevap bulmaya çalışmaktadır. Envanter kontrol sistemi parametreleri ve stratejik kararlar (tedarikçi seçimi, fabrika açılması kararı gibi) genetik algoritma kullanarak belirlenmektedir. Daha sonra belirlenen değişkenler simülasyon modeli kullanılarak değerlendirilmektedir. Dahası, sistem davranışının daha iyi anlaşılabilmesi için kapsamlı istatistiksel analizler verilmektedir. Hesaba dayalı sonuçlar sadece mali fonksiyonlar değil diğer performans ölçütlerinin (ortalama hizmet seviyesi gibi) simülasyon optimizasyonu kullanarak geliştirilebileceğini göstermiştir. Önerilen simülasyon optimizasyonu belirsiz, dinamik ve karmaşık gerçek hayat tedarik zinciri problemlerinde dikkate değer katkılar sunmaktadır.

Anahtar Kelimeler: tedarik zinciri, kapalı çevrim tedarik zinciri, simülasyon optimizasyonu, genetik algoritma, stok kontrol sistem

This thesis is dedicated to my wonderful family, Dad, Mom, Sisters, Brother-in-laws, Nephews and Nieces

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LIST OF ABBREVIATIONS

ACO	Ant Colony Optimization
AHP	Analytical Hierarchy Process
CLRPMB	Capacitated LRP with Mixed Backhauls
CLSC	Closed Loop Supply Chain
CLSCP	Closed Loop Supply Chain Problem
FSCP	Forward Supply Chain Problem
GA	Genetic Algorithm
ILP	Integer-Linear Program
IRP	Inventory Routing Problem
LP	Linear Programming
LRIP	Location Routing Inventory Problem
LRP	Location Routing Problems
MIP	Mixed Integer Programming
NPLO	Number of Partially Lost Orders
NTLO	Number of Totally Lost Orders
NTMO	Number of Totally Met Orders
PLOQ	Partially Lost Order Quantity
PSO	Particle Swarm Optimization
RL	Reverse Logistic
SA	Simulated Annealing
SC	Supply Chain
SCM	Supply Chain Management
SO	Simulation Optimization
TLOQ	Totally Lost Order Quantity
TMOQ	Totally Met Order Quantity
TS	Tabu Search
VNS	Variable Neighborhood Search

CHAPTER 1

INTRODUCTION

1.1 Theoretical Background

As the supply chain (SC) gets bigger, it becomes increasingly complex as the number of variables to handle increase along with the difficulty to coordinate material flows between SC members. Thus, there is a need to identify the coordination mechanisms to cope with these issues. An SC should have the capability to evaluate various alternatives in terms of SC members and management policies, and it should reconfigure itself as conditions change. Coordination helps to improve the quality of decision-making by optimizing some decision variables.

Managing inventory is the most challenging task in the context of coordination. Many inventory management models have been proposed and applied for over 60 years but there is a growing need for robust methodologies in order to design high performance SC networks where the business return on investment can be reasonably improved with well-managed inventory control methodologies because of decreasing both direct expenses of a business and its investment (Badri, 1999). The method for the solution of such complex tasks needs the use of systems analysis and systematic approach to the problem of inventory management in general. Recently, most companies focused on creating their own business models that reduce or eliminate inventory uncertainty since there is no standard methodology for all companies – each company is unique and includes many different features and limitations. At this point, inventory management models can be distinguished by the assumptions about the variables used in the models. However, there are many sources of both uncertainty and variability in the system (Ziukov, 2015). Therefore, understanding and analyzing of the system perfectly are needed to develop an effective strategy to deal with complexity.

In literature, researchers are used various numbers and types of variables to create their models. Over the years, exact optimization models, approximate optimization models, simulation models, and SO models have been deployed related with inventory control modeling and problem solving in the SC.

Exact optimization models include linear and nonlinear programming, dynamic programming, integer programming, sequence enumeration models, and calculus dominated models. These models give the best solutions mathematically under some strict assumptions and simplification. Whether assumptions and simplification are acceptable depend much on the context and the purpose of the analysis. If they make the conclusions misleading, they are not acceptable; if they simplify the problem without changing the conclusions, they are acceptable (Ng, 2016).

Approximate optimization models include heuristic algorithms (metaheuristics or problem-specific heuristics) and approximation algorithms. Approximate optimization models provide a good solution to the problem, but not necessarily optimum solution while exact methods guarantee to give an optimum solution. However, exact methods need more time to find optimal solutions to hard problems. Approximate optimization models produce high-quality solutions in a reasonable time for complex problems (Talbi, 2009). The field of approximation algorithms brings mathematical rigor to the study of heuristic, allowing researchers to prove how well the heuristic operates on all instances, or giving researchers some idea of the types of instances on which the heuristic will not operate well (Williamson and Shmoys, 2011). In same manner, metaheuristic models optimize a problem by iteratively trying to improve a candidate solution with regard to a given measure of quality (Suh et al., 2011). Metaheuristics are not problem-specific and can make use of domain-specific knowledge in the form of heuristics (Desale et al., 2015). They require much less work than developing a problem-specific heuristics for a specific application. Metaheuristics can also obtain better quality solutions than problem-specific heuristics.

Simulation models can consider a dynamic and stochastic environment for SC network. Moreover, simulation-based models can give reasonable solutions without analytical assumptions and simplifications because almost every possible detail of actual system may be incorporated in a simulation model. Note that analytical assumptions and simplifications are generally used to make the model easier to implement but they can exclude relevant details of the real-world system and this lead to inaccurate representation of the proposed system. Also, simulation has an ability to capture specific real-world object characteristics and to incorporate a great level of detail (Paul and Chanev, 1998). However, simulation models do not provide the capability of finding the optimum set of decision variables in terms of predefined objective function(s). Herein, SO can be used with much details, realities, and complexities as the modeler wants (Kabirian and Ólafsson, 2011).

1.2 Research Goals and Motivation of the Thesis

Up to now, tremendous attentions have been appealed towards the research work on exact optimization models in achieving competitive advantage through the SC. On the other hand, none of these models is appropriate to work for all problems. Thus, proposed models can have specific characteristics which make them useful for certain types of problems. It is challenging in the case of real-world problems due to the presence of complex interactions between SC members. Therefore, the complexities and uncertainties in companies have motivated researchers to search for competitive advantages considering SO models. Especially, inventory control and supplier selection based SO model are of vital importance for companies' success since SC members should be replenished without hurting the level of product availability. Managers can successfully increase company's competitiveness and responsiveness by using SO models that have an ability to extract dynamics of the system considered and to transform it into an understandable structure for managerial decision-making. SO models along with modern computing power provide a significant opportunity to respond effectively in a dynamic and stochastic environment. To remain competitive and viable in today's business climate, SO models can be explicitly considered as a complementary tool. This thesis provides a practical and a simplified approach that integrates SO models into the coordination and implementation problems in SC.

The main goal of this thesis is to develop flexible, adaptable and generic SO models to solve SC problems under stochastic and dynamic environments (see, Figure 1.1). Due to its ability of capturing the high complexity of FSCPs/CLSCPs, SO can be efficiently used to cope with the stringent pressures from today's companies.

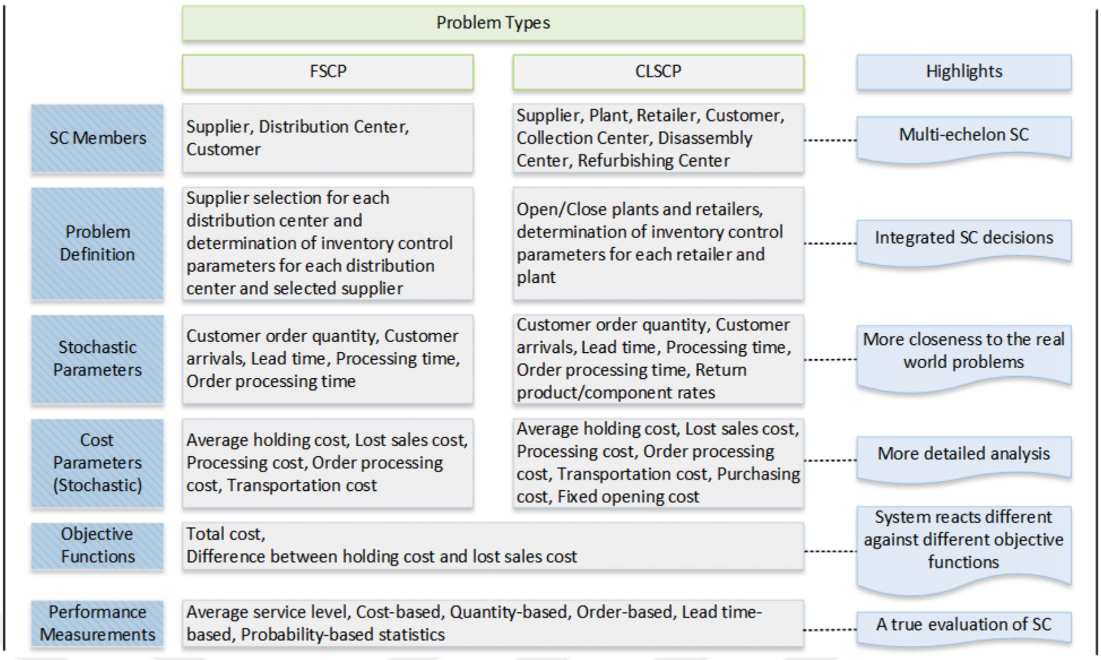


Figure 1.1 Summary of the research objectives and the framework of the thesis

Basically, this research serves the following goals:

1) Unveil the extent to how SO models have been used to model complicated and mathematically intractable problems for FSCPs and CLSCPs.
2) Provide an efficient reuse in real-world problems while decreasing the amount of time needed to develop the model. This is very important in real-world settings because proposed models lead to a large number of variants of variants born of the requirement to manage a wide range of decisions in the SC.
3) Make a decision about the objective of the forward SC network and the CLSC network where the minimization of total cost and the minimization of the differences between the total overordering cost and the total underordering cost are taken into account.
4) Provide detailed performance analysis of SO models including cost-based analysis, probability-based analysis (order met probability (P1) and overall order met probability (P2)), quantity-based analysis (totally met order quantity (TMOQ), totally lost order quantity (TLOQ), and partially lost order quantity (PLOQ)), order-based analysis (number of totally met orders (NTMO), number of totally lost orders (NTLO), and number of partially lost orders (NPLO)).

The overall goal is to extract dynamics of the system considered and transform it into an understandable structure for managerial decision-making. Therefore, inventory managers can easily determine the differences between SC members and then conduct further investigations to establish plausible explanations for differences.

1.3 Organization of the Thesis

This thesis consists of seven chapters. Chapter 1 presents an introduction that contains theoretical background, research goals and motivation of the thesis, and finally the organization of the thesis. The remainder of this thesis is created as follows.

Chapter 2 presents definitions and main concepts of SC and CLSC. Also, general definitions about inventory management are given. Additionally, general performance measures for SC and CLSC can be found in this chapter.

Chapter 3 discusses the relevant contributions in the field of SC and CLSC management. A literature review, which consist of three main parts, is given. Section 3.2 gives literature about SCM. Studies related with SC (only forward network) are categorized according to the solution methodologies. CLSC related literature are given in Section 3.3. Section 3.4 is devoted to the literature used SO as a solution methodology. Finally, a conclusion is given to summarize the chapter.

Chapter 4 describes the proposed methodology that is used throughout the thesis. Detailed information about proposed SO can be found in Section 0. Details of the GA and simulation models for both SC and CLSC problems are given in this section. And, Section 4.3 involves objective functions and other performance measures that are considered for both SC and CLSC problems.

In Chapter 5, a detailed analysis of forward SC network is given. This chapter begins with a brief introduction and a more specific literature for the considered problem. Problem definition of forward SC network is given in Section 5.2. And a brief information about SO considered for the problem can be found in Section 5.3. Section 5.4 is devoted to the analysis of continuous review models in order to give a deep insight into the problem. Then, a comparison of continuous and periodic review models is given in Section 5.5. Finally, Section 5.6 gives a conclusion for this chapter.

Chapter 6 describes the proposed CLSC network. Section 6.1 gives an introduction for considered problem. And a brief review table for SO literature is added into this section to demonstrate the importance of proposed SO for CLSC. Problem definition and proposed SO are given in Sections 6.2 and 6.3, respectively. Results and discussions for CLCS are given in section 6.4. This section is divided into three main sections, namely forward network analysis, reverse network analysis and lead time-based analysis. Finally, a conclusion is included.

Finally, Chapter 7 gives an overall summary, concluding remarks and contributions of the thesis. Also, suggestions for future research directions are included.

CHAPTER 2

DEFINITIONS AND MAIN CONCEPTS OF SUPPLY CHAIN AND CLOSED LOOP SUPPLY CHAIN

In this chapter, a general view of what an SC is and the various definitions are given to provide a strategic framework within SCs.

2.1 Supply Chain Management

Council of Supply Chain Management Professionals (CSCMP) defines the Supply Chain Management (SCM) as follows:

"*Supply Chain Management encompasses the planning and management of all activities involved in sourcing and procurement, conversion, and all logistics management activities. Importantly, it also includes coordination and collaboration with channel partners, which can be suppliers, intermediaries, third-party service providers, and customers. In essence, supply chain management integrates supply and demand management within and across companies. Supply Chain Management is an integrating function with primary responsibility for linking major business functions and business processes within and across companies into a cohesive and high-performing business model. It includes all of the logistics management activities noted above, as well as manufacturing operations, and it drives coordination of processes and activities with and across marketing, sales, product design, finance, and information technology*."

An SC consists of not only manufacturer and suppliers but also transporters, warehouses, retailers and customers. SC involves all of the manufacturing processes, coordination of order information and product flows, marketing, SC design processes, and all transportation activities. SC has to be considered as a whole with its all members because of the fact that each members' performance affects the overall performance of SC (Yener, 2003). There are three main flows in an SC: (1) product flow, (2) information flow, and (3) financial flow. Product flow means that products flow through SC (from beginning to the end customers). Information flow contains information such as product orders. And, the financial flow includes payment information.

Several decision phases such as design, planning, and operational should be considered to achieve a successful SCM. SC design includes long-term (strategic) decisions as follows:

- Determining the number, location, and size of SC facilities,
- Selecting of an appropriate information technology,
- Providing strategic collaborations with suppliers, third-party firms, distributors etc.

Planning related decisions are known as tactical management problems that are short-term decisions. Problems handled at this level include:

- Procurement contracts,
- Production-related decisions such as scheduling,
- Inventory-related decisions including inventory transportation decisions,
- Determining transportation strategy.

Third decision level includes detailed daily (operational) decisions such as:

- Daily and weekly demand forecasting ,
- Daily production scheduling and detailed production planning for each SC member,
- Managing orders and raw materials inventory.

All decision types affect SC costs. For example, changing the number of facilities affects inventory cost, transportation cost, and facility cost (Chopra and Meindl, 2010). Every SC aims that maximizing its profit while satisfying customers' needs. To do so, a manager should consider all decision levels.

Several other issues are handled in the context of SCM such as Reverse Logistic (RL), Green Supply Chain, Lean Supply Chain, and CLSC. These problems are become more important problems due to the environmental issues. In the lean SC, all SC activities are properly designed and systematically executed. Green SC integrates environmental thinking into SCM (Aravendan and Panneerselvam, 2015). RLs include all activities related to the conversion and the flows of goods and services with their information from original sources to final consumers (Ramezani et al., 2013a). RL can be divided into recovery network and closed-loop network. CLSC can be defined as the design, control, and operation of a system to maximize value creation throughout the entire product lifecycle with the dynamic recovery of value from different types and volumes of returns over time (Guide and Van Wassenhove, 2009).

The design of CLSC is becoming increasingly important to create appropriate forward/reverse networks. It includes decisions about the location of various types of facilities in both forward and reverse networks. Also, routing and coordination of physical flow are critically important to manage arising flows efficiently (Jeihoonian et al., 2017).

Another important issue is the uncertainty in SCM. Under today's circumstances, many parameters such as demand are dynamic and uncertain. Therefore, SCM problems should be handled as dynamic and stochastic problems. A facility can be opened or closed, facilities' capacity can be change over time, and a vehicle can change its route according to the conditions during a planning horizon. Controlling uncertainty, firms can reduce the effect on SC performance and increase the customer service levels. Uncertainty can be represented in several ways. Gupta and Maranas (2003) gave two ways: (1) scenario-based approach, and (2) distribution-based approach. Each scenario can be defined as a probability level by an expectation of occurrence in scenario-based approach. If it is not possible to determine a discrete scenario, the distribution-based approach is used. For example, demand can be defined by using a normal distribution.

Especially firms with wide range products and high customization are facing with high risks due to interruptions, delays in production and delivery. This leads to lost sales (loss of firm reputation) along loss of economic gains (Sreedevi and Saranga, 2017).

As a result, a manager has to take into account uncertainty in order to compete in this complex environment.

2.2 Inventory Management

Almost all firms hold inventory to meet customers' orders in time. Therefore, every SC member should identify its inventory management strategy. Types of inventory can be listed as raw materials, work in progress, spare parts and finished goods.

The need for holding inventory is given in the book of Cachon and Terwiesch (2013) as:

- Process flow time
- Seasonal demand
- Economies of scale
- Separation of steps in a process
- Stochastic demand

There are several types of inventory such as cycle inventory, safety inventory, pipeline inventory etc. Short descriptions can be given as follows (Chopra and Meindl, 2010):

Cycle Inventory is the inventory that is held on a regular basis instead of once per year. If a firm produce or purchase in large amounts, it needs cycle inventory.

Safety Inventory is held to compete with fluctuation in demand. The main aim of holding safety stock is to prevent stockout.

Pipeline Inventory is the inventory in the process of transfer. While the products are still in the transfer process, it is considered as a part of the inventory.

The main objective is to decide how much inventory should be held and where the inventories should be stored, while minimizing inventory holding cost. Every member of an SC holds its own inventory. An SC member should consider other SC members' inventory policies while determining its own inventory policy. To achieve an efficient inventory management, one should provide the coordination of inventory between SC members.

If a manufacturer stores its inventory more than one place, each stage where inventory is held called *echelon*. The m*ulti-echelon inventory system* is an inventory system with multiple echelons of inventory (Hillier and Lieberman, 2010). Multi-echelon inventory system needs coordination in order to ensure effective inventory control management.

For effective control of inventory management, the system can be divided into pull and push systems. In a push system, inventory begins with forecasting of customer demand. Firms make products based on prediction of customer demand in order to push orders to the customers. In a pull system, firms make enough products when there is an order by the customer. In a pull system, orders come directly from customers, in push system manufacturer or retailer makes demand forecasting and sends orders to the customers.

Lead-time is an important component of inventory management. *Lead-time* is the duration between the arrival time of an order and delivery of products.

2.3 Performance Measures and Metrics for SCM

Performance measurement of SC is a crucial task to make a true evaluation of SC. Performance measures can be qualitative or quantitative. Qualitative measures do not contain numerical values. Therefore, it makes difficult to analyze the system by using these unclear measures. Qualitative measures should be converted to quantitative measures. Quantitative measures need numerical data. Sometimes these numerical data may not represent the SC systems. Therefore it should be integrated with qualitative measures (Beamon, 1999).

Generally, SC studies considered cost as an objective function or a combination of cost and customer satisfaction (Beamon, 1999). Cost can include metrics such as inventory cost, transportation cost, operating cost. Customer satisfaction related measures include fill rate, average service level, stockout probability.

(Gunasekaran et al., 2001) gave a list of different performance measures that can be used for SC decision levels for different activities for SC. Some of the most used performance measures are given as follows:

- Total cash flow time
- Rate of return on investment
- Flexibility to meet customer needs
- Delivery lead time

- Total transportation cost
- Manufacturing cost
- Inventory carrying cost
- Labor efficiency
- Product development time
- Service variety

Also, there are several performance measures such as time-dependent measures (i.e., new product development time, delivery time), flexibility measures (Chen and Paulraj, 2004), performance measures related to environmental consciousness (i.e., cost for disposal, amount of waste, total energy use) (Hervani et al., 2005).

2.3.1 Inventory Related Performance Measures

Inventory management has an important effect on SC performance. Firms should have enough inventory when they are needed while controlling inventory metrics (i.e., cost). There several performance measures related with inventory (Chopra and Meindl, 2010). Some of the inventory related performance measures are given as follows:

- *Average inventory* is the average amount of inventory which can be in units, days of demand, and financial value. Average inventory is held for each period and each replenishment period in this study.
- *Fill rate* is the ratio of orders/demand that is satisfied on time from on-hand inventory. In this study, fill rate is considered as average service level for SC members.
- *Average replenishment batch size* determines the average amount of order for each replenishment order. The amount of order replenishment is calculated dynamically within SC simulation models in this study.
- *Reorder cost* is the cost of placing an order and occurs several times.
- *Holding cost* is the cost of holding one unit of inventory for a period of time.
- *Shortage cost (lost sales cost)* is the cost that occurs when a firm runs out of stock and cannot meet customer demand.

Cost-related performance measures are calculated and added to the total SC cost such as holding cost, lost sales cost etc. throughout the study (see Section 4.3).

CHAPTER 3

LITERATURE REVIEW

3.1 Introduction

SCM is tackled for many years in both academic and real world. Many issues arise in the context of SCM. SCM problems are generally divided into three categories: (1) strategic decisions, (2) tactical decisions, and (3) operational decisions. The strategic level decision involves decisions for designing of an SC (facility location problems, determining number of facility etc.) (Farahani et al., 2014). Tactical and operational decisions are the most considered problems in SCM problems. The aim of these levels is to ensure the coordination between facilities to distribute, store and transform materials into products and to meet customer demands (Guerrero et al., 2013).

In the context of this thesis, different levels of SC and different types of SC problems are handled. Therefore, a literature review is given on three main topics: (1) studies which are discussed only forward SC problems, (2) studies which are tackled with CLSC problems, (3) studies which are used SO as a solution methodology.

The first section (Section 0) is categorized according to solution methodologies in order to solve forward SC problems. Three main categories are given as follows:

- Exact methods
- Metaheuristics and multi-phase hybrid approaches
- And, stochastic and dynamic approaches

A review table where studies are arranged considering SC members, methodology and some specific problem types of CLSC is given in Section 3.3. In Section 3.4, studies related with SO are handled to represent most related studies to this thesis. Finally, a general conclusion of literature review is given in Section 3.5. Also, a summary of relevant literature is given in related sections (Section 4.1 and 5.1).

3.2 Supply Chain Management

In literature, SC problems are solved by using numerous techniques and methods, some of which appear to be particularly attractive as they are successfully used by several authors. Many studies are used exact methods to solve the problem by minimizing the total SC cost. Additionally, there are a large number of papers considered the problem as deterministic. Papers focused on stochastic and fuzzy data are very limited. Besides, there is a critical gap in the context of dynamic version of the problem. It is very important to evaluate an SC in a dynamic environment due to its competitive and dynamic nature.

3.2.1 Exact Methods

Exact methods (i.e., branch and bound, linear programming, integer programming) are widely used to find optimal solutions for SC problems. This section is focused integrated forward SC such as inventory routing problem (IRP), location routing problems (LRPs) etc. due to the large application areas.

Yu et al. (2008) studied an IRP with split delivery and vehicle fleet size constraint. In the study, the model is solved by using a Lagrangian relaxation method in which the relaxed problem is decomposed into an inventory problem and a routing problem that are solved by a linear programming (LP) algorithm and a minimum cost flow algorithm, respectively, and the dual problem is solved by using the surrogate subgradient method. Lee et al. (2010) determined the optimal location, allocation, and routing with minimum cost to the SC network. The study proposed two mixed integer programming (MIP) models, one without routing and one with routing, and a heuristic algorithm based on LP-relaxation in order to solve the model with routing. Nikbakhsh and Zegordi (2010) presented a mathematical model, a heuristic and a lower bound for the two-echelon LRPs with time window constraints. Reza Sajjadi and Hossein Cheraghi (2011) presented a novel non-linear MIP model for the multi-product capacitated location routing inventory problem (LRIP), where a two-layer distribution system consisting of depots and customers was studied. Hanczar (2011) presented a mathematical model to determine an optimal joint inventory/transportation policy. Albareda-Sambola et al. (2012) used MIP formulation for a multi-period discrete facility location problem where transportation costs are considered together with location costs to design the operating facility pattern along a time horizon. Hamidi et al. (2012) focused on modeling a complicated four-layer and multiproduct LRP by using a MIP model. The distribution network consists of plants, central depots, regional depots, and customers. Aghezzaf et al. (2012) formulated the single-vehicle cyclic IRP as a MIP with a nonlinear objective function. Aksen et al. (2012) considered a biodiesel production company that collects waste vegetable oil from source points that generate waste in large amounts. For this selective and periodic IRP, they proposed two different formulations (MIP). Ramkumar et al. (2012) proposed a MIP for the multi-commodity, multi-depot IRP (pick-up and delivery, and sequence). de Camargo et al. (2013) proposed a new formulation for the LRP and solved by a specially tailored Benders decomposition algorithm. Coelho and Laporte (2013) proposed a branch-and-cut algorithm for the solution of IRPs with multiple products and multiple vehicles. Martínez-Salazar et al. (2014) presented a mathematical formulation considering two objectives: reduction of distribution cost and balance of workloads for drivers in the routing stage. Rath and Gutjahr (2014) proposed an exact solution method as well as a ‘‘math-heuristic’’ technique building on a MILP formulation with a heuristically generated constraint pool. Validi (2014) developed two-layer and three-layer multi-objective 0-1 mixed-integer Analytical Hierarchy Process (AHP)-integrated LRPs. Guerrero (2014) studied a design of an SC problem including routing and inventory management decisions. Two new matheuristic methodologies are developed to solve the problem. Mirzaei et al. (2015) developed a novel formulation of the LRP that considers energy minimization, which is called the energy efficient LRP. They presented a mixed-integer non-linear program that finds the best location-allocation routing plan with the objective function of minimizing total costs, including energy, emissions, and depot establishment. Soysal et al. (2015) presented a multi-period IRP model that includes truck load dependent (and thus route dependent) distribution costs for a comprehensive evaluation of CO2 emission and fuel consumption, perishability, and a service level constraint for meeting uncertain demand. They applied chance-constrained programming model to a case study on the fresh tomato distribution operations of a supermarket chain. Van Anholt et al. (2016) proposed a MILP for large-scale multi-period IRPs. A branch and cut algorithm is used for IRPs by Avella et al. (2017).

3.2.2 Metaheuristics and Multi-Phase Hybrid Approaches

Metaheuristics give better results, faster and applicable for large instances of SC problems when compared to exact methods. Also, there are hybrid metaheuristic algorithms that integrates two or more algorithms to solve SC problems.

Aziz and Moin (2007) used a hybrid GA to find the optimum vehicle routing while minimizing the transportation and inventory costs. Chen and Lin (2009) used a predicting particle swarm optimization (PSO) algorithm to solve the multi-product multi-period IRP with stochastic demand. Derbel et al. (2010) developed an iterative local search by considering the decisions of location and routing simultaneously to minimize the total cost. Kang and Kim (2010) considered a two-level SC in which a supplier serves a group of retailers in a given geographic region and determines a replenishment plan for each retailer by using the information on demands of final customers and inventory levels of the retailers. They used heuristic algorithms to minimize the sum of the fixed vehicle cost, retailer-dependent material handling cost, and inventory holding cost of the whole SC. Crainic et al. (2011) tackled a two-echelon LRP by a tabu search (TS) metaheuristic. Geiger and Sevaux (2011) determined initial routing by saving heuristics and latter improved using the Record-To-Record Travel Algorithm. Popović et al. (2012) developed a Variable Neighborhood Search (VNS) heuristic for solving a multi-product multi-period IRP in fuel delivery with multi-compartment homogeneous vehicles, by considering deterministic consumption that varies with each petrol station and each fuel type. Ting and Chen (2013) proposed a multiple ant colony optimization (ACO) algorithm to solve the LRP with capacity constraints on depots and routes. Li et al. (2013) formulated a LIRP model with no quality defects returns focusing on the existing problem in e-commerce logistics system. To solve the problem, a hybrid genetic simulated annealing (SA) algorithm is proposed. Bashiri et al. (2014) used SA algorithm for solving a capacitated LRP model with auxiliary vehicle assignment in which the length of each route is not restricted by main vehicle capacity. Rosmaini and Mawengkang (2014) proposed a neighborhood search for the LRP to minimize the overall cost by simultaneously selecting a subset of candidate facilities and constructing a set of delivery routes that satisfy some restrictions. Vincent and Lin (2014) introduced the open LRP that is a variant of the capacitated LRP. They used SA-based heuristic for solving the problem. Wang et al. (2014) constructed a nonlinear integer open LRP for relief distribution problem considering travel time, the total cost, and reliability with split delivery. They proposed the non-dominated sorting GA and non-dominated sorting differential evolution algorithm to solve the proposed model. Mjirda et al. (2014) addressed a multiproduct IRP and proposed a two-phase VNS metaheuristic to solve it. In the first phase, VNS is used to solve a capacitated vehicle routing problem at each period to find an initial solution without taking into account the inventory. In the second phase, the initial solution is iteratively improved while minimizing both the transportation and inventory costs. Nekooghadirli et al. (2014) presented a multi-objective imperialist competitive algorithm for the LRIP. Seyedhosseini et al. (2014) proposed a model that simultaneously determines the number and the location of DCs that should be opened, the assignment of customers to DCs, the allocation of customers to active routes and the arrangement of customers in each route, reorder point and economic order quantity for each DC, and finally, the level of the safety stock that is to be kept per DC. The problem is solved by a meta-heuristic algorithm, which minimizes the expected total cost of the network. Karaoglan and Altiparmak (2015) considered a capacitated LRP with mixed backhauls (CLRPMB) which is a general case of the capacitated LRP. CLRPMB is defined for finding locations of the depots and designing vehicle routes in such a way that pickup and delivery demands of each customer must be performed with the same vehicle and the overall cost is minimized. To solve the problem authors used a memetic algorithm to solve the problem. Macedo et al. (2015) proposed a skewed general VNS based heuristic to solve the integrated location routing scheduling problem consists in determining the depots that should be opened, the routes that should be performed, and the way these routes are scheduled within the workdays of the vehicles. Ardjmand et al. (2015) proposed a novel GA for the location and routing in facilities and disposal sites. Noor and Shuib (2015) proposed the development of multi-depot test instances using single linkage and complete linkage clustering techniques. This study concerned solving IRP with multi-depot, multi-product, multi-vehicle and heterogeneous vehicle fleet. Hiassat et al. (2017) determined the number and location of warehouses, the inventory level at each retailer, and the routes traveled by each vehicle by using GA.

Most researchers used hybrid metaheuristics for SC problems. Bozkaya et al. (2010) proposed a hybrid heuristic (GA-TS) optimization methodology for solving the problem of determining the optimum set of locations for a firm, which operates a chain of facilities under competition. Karaoglan and Altiparmak (2010) solved a LRP with simultaneous pickup and delivery by using a hybrid heuristic approach based on GA and SA. Govindan et al. (2014) proposed a novel multi-objective hybrid approach called MHPV, a hybrid of two known multi-objective algorithms: namely, multi-objective PSO and adapted multi-objective VNS. Shouying and Huijuan (2014) presented a hybrid GA containing heuristic rule considering the urgency of flood, the uncertainty of rescue time (travel time of boats and rescue time of workers) and the possible repeated rescue of different kinds of boats, the paper established a fuzzy rescue time Location Allocation Problem model with time windows. Marinakis et al. (2016) applied a hybrid Clonal Selection Algorithms (CSA), where, in the two basic phases of the CSA, a VNS algorithm and an Iterated Local Search algorithm have been utilized respectively.

Multi-phase algorithms are considered in many studies due to the problem structure. These studies usually divided the problem into two sub-problems. Prins et al. (2006) presented a new metaheuristic to solve the LRP with capacitated routes and depots. The first phase executes a greedy randomized adaptive search procedure (GRASP), based on an extended and randomized version of Clarke and Wright algorithm. This phase is implemented with a learning process on the choice of depots. In the second phase, new solutions are generated by a post-optimization using a path relinking. Contardo et al. (2014) proposed a three-phase heuristic for the capacitated LRP. In the first stage, a GRASP followed by LS procedures to construct a bundle of solutions. In the second stage, an integer-linear program (ILP) is solved by taking different routes belonging to the solutions of the bundle as input, with the objective of constructing a new solution as a combination of these routes. In the third and final stage, the same ILP is iteratively solved by column generation to improve the solutions. Raa (2015) used multi-start two-phase heuristic solution method that consists of an insertion-based construction phase and a local search-based improvement phase.

3.2.3 Stochastic and Dynamic Approaches

To enhance the reliability of representation of an SC problem, some parameters are defined as stochastic. Besides, several literature are considered real-time to model dynamism in their studies. Jarugumilli et al. (2006) considered a logistics network where a single warehouse distributes a single item to multiple retailers. They proposed a solution methodology where in the size of the state space is reduced at each stage. In this work, simulation is used to develop the framework for the real-time control and management of inventory and routing decisions. Javid and Azad (2010) presented a novel model to simultaneously optimize location, allocation, capacity, inventory, and routing decisions in a stochastic SC system. Each customer’s demand is uncertain and follows a normal distribution, and each distribution center maintains a certain amount of safety stock. To solve the model, first an exact solution method by casting the problem as a mixed integer convex program is presented, and then a heuristic method based on a hybridization of TS and SA is proposed. Forouzanfar et al. (2012) presented a novel mathematical model considering the riskpooling, lead time, multi-echelon inventory under the demand uncertainty, routing of vehicles from DCs to customers in order to give services in a stochastic SC system, simultaneously.

Cáceres-Cruz et al. (2012) introduced a simulation-based algorithm for solving the single period IRP with stochastic demands. Their approach, which combines simulation (Monte Carlo) with heuristics, considers different potential inventory policies for each customer, computes their associated inventory costs according to the expected demand in the period, and then estimates the marginal routing savings associated with each customer policy entity. That way, for each customer it is possible to rank each inventory policy by estimating its total costs, i.e., both inventory and routing costs. Finally, a multi-start process is used to construct iteratively a set of promising solutions for the IRP. Bertazzi et al. (2013) studied a stochastic inventory routing problem in which a supplier has to serve a set of retailers. For each retailer, a maximum inventory level is defined and a stochastic demand has to be satisfied over a given time horizon. An order-up-to level policy is applied to each retailer, i.e. the quantity sent to each retailer is such that its inventory level reaches the maximum level whenever the retailer is served. The problem is to determine a shipping strategy by a hybrid rollout algorithm that minimizes the expected total cost, given by the sum of the expected total inventory and penalty cost at the retailers and of the expected routing cost. Shukla et al. (2013) presented a portfolio methodology that is based on EA to solve complex dynamic optimization problems.

Chen et al. (2014) developed a fuzzy random MIP model of LRIP in an e-commerce distribution system. Demands of customers and distribution centers have been assumed to be fuzzy random variables. A two-stage heuristic algorithm based on TS has been designed for solving the developed model. Agra et al. (2015) described a stochastic short sea shipping problem where a company is responsible for both the distribution of oil products between islands and the inventory management of those products at consumption storage tanks located at ports. A two-stage stochastic programming model with recourse is presented where the first stage consists of routing, loading and unloading decisions, and the second stage consists of scheduling and inventory decisions. Rayat et al. (2017) solved a multi-product multi-period LRIP with stochastic demand by using a modified archived multi-objective SA algorithm. Also, they considered partial backordering in case of stock out occurrence under the disruption risks.

3.3 Closed Loop Supply Chain Management

Product recoveries at the end of their life are crucial to achieve sustainable business practices. Successful product recovery processes can also be useful to save landfill space by decreasing the amount of total waste. In addition, they reduce the risks of hazardous wastes and conserve energy with component reuse (Toyasaki et al., 2013). In this context, the traditional SC need to be expanded by CLSC that focuses on taking back products from consumers and recovering added value by reusing the entire product, and/or some of its modules, components, and parts (Guide and Van Wassenhove, 2009). In literature, many guidelines are available to develop a CLSC and there is a growing number of interests in providing a general framework for CLSC. A brief review of CLSC models is given in Table 3.1.

Modeling SCs is hard to handle, especially where the modeling has to consider uncertainty. In general, two forms of uncertainties are available in SC. The uncertainty of linkage is the first one. It is principally caused by the interaction or cooperation among SC members. The second form of uncertainty is related with the inner operations in SC and it is mostly caused by the ineffective coordination or control mechanisms of the system (Huang et al., 2009). To restrain the impacts of the uncertain environment on CLSC system, Huang et al. (2009) presented a class of dynamic models to analyze different system structure of CLSC and determined the primary uncertainties in the CLSC. Pishvaee and Torabi (2010) developed a CLSC network under uncertain demands, returns, delivery times, costs and capacities to minimize total costs and total delivery tardiness. Shi et al. (2011) optimized the profit of the CLSC network by integrating three aspects which are inventory control, production, and product acquisition management under demand and return uncertainty. Zeballos et al. (2012) presented the problem of design and planning of CLSC incorporating the uncertainty in the quality and the quantity of returned products. Ramezani et al. (2013a) proposed a stochastic multi-echelon problem considering single sourcing of customers in CLSC network with multi-level capacities. The study maximized the total profit and customer service level while minimizing the total number of defects. Ramezani et al. (2013b) integrated strategic decisions with tactical decisions to extend the existing CLSC models where uncertain demand and return rate are defined by a set of finite scenarios. Saeedi et al. (2015) proposed De Novo-CLSC with queuing systems to cope with the uncertainty of the parameters.

For a general design of CLSC network, Amin and Zhang (2013a) created a facility location model whose objective is to determine how many and which SC members (i.e. plants, collection centers) should be opened, and which products and in which quantities should be stocked in them. Amin and Zhang (2013b) presented the framework of three-stage CLSC network where SC members (i.e. suppliers, remanufacturing subcontractors, and refurbishing sites) are firstly evaluated by a fuzzy quality function deployment model; then stochastic programming model is proposed to configure the CLSC network; finally a multi-objective model is used to select the best alternatives. Vahdani et al. (2013) incorporated reliability concepts into the CLSC network design with the strategic network design decisions by providing tactical planning decisions. Moghaddam (2015) determined the optimal set of candidate suppliers along with the optimal order quantities in CLSC network. In addition, the problem is formulated as a multi-objective optimization model whose objective functions are to maximize the total profit and to minimize the total number of defective parts, the total number of late delivered parts, the economic risk factors. Zhalechian et al. (2016) developed a CLSC model in which routing and inventory decisions are integrated with location allocation decisions. Govindan et al. (2016) proposed a generic CLSC network for a manufacturing firm considering three objectives that correspond to the benefits of the proposed CLSC network on economy, environment, and society.

Table 3.1 A review of CLSC models.

	Forward SC Member	Reverse SC Member	Solution Method	a*	b*	c*	d*	e*	f*	g*
Zeballos et al. (2012)	Factories, Warehouses, Customers	Sorting Centers	Mixed Integer Linear Programming Model		√		√		√	
Özceylan and Paksoy (2013)	Raw Material Suppliers, Plants, Retailers, Customers	Collection Centers, Disassembly Centers, Refurbishing Centers	Mixed Integer Programming Model		√		√	√		
Vahdani et al. (2013)	Raw Material Suppliers, Iron and Steel Facilities, Metal Manufacturing Facilities, Distribution Centers and Customer Zones	Collection Centers, Steel Scrap Processing Facilities	Interval Fuzzy Possibilistic Chance-Constrained Model				√		√	√
Amin and Zhang (2013a)	Plants, Demand Markets	Collection Centers, Disposal Center	Mixed Integer Linear Programming Model	√			√		√	√
Ramezani et al. (2013a)	Suppliers, Manufacturing Centers, Distribution Centers	Collection Centers, Disposal Centers, Remanufacturing Centers	Stochastic Multi-Objective Programming Model	√			√		√	√
Ramezani et al. (2013b)	Suppliers, Plants, Distribution Centers, Customers	Collection Centers, Repair Centers, Disposal Centers	Mixed Integer Linear Programming Model	√			√		√	
Özkır and Başlıgil (2013)	Suppliers, Plants, Distribution Centers, Customers	Collection Points, Reverse Centers, Recovery Facilities	Fuzzy Multiple Objective Optimization Model		√		√		√	√
Özceylan et al. (2014)	Subassembly Suppliers, Assemblers, Retailers, Customers	Collection Centers, Refurbishing Centers, Disassemblers, Disposal Location	Mixed Integer Nonlinear Programming Model		√	√		√		
Ramezani et al. (2014)	Suppliers, Plants, Distribution Centers, Customers	Collection Centers, Repair Centers, Disposal Centers	Financial Approach, Mixed Integer-Linear Programming Model		√	√		√		
Jindal and Sangwan (2014)	Raw Material Suppliers, Plants, Distributors, Retailers, Customers	Collection/Repair Centers, Disassembly Centers, Refurbishing Centers, Recycling Centers, Disposal Centers	Fuzzy Mixed Integer Linear Programming Model	√			√		√	

Table 3.1 A review of CLSC models (continued).

	Forward SC Member	Reverse SC Member	Solution Method	a*	b*	c*	d*	e*	f*	g*
Subulan et al. (2015)	Distribution Centers/Plants	Centralized Return Points or Collection, Retreading (Remanufacturing), Recycling	Interactive Fuzzy Goal Programming Model		√		√		√	√
Saeedi et al. (2015)	Hybrid Distribution/Collection Centers, Customer Zones	Hybrid Distribution/Collection Centers, Production/Recovery, Disposal Centers	Mixed Integer Nonlinear Programming Model with De Novo Programming Model				√		√	√
Moghaddam (2015)	Suppliers, Manufacturing/Refurbishing	Manufacturing/Refurbishing, Disassembly, Disposal Facilities	Hybrid Monte Carlo Simulation Integrated with Goal Programming Methods				√	√		√
Dai and Zheng (2015)	Raw Material Suppliers, Manufactures, Distributor Centers, Customer Zones	Collection Centers, Decomposition Centers	Monte Carlo Simulation with Hybrid Genetic Algorithm, Fuzzy Programming and Chance-Constrained Programming		√		√		√	
Vahdani and Mohammadi (2015)	Hybrid Metal Manufacturing Facilities, Bidirectional Facilities, Customer Zones	Hybrid Metal Manufacturing Facilities, Bidirectional Facilities, Disposal Centers	Interval Programming, Stochastic Programming, Robust Optimization Approach, and Fuzzy Multi-Objective Programming, Self-Adaptive Imperialist Competitive Algorithm	√			√		√	√
Kalaitzidou et al. (2015)	Generalized Production/Distribution/Recovery/ Re-Distribution	Traditional Collection, Redistribution Centers	Mixed Integer Linear Programming Model		√		√	√		
Hasani et al. (2015)	Suppliers, Manufacturers, Warehouses/Distributors, Wholesalers	Collection/Recovery Facilities, Wholesalers	Mixed Integer Nonlinear Programming Model, Memetic Algorithm		√		√		√	

Table 3.1 A review of CLSC models (continued).

	Forward SC Member	**Reverse SC Member**	**Solution Method**	**a***	**b***	**c***	**d***	**e***	**f***	**g***
Keyvanshokooh et al. (2016)	Manufacturing/Remanufacturing Centers, Distribution Centers, Retailers	Collection Centers, Disposal Centers	Hybrid Robust Stochastic Programming Model		√	√			√	
Zohal and Soleimani (2016)	Suppliers, Manufacturing Facilities (Factories), Distribution Centers	Collection Centers, Recycling Centers, Disposal Centers	Integer Linear Programming Model, Ant Colony Optimization	√		√		√		√
Zhalechian et al. (2016)	Suppliers, Distribution Centers, Retailers	Distribution Centers, Retailers, Potential Remanufacturing Centers	Mixed-Integer Nonlinear Programming, Self-Adaptive Genetic Algorithm and Variable Neighborhood Search Algorithm		√		√		√	√
Govindan et al. (2016)	Hybrid Manufacturing Facility, Warehouse, Distribution Center	Collection Center, Hybrid Recovery Facility	Mixed Integer Linear Programming Model		√		√	√		√
Amin and Baki (2017)	Suppliers, Plants, Distribution Centers, Markets	Collection Centers, Disposal Center	Corley Model, Fuzzy Programming Model		√		√		√	√
Jeihoonian et al. (2017)	Suppliers, Manufacturing Facilities, Distribution Centers, End-Users	Collection Centers, Disassembly Centers, Bulk Recycling Centers, Disposal Centers, Material Recycling Centers, Remanufacturing Centers	Accelerating Benders Decomposition Model	√		√			√	
Proposed method	Suppliers, Plants, Retailers, Customers	Collection Centers, Disassembly Centers, Refurbishing Centers, Disposal Centers	SO method		√		√		√	

*a-Single Period, b-Multiple Period, c-Single Product, d-Multiple Product (components), e-Deterministic Parameters, f-Uncertain (Random) Parameter, g-Multi-Objective

3.4 Simulation Optimization

Because of the fact that the simulation is not an optimization tool, simulation is coupled with optimization model that orchestrate the simulation of a sequence of system configurations to provide an optimal or near optimal solution (Law and McComas, 2000). Detailed information about SO literature can be found in a number of review papers such as (Long-Fei and Le-Yuan, 2013), (Figueira and Almada-Lobo, 2014), (Juan et al., 2015), (Jalali and Nieuwenhuyse, 2015) and (Xu et al., 2015).

There are several application areas of SO such as operations (health), manufacturing, engineering, transportation and logistics, and so on. As we mentioned in Section 4.2.1, there are several algorithms used for SO. GAs are the most used algorithms in many areas (also for SC problems) due to its ease of use (Amaran et al., 2016).

SO ensures a detailed representation of complex SCs and also allows the solution of large complex problems in acceptable time (Nikolopoulou and Ierapetritou, 2012). However, in the area of forward/reverse/CLSC SO models are still being investigated by relatively few researchers. For example, Daniel and Rajendran (2005) used GA to optimize base stock levels to minimize the total SC cost (sum of holding and shortage costs). Simulation is used to evaluate determined base stock levels. Köchel and Nieländer (2005) applied simulation optimization in order to define optimal policies (i.e., order point, and order lot size) in multi-echelon inventory systems. They used GA to determine inventory policies and evaluate decision variables by using simulation. Keskin et al. (2010) used a scatter search-based metaheuristic and simulation for an integrated vendor selection and inventory replenishment decision (order quantity and reorder point of plants) problem. Kleijnen et al. (2010) applied simulation optimization approach to an inventory system and a call center simulation. They combined a sequentialized experimental design, a Kriging metamodel and an integer nonlinear programming. Sanchez et al. (2010) compared five different evolutionary algorithms for an inventory problem. Zhou and Xue (2011) proposed a SO model that integrates the simulation model and GA to solve reverse logistics problem in the context of emergency. Varthanan et al. (2012) proposed a simulation-based AHP and discrete PSO algorithm for an integrated production-distribution problem. In this study, stochastic demand is used while calculating objective functions. Shokohyar and Mansour (2013) developed a sustainable recovery network where social, environmental, and economical objectives are considered simultaneously to manage total waste from electrical and electronic equipment in Iran. Herazo-Padilla et al. (2013) solved a location-routing problem by using hybridization of ACO and discrete-event simulation. Ammeri et al. (2014) combined GA and simulation to solve lot-sizing problem. Another study which combines GA and simulation is presented by Azadeh et al. (2014). Their aim is to select suppliers and new facilities to minimize delivery time and final production cost. Juan et al. (2014) integrated Monte Carlo (MC) simulation with a heuristic to solve stochastic IRP. Zolfagharinia et al. (2014) developed a hybrid solution method that integrates discrete event simulation and meta-heuristic algorithm (VNS) to determine optimal solution for inventory control problem including joint purchasing and remanufacturing in a reverse SC. Sel and Bilgen (2014) presented a combined approach (simulation and MIP based Fixed and Optimize heuristic) to solve a production and distribution planning problem. Godichaud and Amodeo (2015) proposed a simulation model combined with a multi-objective evolutionary algorithm to optimize multi-level SC problem. Chu et al. (2015) used cutting plane algorithm for optimizing distribution inventory systems and MC for estimation of objective function. An agent-based simulation is used to model the inventory system. Güller et al. (2015) proposed an integrated approach. In this study, multi-objective PSO is used to determine inventory control parameters (i.e., reorder points and order quantity) and simulation is used to evaluate control parameters (total inventory cost and service level). Ye and You (2016) optimized base stock levels by using aggregated surrogate model and MC simulation. Avci and Selim (2017) introduced a multi-objective simulation optimization approach for an inventory optimization problem. They used a non-dominated sorting GA II to determine supplier flexibility and safety stock levels.

3.5 Conclusion

This chapter gives a comprehensive literature review about SC and CLSC, as well as studies related to subjects covered in this study. As it is seen from the literature review, many different SC approaches are still attractive as several authors successfully use them. Contributions to the field cover mathematical programming, heuristics, and metaheuristics as well as computer simulation.

Studies related with SC are mainly focused on exact methods, heuristics and metaheuristics. LP and MIP are used to solve many integrated SC problems. Mainly used metaheuristic approaches can be given as GA, TS, ACO, and SA. In addition, hybridization of these metaheuristics is used for forward SC problems. Analytical approaches do not provide a true representation of complex and real-world problems. In this respect, reasonable solutions can be achieved without analytical assumptions and simplifications through simulation-based approaches.

Although stochastic and dynamic studies are found in the literature, it is not enough to correspond SC environment by considering its all complexity and dynamism. Generally, demand is considered as stochastic and, fuzzy mathematical models and stochastic metaheuristics are used in reviewed studies.

In the context of CLSC, mainly MIP, MILP, MINLP, and fuzzy mathematical programming is used. From the literature it is clear that many works addressed the CLSC network problem but the design of CLSC network is still an important research problem, and there is a need to develop a generic framework including uncertain parameters in both forward and reverse flow. The reality of CLSC is generally much more complex than corresponding forward flow problems (Rogers et al., 2012) since reverse flow provides ill-known parameters influencing the forward flow and therefore making the entire SC environment uncertain (Jindal and Sangwan, 2014).

This complexity has encouraged the development of simulation model for SC problems that can include the behavior of all the entities involved, their interactions, and uncertain functional properties associated with these systems (Nikolopoulou and Ierapetritou, 2012). However, SO models are still being investigated in the area of forward/reverse/CLSC. To fill the gap in this area, simulation optimization is proposed for both of FSCPs and CLSCPs considering stochastic parameters and dynamic environment. Also, a detailed statistical analysis is given to provide advanced understanding which cannot be obtained by analytical approaches.

CHAPTER 4

METHODOLOGY

4.1 Introduction

SO is a powerful tool which optimizes decision variables of a simulated system, and it usually evaluates the objective function by using a simulation model (Jalali and Nieuwenhuyse, 2015). The most commonly used term for this approach is *"Simulation Optimization"* or *"Optimization via Simulation"*. These two terms more accurately represent that the approach where the inputs are called variables and the outputs are called objective functions (also, response is used) (Fu, 2002). SO deals with uncertain problems that make it more difficult than the deterministic problems. SO tries to optimize determined decision variables by using an estimated objective function (Banks et al., 2004). There are several commercial optimization routines (e.g., OptQuest, AutoStat, OPTIMIZ, SimRunner, Optimizer), and simulation software packages (AutoMod, Arena, SIMUL8, ProModel, WITNESS) that uses these optimization routines (Fu, 2002). These packages can be used to optimize selected system parameters to minimize/maximize an objective function.

In this study, SO, which provides closeness to a real-world problem, is used to solve both strategic and operational decisions in SC management problems. GA optimizes predetermined decision variables; simulation evaluates decision variables and returns responses to the genetic algorithm. This methodology is an iterated process that consists of two parts: (1) generating candidate solutions by GA, (2) evaluating candidate solutions by SC simulation model. The simulation model is designed for two different multi-echelon SC problems, namely a forward SC and a CLSC problem. Also, two inventory replenishment policy (periodic and continuous inventory review) is modeled for both SC problems. Proposed methodology is used to optimize decision variables of determined SC problems. Detailed information about proposed methodology is given in Section 4.2.

4.2 Proposed Methodology

SO provides a significant opportunity to solve SC problem because SO has the ability of capturing the advantages of both simulation and optimization based methods simultaneously (Fang and Li, 2014; Smew et al., 2013).

Proposed SO approach (Figure 4.1) includes two fundamental tools: (1) An optimization tool (GA) is used to find the optimal result; (2) A simulation tool evaluates performances of candidate solutions. In this study, GA is developed to assign new values for selected decision variables (i.e., generating candidate solutions). In each cycle, simulation sends response to the GA as the most recent fitness function to be evaluated, and GA once more tries to find better decision variables values to increase model performance. In GA, selection, crossover and mutation are repeatedly applied to form new generations.

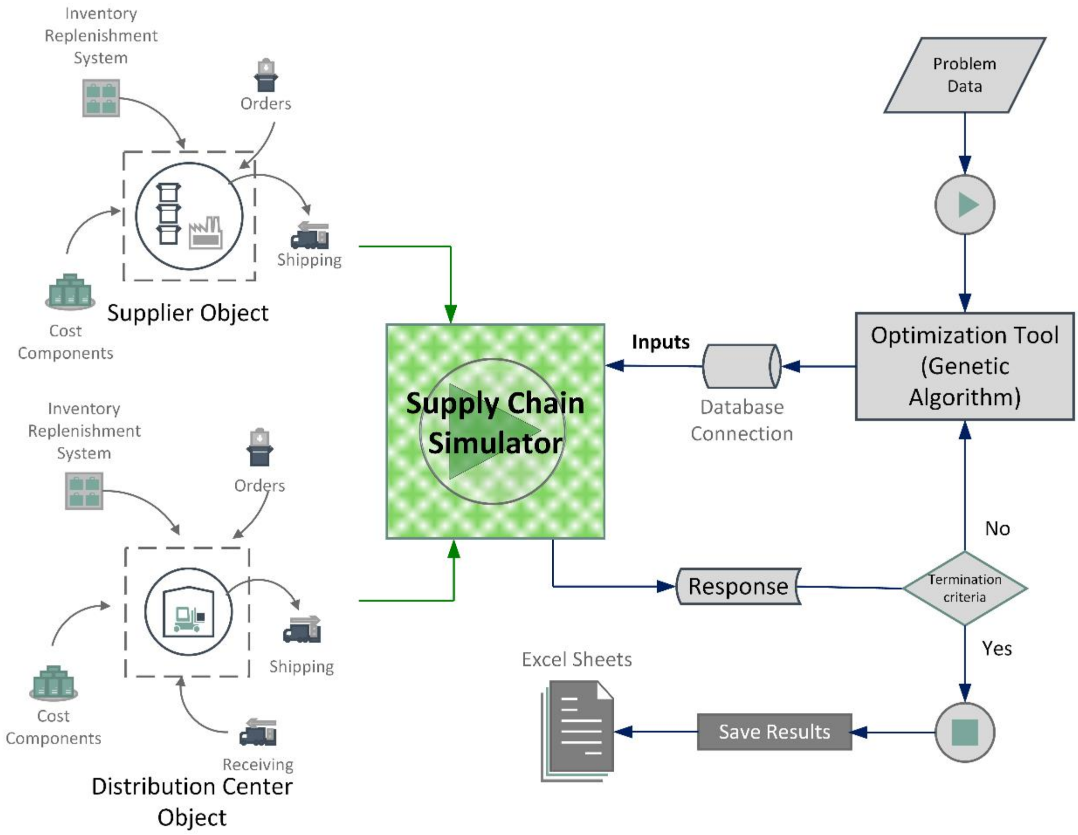


Figure 4.1 General structure of the proposed Simulation Optimization approach.

In this study, Simio (Version: 7.121.12363) is used to create SC simulation models, and C# (Visual Studio Community 2015) is used to code GA and to store data.

Simio makes modeling dramatically easier by providing a new object-based approach. It enables users to use single paradigm, or combine multiple paradigms in the same model and this is one of the unique and powerful properties of Simio (Kelton et al., 2015). Also, object-oriented approach such as Simio based simulation model provides the capability to enhance the correspondence between objects and their semantic representation and to allow the user to control the levels of detail and summarize and aggregate data during decision-making (Liao and Hu, 2011).

In this study, several objects are used to create SC simulation model. These objects represent SC members (supplier, customer, plant, etc.). Some of the objects already exist in Simio Standard Library, but several ones are designed for the proposed simulation model specifically. These objects can be reused where needed. Therefore, this approach yields a flexible, parametric, reusable, extensible, and time efficient simulation model creation. Detailed information about the simulation model is given in Section 4.2.3.

4.2.1 Simulation Optimization

SO problem can be formulated as a minimization problem:

$$min_{x \in X} \, J(x) \tag{4.1}$$

where x is a p-dimensional vector of all the solution variables and X is the feasible solution space. The objective function J cannot be obtained directly, but rather is an expectation of another quantity $L(x; w)$, to which we have access by running stochastic simulations, i.e.,

$$J(x) = E[L(x; w)] \tag{4.2}$$

where w represents the stochasticity in the system. In our setting, a sample of w represents a simulation run and $L(x; w)$ is a sample performance estimate obtained from the output of the simulation run. Multiple simulation runs should be performed to provide a good estimate of $E[L(x; w)]$. Let $\widetilde{N}$ specifies the number of simulation runs and w_j is the j^{th} sample of the randomness w. Thus, $L(x, w_j)$ is the performance estimate obtained from the output of the simulation run j. The standard approach is to estimate $E[L(x; w)]$ by the sample mean performance measure.

$$\bar{J}(x) \equiv \frac{1}{\widetilde{N}} \sum_{j=1}^{\widetilde{N}} L(x; w_j) \tag{4.3}$$

As $\widetilde{N}$ increases, $\bar{J}(x)$ becomes a better estimate of $E[L(x; w)]$. Details about SO models can be found in (Xu et al., 2015). SO method vary greatly depending on the problems. Considering the underlying structure of the decision variables, SO problems can be divided into two types: continuous variable optimization problems and discrete variable optimization problems (Table 4.1). Each approach for SO problems is briefly explained as follows.

Table 4.1 The classification of SO problems.

SO problems	**Continuous decision variables**	Gradient-based methods Stochastic approximation methods Sample path methods Response surface methodology
	Discrete decision variables	Ranking and selection Multiple comparison procedure Ordinal optimization Metaheuristics

Note: Adapted from (Wang and Shi, 2013)

4.2.1.1 Continuous Decision Variables

The feasible region is uncountable and infinite. In addition, variables are characterized as continuous (Wang and Shi, 2013).

4.2.1.1.1 Gradient-based Methods

Gradient-based methods are important to be able to solve intractable problems. They try to mimic their counterpart in deterministic optimization (Fu and Glover, 2005). Furthermore, the availability of gradients is reasonably helpful to obtain improved solutions based on an iterative scheme (Fu, 2006).

4.2.1.1.2 Stochastic Approximation Methods

In stochastic approximation methods, noisy observations are used to create the regression function of a stochastic response surface and the optimal solution is found through some recursive procedures. However, one of the key drawbacks of stochastic approximation methods is that the convergence rate can be very low (Wang and Shi, 2013).

4.2.1.1.3 Sample Path methods

Sample path methods only use simulation to produce one sample path, and they obtain an estimated optimal solution that depends on the sample path (Andradottir, 1998). Sample path methods can be efficiently used to overcome the difficulties encountered by stochastic approximation method (Wang and Shi, 2013).

4.2.1.1.4 Response Surface Methodology

Response surface methodology has its roots in statistical design of experiments. The basic aim of this methodology is to build an approximate functional relationship between the input variables and the output objective (Fu and Glover, 2005). One of the key advantages of response surface methodology is that many statistical methods, in particular, statistical design of experiments, may be incorporated into this methodology (Wang and Shi, 2013).

4.2.1.2 Discrete Decision Variables

The feasible region is finite or countably infinite. Also, variables are characterized as discrete (Wang and Shi, 2013).

4.2.1.2.1 Ranking and Selection

Ranking and selection is statistical method specifically created to choose the best system or a subset of systems from among a collection of competing alternatives. When certain assumptions are satisfied, ranking and selection methods generally guarantee that the probability of a correct selection will be at least some user-specified value (Goldsman and Nelson, 1994).

4.2.1.2.2 Multiple Comparison Procedure

Multiple comparison procedures are applicable when comparisons among a finite and generally small number of systems (say 2 to 20) are needed. Proposed procedures depend on the type of comparison desired and properties of the simulation output data. They account for the error that arises when making simultaneous inferences about differences in performance among the systems (Goldsman and Nelson, 1994).

4.2.1.2.3 Ordinal Optimization

Ordinal optimization approaches reduce the search for an optimal solution from sampling over extensive solution set to sampling over a smaller, more manageable set of good solutions (Swisher et al., 2004). One of the biggest advantages is the exponential convergence rate (Wang and Shi, 2013).

4.2.1.2.4 Metaheuristics

Metaheuristics are known as one of the most practical approaches for solving complex SO problems due to their ability of providing an effective and applicable solution. Moreover, metaheuristics are generally preferred over other optimization models to find the solutions with many local optima and little inherent structure to guide the search (Olafsson, 2006).

4.2.2 Proposed Genetic Algorithm

Optimization model should provide the capability of finding optimal or near-optimal solutions in the early stages of the search process (Wang and Shi, 2013). In this case, meta-heuristics are generally preferred over other optimization models to find the solutions with many local optima and little inherent structure to guide the search (Olafsson, 2006). In literature, many different solution methodologies such as population-based, single-solution based and set-based are available as meta-heuristic models but population-based GA can be considered as the most commonly used model. GA is an optimization model, 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). 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., 2004).

Analyses of previous studies show that GA is a challenging alternative model to cope with noisy outputs and complex systems especially in combinatorial optimization problems. Also, GA ensures the maximum ‘‘black-box’’ approach. Thus, no preliminary considerations about the goal function or initial values of the control parameters need to be taken. This situation is important in the simulation model in which no prior knowledge of the simulation model behavior can exist (Paul and Chanev, 1998).

GA is a family of randomized search procedures (Azadivar and Tompkins, 1999). The main characteristic of GA is the simultaneous evaluation of many solutions. This feature can be an advantage to enable a wide search and to potentially avoid convergence to a non-global optimum (Zong Woo et al., 2001). GA has several iterative operations. Initialization is the first procedure that generates an initial population. The population consists of individuals, which are called chromosomes. Each individual is evaluated by its fitness function. After generation of the initial population, selection, crossover and mutation are applied to generate new generations. Basic steps of GAs in the proposed SO models are summarized as follows:

Step 1: Initialization.

GA randomly generates an initial population of chromosomes. In GA, a potential solution of the problem is denoted as a set of parameters. These parameters are united together to create a chromosome. In this study, two different chromosome structures are used. One is for forward SC problem, the other one is for CLSC problem.

1. Chromosome structure for SC problem is composed of two parts. The first part of the chromosome represents supplier selection for DCs (Figure 4.2). The second part of the chromosome represents a determination of the initial inventory, reorder point, and order-up-to level of each DC and each Supplier.

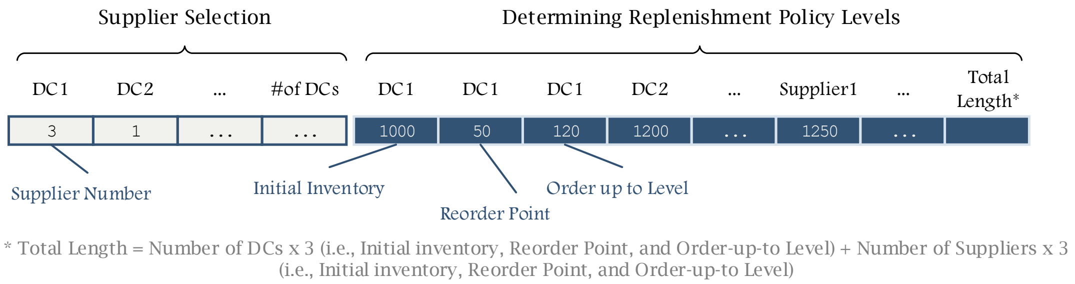


Figure 4.2 Chromosome structure of forward SC problem.

2. Chromosome structure for CLSC consists of two parts. The first part of the chromosome denotes facilities (plants and retailers) to be opened. Thus, we determine which retailer is used to meet customer’s orders and which plant is used to satisfy retailer’s replenishment order. The second part of the

chromosome denotes the determination of component inventory level for plants and the initial inventory, reorder point, and order up-to level of each plant and each retailer (Figure 4.3).

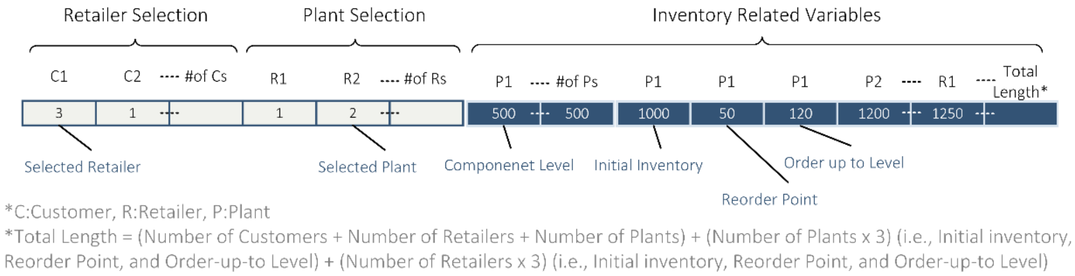


Figure 4.3 Chromosome structure of CLSC problem.

Step 2: Evaluation.

In this step, each chromosome is evaluated using the fitness value of each alternative solution, which is automatically taken from simulation model to form a new generation in GA. Fitness value f_k is computed for chromosome k by using the objective function value as given in Eq. (4.4):

$$f_k = \frac{1}{\text{Objective Function}} \tag{4.4}$$

Step 3: Selection.

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 the crossover. 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. Tournament selection is better than other selection operators because it does not use fitness function directly. The working principle of tournament selection and its advantages can be found in (Miller and Goldberg, 1995).

Step 4: Crossover.

In crossover operator, 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. Also, this is known as single point crossover (Figure 4.4).

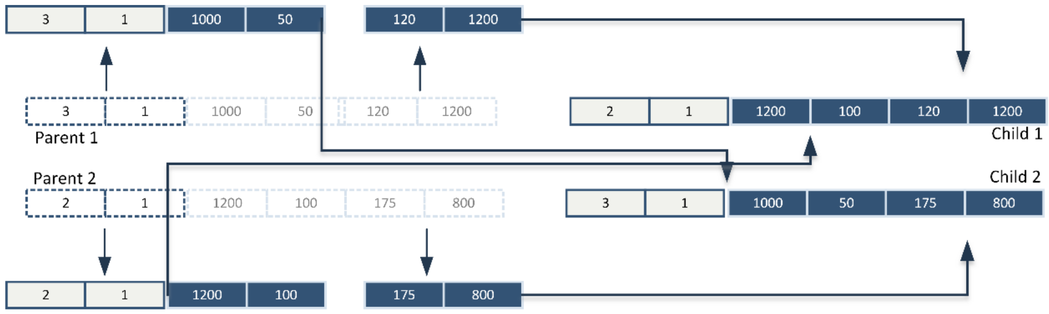


Figure 4.4 Crossover operator of GA.

Step 5: Mutation.

After applying crossover, mutation is randomly performed to each child individually with a small probability. In this way, a small amount of random search is provided. Mutation operator is illustrated in Figure 4.5.

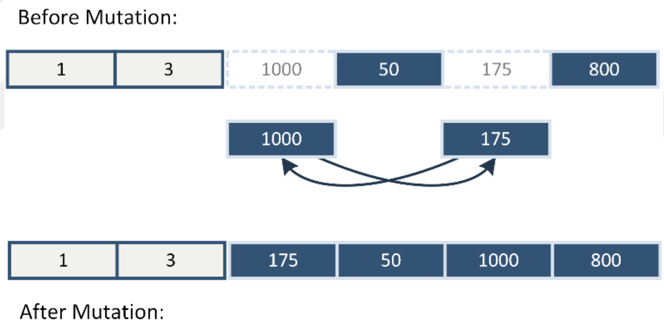


Figure 4.5**.** Mutation operator of GA.

Step 6: Check termination criteria.

The best chromosome is extracted at the end of the each iteration and used for the evolution of the next iteration. This is repeated until the desired number of iterations completed.

4.2.3 Characteristics of the Simulation Model

As mentioned earlier, several objects are used to create both SC and CLSC simulation models. These objects have their own properties that can be used to identify for specified problem. There are seven specific objects for both SC and CLSC problems (Table 4.2). Several properties are determined and can be used in case of need. The aim of designing specific objects for SC problems is increasing the modularity and reusability.

Table 4.2 Summary of simulation model objects

Object Name	**Basic Properties**	**Cost Components**
Customer	Interarrival time Entities per arrival To collection centers rate	-
Supplier	Processing time Initial Inventory Reorder point Order up to quantity Review period Order processing time Inventory holding period	Average holding cost Lost sales cost Processing cost Order cost per use Order processing cost rate Cost per use
DC/Retailer	Processing time Initial Inventory Reorder point Order up to quantity Review period Order processing time Inventory holding period	Average holding cost Lost sales cost Processing cost Order cost per use Order processing cost rate Cost per use
Plant	Processing time Initial Inventory Reorder point Order up to quantity Review period Order processing time Inventory holding period Bill of materials Component Inventory Level	Fixed opening cost Cost per use Order cost per use Lost sales cost Order holding cost rate Average holding cost Purchasing cost from suppliers Purchasing cost from refurbishing centers Purchasing cost from collection centers
Collection Center	Processing time Order processing time To plants rate To disassembly centers rate	Collection cost per unit Order processing cost Processing cost
Disassembly Center	Processing time Order processing time To refurbishing rate To dispose rate Bill of materials	Disassembly cost per batch Order processing cost Processing cost
Refurbishing Center	Processing time Order processing time	Refurbishing cost per batch Order processing cost Processing cost

Customers: a customer fulfills its demand from a determined DC or retailer. Arrival process is Poisson. Also, the customer can send a percentage of demand to the collection centers as returned products in the case of CLSC model.

Suppliers: a supplier provides raw materials, sub-assemblies or finished products. It can receive orders from a plant or a DC/retailer. It has an order process to prepare orders. Also, a supplier has its own inventory replenishment system. Therefore, properties related with inventory replenishment system (namely, initial inventory, reorder point, order up to quantity and inventory review period) already exists on this object.

DCs/Retailers: DC and retailer is the same object that they can receive orders from customers. This object can order a product from a manufacturer supplier or a plant. An order can be sent totally or partially according to its inventory. It has an order process to prepare orders. Also, inventory replenishment system exists on this object as well. Therefore, properties related with inventory replenishment system (namely, initial inventory, reorder point, order up to quantity and inventory review period) already exists on this object.

Plants: a plant manufactures finished products from raw materials. It can receive raw materials from suppliers or refurbishing centers. On the other hand, it can provide finished products directly from collection centers. This object has its own replenishment system and related properties as in supplier and DC/retailer objects. Also, a property named component inventory level is added in order to track components inventory level. Thus suppliers can control component inventory level, and sends components to the plants.

Collection Centers: a collection center receives returned products from customers and sends them directly to the plants or disassembly centers.

Disassembly Centers: a disassembly center receives products from collection centers. It sends a percentage of products to the disposals. Rest of the products are disassembled into its components/parts.

Refurbishing Centers: a refurbishing center receives components/parts from disassembly centers and applies a process to make components renewed. Then, sends components to the plants.

Building a simulation model starts with the creating of new instances of SC objects by taking into account related problem parameters. Then, the connection between these objects is completed in order to obtain both of order information and product flows. After building SC simulation model objective function and required responses are determined as in Figure 4.6.

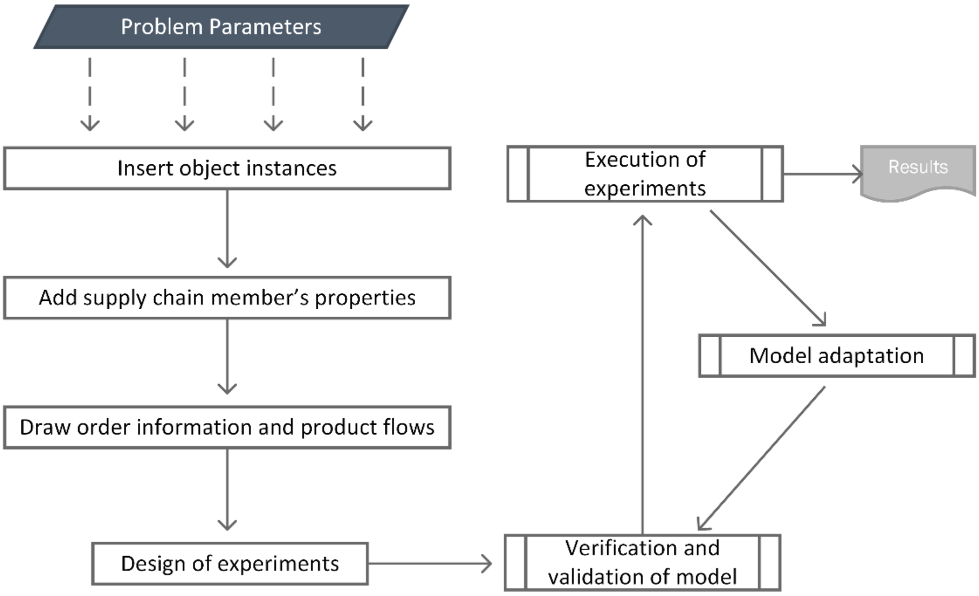


Figure 4.6 Building of an SC simulation model.

4.2.3.1 Inventory Control Systems

Throughout the thesis, two inventory control review policies are modeled. These are continuous review replenishment policy and periodic review replenishment policy. The inventory replenishment system is modeled for each related SC member. Although continuous review policy can replenish any time, periodic review policy has a determined replenishment time. Definitions of considered inventory review policies in this study are given as follows:

Periodic review: Inventory levels of selected SC member are all inspected at every R time units where R is a fixed constant. It should be noted that only this value is considered to be constant and assumed to be the same for each SC members which considers inventory. At the beginning of each review period, the inventory level of each SC member is increased until the order-up-to level whenever it decreases to a value smaller than or equal to the reorder point (Figure 4.7). Note that the replenishment lead time of each SC member should be smaller than the review period.

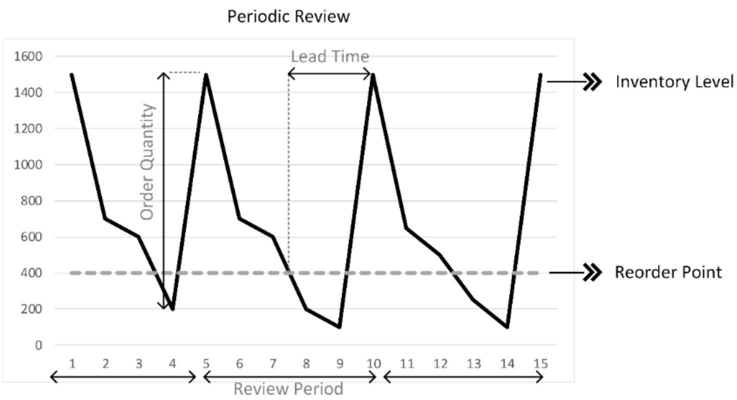


Figure 4.7 Periodic review inventory control system

Continuous review: Inventory levels of selected SC member are all inspected using continuous (s, S) policies. According to continuous (s, S) policies in a lost sales environment whenever the inventory level declines below the reorder point (s), an order is given to increase the inventory level of SC member until the order-up-to level (S) (Figure 4.8).

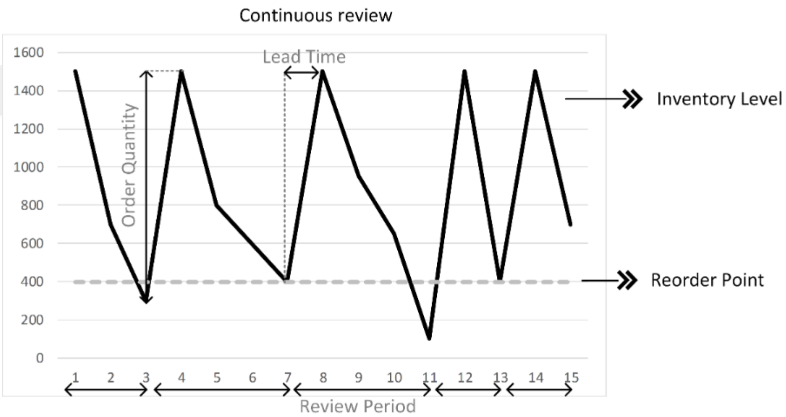


Figure 4.8 Continuous review inventory control system

4.2.3.2 Model Verification and Validation

Note that proposed inventory control system should be verified and validated to the degree needed for the simulation models. Verification ensures that the simulation model treats as the developer intended while validation controls that the simulation model is being created correctly. In this study, verification and validation of the models are performed by comparing some developed expectations and comparing expectations to the simulation model results. Furthermore, animation of the model is used another tool for validation and verification purposes. Thus, verification of the proposed model is performed by considering the expected throughput. Also, simulation models are considered valid when the accuracy of experimental conditions is within a desired range that is determined by model developers. As an example of experimental conditions, it can be said that increased levels of inventory parameters will definitely improve not only average holding unit levels but also order met probabilities both at DCs and Suppliers at the expense of increased total cost. Another example is that the decrease in the lost sales costs is offset by the increase in average holding costs. Considering these experimental conditions, the overall process is controlled to increase confidence in the simulation model.

4.3 Objective Functions

Throughout the study, determined problems are solved by considering two different objective functions. The first one is total SC cost (TSCC), and the second one is total difference cost function over periods (THL). While calculating the objective functions, several cost components are used for forward SC and CLSC problem.

4.3.1 Objective Functions for Forward SC Problem

Cost components for forward SC are given in Table 4.3.

Table 4.3 Cost components for forward SC members.

Suppliers	**DCs**
Average Holding Cost	Average Holding Cost
Lost Sales Cost	Lost Sales Cost
Processing Cost	Processing Cost
Order Cost Per Use	Order Cost Per Use
Order Processing Cost Rate	Order Processing Cost Rate
Cost Per Use	Cost Per Use

Cost components are calculated for each period and then summed up. Notations and parameters are given in Table 4.4.

Table 4.4 Parameters and notations used in forward SC network.

Parameters	
I	DCs $(i = 1,2, \dots, I)$
J	Suppliers $(j = 1,2, \dots, J)$
N	Set of periods $(n = 1,2, \dots, N)$
X_i^n	Inventory level of DC i at the end of period n
X_j^n	Inventory level of supplier j at the end of period n
${}^{-}X_i^n$	Unmet customer order quantity of DC i at the end of period n
${}^{-}X_j^n$	Unmet customer order quantity of supplier j at the end of period n
${}^{+}X_i^n$	Remaining inventory quantity of DC i at the end of period n
${}^{+}X_j^n$	Remaining inventory quantity of supplier j at the end of period n
$\mathrm{h_i}$	Inventory holding cost rate of DC i for each unit of inventory
$\mathrm{h_j}$	Inventory holding cost rate of supplier j for each unit of inventory
$\mathrm{k_i}$	Lost sales cost rate of DC i for each unit of stockout
$\mathrm{k_j}$	Lost sales cost rate of supplier j for each unit of stockout
p_i	Processing cost of DC i
p_j	Processing cost of supplier j
P_i	Processing time of DC i
P_j	Processing time of supplier j
c_i	Order cost per use of DC i
c_j	Order cost per use of supplier j
O_i	Order processing cost of DC i
O_j	Order processing cost of supplier j
s	Reorder point for DCs and suppliers
$\mathrm{I}\{.\}$	Indicator function of the set

Total SC Cost for DCs for period n ($TSCC_i^n$) is given as follows:

$$TSCC_i^n = \mathrm{h_i}\,{}^{+}X_i^n + \mathrm{I}\{X_i^n \le s_i\}\left(\mathrm{k_i}\,{}^{-}X_i^n + p_i P_i + c_i + O_i\right) \tag{4.5}$$

where, $\mathrm{I}\{.\}$ specify indicator function of the set. Similarly, TSCC for Suppliers for period n ($TSCC_j^n$) is calculated as follows:

$$TSCC_j^n = \mathrm{h_j}\,{}^{+}X_j^n + \mathrm{I}\{X_j^n \le s_j\}\left(\mathrm{k_j}\,{}^{-}X_j^n + p_j P_j + c_j + O_j\right) \tag{4.6}$$

Finally, the total cost of each DC and each Supplier are summed up to calculate $TSCC$ over periods as follows:

$$\begin{aligned} TSCC &= \sum_{n=1}^{Periods\ Considered} (\mathrm{TSCC_n}) \\ &= \sum_{n=1}^{Periods\ Considered} \left(\sum_{\mathrm{i=1}}^{\mathrm{I}} TSCC_i^n + \sum_{\mathrm{j=1}}^{\mathrm{J}} TSCC_j^n\right) \end{aligned} \tag{4.7}$$

Difference between overordering cost and underordering cost for DCs for period n ($\mathrm{H_{in}} - \mathrm{L_{in}}$) is calculated as follows:

$$H_i^n - L_i^n = |\, \mathrm{h_i}^{+} X_i^n - \mathrm{I}\{X_i^n \leq s_i\}\, (\mathrm{k_i}^{-} X_i^n)| \tag{4.8}$$

Difference between overordering cost and underordering cost for Suppliers for period n ($\mathrm{H_{jn}} - \mathrm{L_{jn}}$) is calculated as follows:

$$H_j^n - L_j^n = \left|\, \mathrm{h_j}^{+} X_j^n - \mathrm{I}\left\{X_j^n \leq s_j\right\} \left(\mathrm{k_j}^{-} X_j^n\right)\right| \tag{4.9}$$

Finally, the difference between overordering cost and underordering cost of each DC and each Supplier are summed up to calculate total difference cost function over periods (THL) as follows:

$$THL = \sum_{n=1}^{Periods\ Considered} (\mathrm{THL_n}) = \sum_{n=1}^{Periods\ Considered} \left(\sum_{\mathrm{i=1}}^{\mathrm{I}} (H_i^n - L_i^n) + \sum_{\mathrm{j=1}}^{\mathrm{J}} (H_j^n - L_j^n)\right) \tag{4.10}$$

4.3.2 Objective Functions for CLSC Problem

CLSC problem consists of two types of flow, one is forward flow and the other one is reverse flow. Therefore, cost components are different from previous objective functions.

Cost components for CLSC members are given in Table 4.5. Also, transportation cost between entities is considered.

Table 4.5 Cost components for the CLSCP.

Forward Flow		**Reverse Flow**
Plants	**Retailers**	**Collection Centers**
Fixed Opening Cost	Fixed Opening Cost	Processing Cost Rate
Order Cost per Use	Order Cost per Use	Collection Cost per Unit
Unit Lost Sales Cost	Unit Lost Sales Cost	Order Cost per Use
Order Holding Cost Rate	Order Holding Cost Rate	**Refurbishing Centers**
Cost per Use	Cost per Use	Processing Cost Rate
Processing Cost Rate	Processing Cost Rate	Refurbishing Cost per Batch
Average Holding Cost	Average Holding Cost	Order Cost per Use
Purchasing Cost (From Suppliers, From Plants, From Refurbishing Centers)		**Disassembly Centers**
		Processing Cost Rate
		Disassembly Cost per Batch
		Order Cost per Use

Table 4.6 Parameters and notations used in CLSC network.

Parameters	
I	Plants $(i = 1,2, \dots, I)$
J	Retailers $(j = 1,2, \dots, J)$
C	Collection Centers $(c = 1,2, \dots, C)$
D	Disassembly Centers $(d = 1,2, \dots, D)$
R	Refurbishing Centers $(r = 1,2, \dots, R)$
M	Suppliers $(m = 1,2, \dots, M)$
B	Disposals $(b = 1,2, \dots, B)$
V	Customers $(v = 1,2, \dots, V)$
N	Set of periods $(n = 1,2, \dots, N)$
s_i	Reorder point for plant i
s_j	Reorder point for retailer j
X_i^n	Inventory level of plant i at the end of period n
X_j^n	Inventory level of retailer j at the end of period n
$^{-}X_i^n$	Unmet customer order quantity of plant i at the end of period n
$^{-}X_j^n$	Unmet customer order quantity of retailer j at the end of period n
$^{+}X_i^n$	Time-weighted average inventory level of plant i over period n
$^{+}X_j^n$	Time-weighted average inventory level of retailer j over period n
$\mathrm{h_i}$	Inventory holding cost of plant i for each unit of inventory
$\mathrm{h_j}$	Inventory holding cost of retailer j for each unit of inventory
$\mathrm{k_i}$	Lost sales cost of plant i for each unit of stockout
$\mathrm{k_j}$	Lost sales cost of retailer j for each unit of stockout
p_i	Processing cost of plant i
p_j	Processing cost of retailer j
p_c	Processing cost of collection center i
p_d	Processing cost of disassembly center d
p_r	Processing cost of refurbishing center r
P_i	Processing time of plant i
P_c	Processing time of collection center c
P_d	Processing time of disassembly center d
P_r	Processing time of refurbishing center r
P_j	Processing time of retailer j
l_i	Order cost per use of plant i
l_j	Order cost per use of retailer j
O_i	Order processing cost of plant i
O_j	Order processing cost of retailer j
O_c	Order processing cost of collection center c
O_d	Order processing cost of disassembly center d
O_r	Order processing cost of refurbishing center r
$\mathrm{I}\{.\}$	Indicator function of the set
Q_{ci}	Quantity transported from collection center c to plant i
t_{ci}	Transfer time from collection center c to plant i
f	Unit transportation cost
T_i	Total transportation cost of plant i
T_j	Total transportation cost of retailer j
T_c	Total transportation cost of collection center c
T_d	Total transportation cost of disassembly center d
T_r	Total transportation cost of refurbishing center r
PC_i	Purchasing cost from collection center i
PR_i	Purchasing cost from refurbishing center i
PS_i	Purchasing cost from supplier i
F_i	Total fixed opening cost of plant i
F_j	Total fixed opening cost of retailer j

Cost components are calculated for each period and then summed up. Notations and parameters are given in Table 4.6. In addition, transportation cost is proportional to the unit transportation cost, the transportation time, and the order quantity at each shipment for each SC member.

Total transportation cost for plant i is given as follows:

$$T_i = \sum_{c}^{C}\sum_{i}^{I} Q_{ci}t_{ci}f + \sum_{r}^{R}\sum_{i}^{I} Q_{ri}t_{ri}\, f + \sum_{m}^{M}\sum_{i}^{I} Q_{mi}t_{mi}f \tag{4.11}$$

Total transportation cost for retailer j is given as follows:

$$T_j = \sum_{j}^{J}\sum_{i}^{I} Q_{ji}t_{ji}f \tag{4.12}$$

Total transportation cost for collection center c is given as follows:

$$T_c = \sum_{v}^{V}\sum_{c}^{C} Q_{vc}t_{vc}f \tag{4.13}$$

Total transportation cost for disassembly center d is given as follows:

$$T_d = \sum_{c}^{C}\sum_{d}^{D} Q_{cd}t_{cd}f + \sum_{d}^{D}\sum_{b}^{B} Q_{db}t_{db}f \tag{4.14}$$

Total transportation cost for refurbishing center r is given as follows:

$$T_r = \sum_{d}^{D}\sum_{r}^{R} Q_{dr}t_{dr}f \tag{4.15}$$

Total forward flow cost (suppliers, plants, retailers) (TFC) is given as follows:

$$TFC = \sum_{n}^{N} (\sum_{\mathrm{i}=1}^{\mathrm{I}} \mathrm{h_i}^{+} X_i^n + \mathrm{I}\{X_i^n \leq s_i\} (\mathrm{k_i}^{-} X_i^n + p_i P_i + c_i + O_i + T_i + PC_i + PR_i + PS_i + F_i)) + \sum\nolimits_{\mathrm{j}=1}^{\mathrm{J}} \left(\mathrm{h_j}^{+} X_j^n + \mathrm{I}\left\{X_j^n \leq s_j\right\}\left(\mathrm{k_j}^{-} X_j^n + p_j P_j + l_j + O_j + T_j + F_j \right)\right) \tag{4.16}$$

Total reverse flow cost (collection centers, disassembly centers, and refurbishing centers) (TRC) are given as follows:

$$TRC = \sum_{\mathrm{c}=1}^{2} (T_c + O_c + p_c P_c) + \sum_{\mathrm{d}=1}^{2} (T_d + O_d + p_d P_d) + \sum_{\mathrm{r}=1}^{2} (T_r + O_r + p_r P_r) \tag{4.17}$$

Total CLSC cost (TCC) is given as follows:

$$\mathrm{TCC} = \sum_{n=1}^{N} (\mathrm{TCC_n}) = TFC + TRC \tag{4.18}$$

The minimization of difference between overordering cost and underordering cost (THL) means that proposed model minimizes the differences between the average holding cost ($\mathrm{h_i}^{+} X_i^n$ *or* $\mathrm{h_j}^{+} X_j^n$) and the lost sales cost ($\mathrm{k_i}^{-} X_i^n$ *or* $\mathrm{k_j}^{-} X_j^n$).

$$THL = \sum_{n=1}^{N} (\mathrm{THL_n}) = \sum_{n=1}^{N} (\sum_{\mathrm{i}=1}^{4} (|\mathrm{h_i}^{+} X_i^n - \mathrm{I}\{X_i^n \leq s_i\} (\mathrm{k_i}^{-} X_i^n)|) + \sum\nolimits_{\mathrm{j}=1}^{4} (\left| \mathrm{h_j}^{+} X_j^n - \mathrm{I}\left\{X_j^n \leq s_j\right\} \left(\mathrm{k_j}^{-} X_j^n\right)\right|)) \tag{4.19}$$

4.3.3 Performance Measurements

To remain competitive in today's condition, companies forces themselves to meet customer needs better than their competitors. In this respect, several performance measurements should be used to evaluate proposed systems. Performance measure selection is an important issue in order to understand the system as a whole. Generally, performance measures are categorized into two types for SCs. First one is SC cost, and the second one is customer satisfaction. Average service levels, lost sales, backorder sales etc. can be given as examples of performance measurements. These performance measurements can be used separately or jointly.

In this study, several types of performance measurements are used. These are:

- Average service level
- Cost-based statistics
- Quantity-based statistics
- Order-based statistics
- Probability-based statistics
- Lead time-based statistics

Average service level (see Eq. (4.20) is defined as the ratio of current inventory level in Retailer/Plant to the number of units ordered by the customers/Retailer over total number of incoming orders.

$$Average\ service\ level\ = \frac{\sum_{a=0}^{Per\ Arrival} \min(1, \frac{Current\ Inventory\ Level}{Incoming\ Order\ Quantity})}{Total\ Number\ of\ Incoming\ Orders} \tag{4.20}$$

Table 4.7 Definitions of cost components

Cost Components	Definition
Average holding cost	Proportional to the remaining inventory quantity over period n and holding cost for each unit of inventory
Lost sales cost	Proportional to the unmet customer order quantity over period n and lost sales cost for each unit of stockout
Order cost per use	The cost of any order that is placed at any SC member irrespective of the time spent there
Order processing cost	Proportional to the order processing time and cost per use, which is the one-time cost that is accrued each time any SC member is used, regardless of the usage duration
Processing cost	Proportional to the processing cost and processing time to process a product/component

Cost-based statistics give detailed statistics about average holding cost, order cost per use, lost sales cost, order processing cost and processing cost for each SC members. Definitions of cost components are given in Table 4.7.

Quantity-based statistics consist of totally met order quantity (TMOQ), totally lost order quantity (TLOQ), partially lost order quantity (PLOQ).

Order-based statistics are number of totally met orders (NTMO), number of totally lost orders (NTLO), and number of partially lost orders (NPLO) per each period.

Probability-based statistics include order met probability per period (P1) (Eq. (4.21), and overall order met probability (P2) (Eq. (4.22).

$$\int_{n-1}^{n} \min(1, \frac{Current\ Inventory\ Level}{Incoming\ Order\ Quantity}) dt \tag{4.21}$$

$$\int_{0}^{n} \min(1, \frac{Current\ Inventory\ Level}{Incoming\ Order\ Quantity}) dt \tag{4.22}$$

Lead time-based statistics per each replenishment lead time consist of order met probabilities, average holding unit, and length of the lead time. Statistical analysis is extended by calculating order met probabilities per lead time that is calculated by using Eq. (4.23).

$$\int_{n}^{end\ of\ lead\ time} \min(1, \frac{Current\ Inventory\ Level}{Incoming\ Order\ Quantity}) dt \tag{4.23}$$

4.4 Conclusion

In this chapter, proposed SO for forward SC and CLSC is presented in order to gain a deep insight into the concept. Proposed SO consists of two-phase: (1) optimization phase, and (2) simulation phase. Note that each of these two phases continuous iteratively. Firstly, optimization phase determines decision variables of the related problem. Secondly, simulation evaluates the system as a whole by using determined decision variables for the problem.

To create simulation models, reusable objects are used. Required properties are determined for each object to identify for specifics of the SC problem. These objects provides more flexible, reusable, extensible and efficient simulation model creation.

The proposed SO is applicable for both forward SC network and CLSC network. Only there are some distinctions for both GA and simulation model due to the problem specifications.

Furthermore, objective functions and performance measurements are given in detail for both forward SC network and CLSC network problems. Two different objective functions are used, namely total cost and difference between overordering cost and underordering cost. Also, several performance measurements are determined to provide more comprehension about system behavior.

CHAPTER 5

FORWARD SUPPLY CHAIN PROBLEM AND COMPUTATIONAL RESULTS

In this chapter, proposed SO approach is applied to a forward flow SC problem to substantially present the flexible and comprehensible research on the important decision of whether minimizing the differences between total overordering cost and total underordering cost or minimizing TSCC. We also try to point out several important issues: (1) what the optimal values of initial inventory, reorder point, and order-up-to level are in inventory replenishment policy for each DC and each Supplier; (2) whether SO models can successfully integrate the supplier selection and inventory replenishment policy for SC environment; (3) how to apply statistical analysis skills to compare these SO models with a greater level of detail. According to the results, TSCC can be improved at least 22 % and at most 66 % on average with proposed continuous review model.

5.1 Introduction

Over the past two decades, SC members have been under intense pressure to improve replenishment polices and to find a robust replenishment model for today’s inventory management challenges. One of the critical issues is determining when the product should be reviewed for possible replenishment policy. In literature, two basic types of the review system are available; continuous review and periodic review. The selection of review system depends on the structure of the SC members. In this chapter, continuous and periodic review (s, S) policy considered as a review system. Under the (s, S) policy, an order is placed to increase the product's inventory level to the order-up-to level (S) as soon as this inventory level reaches or drops below the reorder point (s). A positive feature of continuous (s, S) policy is that the inventory level is closely and continuously monitored so that inventory level is always known.

Table 5.1 Summary of the review systems.

	Topic	Review System	Inventory Policy	Solution Method	a*	b*	c*	d*	e*
Tijms and Groenevelt (1984)	Inventory Systems with Service Level Constraints	Periodic and Continuous	(s, S)	Approximation methods				√	√
Ehrhardt and Mosier (1984)	Inventory/Production	Periodic	(s, S)	Power Approximation	√			√	√
Schneider and Ringuest (1990)	Inventory Systems with Service Level Constraints	Periodic	(s, S)	Power Approximation	√			√	√
Hollier et al. (1995)	Inventory Systems Incorporating a Cutoff Transaction Size	Continuous	(s, S)	Mathematical Model	√			√	√
Bashyam and Fu (1998)	Inventory Systems with Service Level Constraints	Periodic	(s, S)	Simulation Optimization				√	√
Feng and Xiao (2000)	Location Inventory System	Periodic	(s, S)	Descent-Search Algorithm	√			√	√
Hu et al. (2005)	Location Inventory Systems with Transshipments	Periodic	(s, S)	Dynamic Programming	√			√	√
Kleijnen and Wan (2007)	Inventory Systems with Service Level Constraints	Continuous	(s, S)	Simulation Optimization				√	√
Wan et al. (2007)	Inventory Systems with Service Level Constraints	Continuous	(s, S)	Simulation Optimization	√			√	√
Mendoza and Ventura (2010)	Supplier Selection and Order Quantity Allocation	Periodic	Power-of-Two	Mixed Integer Nonlinear Programming Model	√		√		√
Kiesmüller et al. (2011)	Inventory Systems	Periodic	(R, S, Q_{min})	Markov Chain Model	√			√	√
Tlili et al. (2012)	Location Inventory Systems with Transshipments	Periodic	(R, s, S)	Simulation Optimization	√			√	√

Table 5.1 Summary of the review systems (continued).

	Topic	Review System	Inventory Policy	Solution Method	a*	b*	c*	d*	e*
Cabrera et al. (2013)	Inventory Location Model with Stochastic Capacity Constraint	Periodic	(R, s, S)	Tabu Search, Particle Swarm Optimization	√			√	√
Al-Hawari et al. (2013)	Assignment and Inventory Policies	Periodic and Continuous	(T, S), (r, Q)	Simulation		√		√	√
Guo and Li (2014)	Supplier Selection and Order Allocation	Continuous	(Q, R)	Mixed Integer Nonlinear Programming Model	√			√	√
Nasr and Maddah (2015)	Inventory Systems	Continuous	(s, S)	Markov Chain Model, Heuristic Policies	√			√	√
Göçken et al. (2017b)	Supplier Selection and Inventory Control System	Continuous	(s, S)	Simulation Optimization	√			√	√
Göçken et al. (2017a)	Supplier Selection and Inventory Control System	Periodic and Continuous	(s, S)	Simulation Optimization	√			√	√

*a-Single Product, b-Multiple Product, c-Deterministic Parameters, d-Uncertain (Random) Parameter (s), e-Single-Objective

This is especially advantageous for critical inventory products such as replacement parts or raw materials and supplies (Taylor, 2013). Although an abundant literature is available related to continuous (s, S) policy, optimum results are found under some strict assumptions and simplification.

At this point, fundamental challenge is computability and tractability in stochastic environment. Especially, (s, S) policy has a potentially infinite number of combinations for reorder point and order-up-to level and hence, researchers have found it arduous to create the optimal policy (Feng and Xiao, 2000). One of the key article has been made by Nahmias (1979) where the authors developed a simulator that determines the best order-up-to level or continuous (s, S) policy by a Fibonacci search of the appropriate response surface. Tijms and Groenevelt (1984) showed tractable approximations for (s, S) policies considering undershoot of the reorder point. Stochastic lead time is allowed while order crossings are prohibited. Although excess demand is backordered in the study, only slight modifications are needed to use lost sales models for (s, S) policies. Ehrhardt and Mosier (1984) presented a proper limiting behavior of S-s when the variance of demand is extremely small. In the study, power approximation that is a computationally simple algorithm for computing approximately optimal values of reorder point and order-up-to level is used. Power approximation requires for the mean and variance of demand and typically performs within a few percent of optimal total cost for a wide variety of demand distribution and parameter setting. Also, Schneider and Ringuest (1990) developed the power approximation to determine the order-up-to level and the reorder point using a specified level of service. Zheng and Federgruen (1991) derived an algorithm to compute optimal (s, S) policies taking account of a number of new properties of the infinite horizon cost function. Also, a new upper bound for optimal order-up-to level and a new lower bound for optimal reorder point are presented. They search in (s, S) policies by consecutively updating the average long-run cost. It was deemed crucial to determine reorder point and order-up-to level so as to satisfy objective function in inventory control system. The one of key intuition in (s, S) policies is that reorder point and order-up-to level are determined either minimizing TSCC (e.g. holding, shortage, ordering cost and etc.) or minimizing the differences between two opposite costs (e.g. holding cost and shortage cost). On the one hand, TSCC per unit time is taken as the most common objective function for determining the optimal (s, S) policies, and includes many cost components in which the definitions of costs can also differ. On the other hand, Levi et al. (2008) showed that balancing holding cost and shortage cost can work significantly better than minimizing the sum of the holding cost and shortage cost. The remarkable detailed information about balancing two underlying opposing costs can be found in Levi et al. (2008) To the best of our knowledge, there is no clear methodology is available about balancing average holding cost against lost sales cost in (s, S) policies using SO models. Hence, we will define SO methodology to minimize differences between overordering cost (average holding cost) and underordering cost (lost sales cost). In this study, cost components of individual SC members include five types of costs: 1) the 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) the average holding cost (i.e., the cost of carrying the products in inventory), 3) the order processing cost (i.e., charged proportional to the order processing time and cost per use), 4) the lost sales cost (i.e., the cost associated with demands occurring when the system is out of stock), 5) the processing cost (i.e., charged proportional to the processing time that is the time needed to prepare products for serving).

To overcome today's inventory management challenges, the exact determination of optimal inventory is needed because a shortage of inventory increases the number of lost sales while holding excess inventory can result in pointless storage cost. In this case, determination of the inventory level to be held in SC members becomes inevitable so as to achieve both strategical and tactical success in SC. How to determine suitable supplier is also one of the most strategic considerations for achieving enduring competitive advantage. In literature, many researchers presented the importance of supplier selection by displaying the effect of decisions throughout the whole SC. 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, SO is used to present the continuous (s, S) and periodic (R,s,S) policies and the supplier selection simultaneously in a two-echelon SC under stochastic environment and lost sales system. Optimization is done by taking two different objective functions into account, namely difference between the overordering cost and the underordering cost (Model 1) and the TSCC (Model 2). We give comparative analysis and suggestions related with the SC members to let them select the suitable model that suits their needs the best because a firm's preference for a continuous decision making strategy, given its competitor's strategy, can change depending on market and firm characteristics. Also, the impact of the Model 1 and Model 2 is analyzed as quoted by the SC members considering cost competition and customer satisfaction based competition. Note that the customer satisfaction based competition is directly affected by the lost sales and can be evaluated considering probability-based analysis, order-based analysis, and quantity-based analysis. In recent years companies not only need to operate at a lower cost and a better service level in order to compete, but they also must develop their own core competencies to be distinguished from competitors and stand out in the marketplace. By considering current state of the companies, many different viewpoints are taken into account by considering uncertainty and dynamic nature of the system. Especially, the importance of supplier selection in the success of the inventory control system has prompted the development of models in an attempt to integrate the implicit decision making in the two areas (Boru, 2015). Therefore, our proposed models including Model 1 and Model 2 provide remarkable contribution to inventory management literature due to the flexible and reusable structure of SO. In addition, comparison of periodic inventory control policy and continuous inventory control policy is given for both Model 1 and Model 2 in Section 5.5. SO provides an efficient reuse in real word problems while decreasing the amount of time needed to develop the model.

5.2 Problem Definition

The strategic effect of inventory level at different members of the SC is significant to remain competitive. Therefore, providing the optimal inventory level for each member of the SC is one of the major challenges for decision makers. In this case, continuous (s, S) and periodic (R,s,S) policies can be considered as the key inventory review systems. Continuous (s, S) policy provides optimal inventory level by placing an order at each member of the SC when inventory level is below reorder point, and by specifying order quantity considering the difference between order-up-to level (maximum inventory level) and the current inventory position. Periodic (R,s,S) policy replaces inventory at every R time units where R is a fixed constant and assumed to be 5 days. It should be noted that only this value is considered to be constant and assumed to be the same for all Suppliers and DCs placed. At the beginning of each review period, the inventory level of each DC and each Supplier is increased until the order-up-to level whenever it decreases to a value smaller than or equal to the reorder point. In this study, (s, S) and (R,s,S) policies are created considering a single-product, two-echelon, inventory system with three DCs replenishing the stocks from five independent Suppliers. The distribution of the customer order quantity at 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. For DCs, replenishment lead time is assumed to be stochastic and includes order processing time at Suppliers, transportation time from Supplier to DCs, and processing time at DCs. It should be noted that inventory level continuous to decrease over the duration of the lead time since the order placed will not be received until the end of the lead time. DCs can take many number of customer orders within this time. If customer order quantity is lower than the current inventory level of DC_i, customer order is fully satisfied (i denotes the DC in the system, $i = 1, 2, \dots I$). If customer order quantity exceeds the current inventory level of DC_i, partial order fulfillment takes place. Unmet customer order quantity is lost. Inventory levels of DCs are controlled by continuous (s, S) and periodic (R,s,S) review systems and each DC is replenished only by a single Supplier. To satisfy each DC's replenishment order, the firm should select the most suitable $Supplier\ j,\ j \in J$ where j denotes the Supplier in the system, $j = 1, 2, \dots J$). It is worth remembering that DCs face stochastic customer demands for a single product and Suppliers receive only the replenishment orders from each DC. The DC's replenishment order is satisfied if the current inventory level of $Supplier\ j$ is greater than or equal to the DC's replenishment order quantity. If $Supplier\ j$ does not have enough inventories to fulfill order, partial order fulfillment takes place depending upon the current inventory level of $Supplier\ j$. Excess DC's replenishment order quantity is lost. The stock in each Supplier is controlled using continuous (s, S) and periodic (R,s,S) policies and is replenished from unlimited sources. For Suppliers, replenishment lead time is also assumed to be stochastic and includes processing time and order processing time. Note that order processing time is defined as 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 for DCs or Suppliers. The processing time is defined as the time needed to prepare products for serving at DCs or Suppliers. The general structure of proposed inventory control system is given in Table 5.1.

Model assumptions are determined as follows:

1) Single product flows through the two-echelon SC
2) 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.
3) Poisson demand process and stochastic lead time are used.
4) 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.
5) If the demand quantity exceeds the current inventory level of SC members, possible order fulfillment takes place and unmet demand is lost.
6) Only transportation time between Suppliers and DCs are considered.
7) Simulation run consists of 20 replications.
8) Each replication length is one year and the length of a period is one month.
9) The inventory level of SC members is not allowed to be negative.

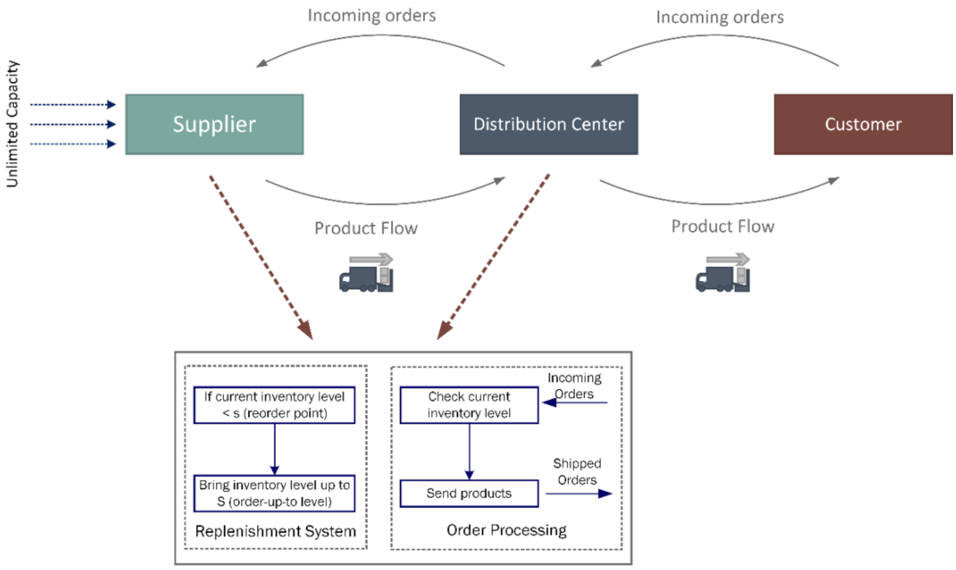


Figure 5.1. The proposed inventory control system

To estimate the performance of a given system design average holding cost, lost sales cost, fixed and variable ordering costs which are given in Table 5.2 together with their corresponding values are considered. The details about the replenishment lead time are also given in Table 5.2.

Table 5.2**.** The parameter values related with replenishment lead time and cost.

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)
Processing Time (P_j): Triangular (3, 5, 7) minutes	Processing Time (P_i): Triangular (1, 2, 3) minutes
Order Processing Time: Uniform (2, 5) hours	Order Processing Time: Uniform (2, 5) hours
-	Transportation Time: Uniform (1.25, 3) days

As mentioned before, two different objective functions are used to optimize inventory control policy parameters and supplier selection. Difference between overordering cost and underordering cost (Model 1, Eq. (4.10) and TSCC (Model 2, Eq. (4.7) calculated by using determined cost functions.

Existing mathematical models could not use all the variables with stochastic properties for our proposed SC; hence these models can only present the optimal values for partial SCs. It is not possible to handle all SC variables that vary dynamically using mathematical models. In general, they require too many assumptions and simplifications to be applicable and effective. To overcome the limitations of existing mathematical models, SO based model is proposed for continuous (s, S) policy and periodic (s, S) policy. SO has an ability of capturing the advantages of both simulation and optimization based models simultaneously. Also, SO is not constrained by analytical assumptions and simplifications. Therefore, proposed SO models provide significant opportunity to find optimum inventory control parameters and to select best Suppliers for DCs.

5.3 Simulation Optimization

In the proposed model, GA is used to optimize the inventory control system and supplier selection. 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. The similar structure of SO model including the optimization model and the simulation model can be found in (Göçken et al., 2015) where periodic inventory control system is used with two DCs and three suppliers. In this study, three DCs and five Suppliers adopted the continuous (s, S) policy and periodic (s, S) policy while using Model 1 and Model 2.

In GA, values of population size, number of iterations, crossover rate and mutation rate are taken as 50, 150, 0.8, and 0.05, respectively. The flowchart of the proposed GA is given in Figure 5.2. In the simulation model, performances of candidate solutions are evaluated.

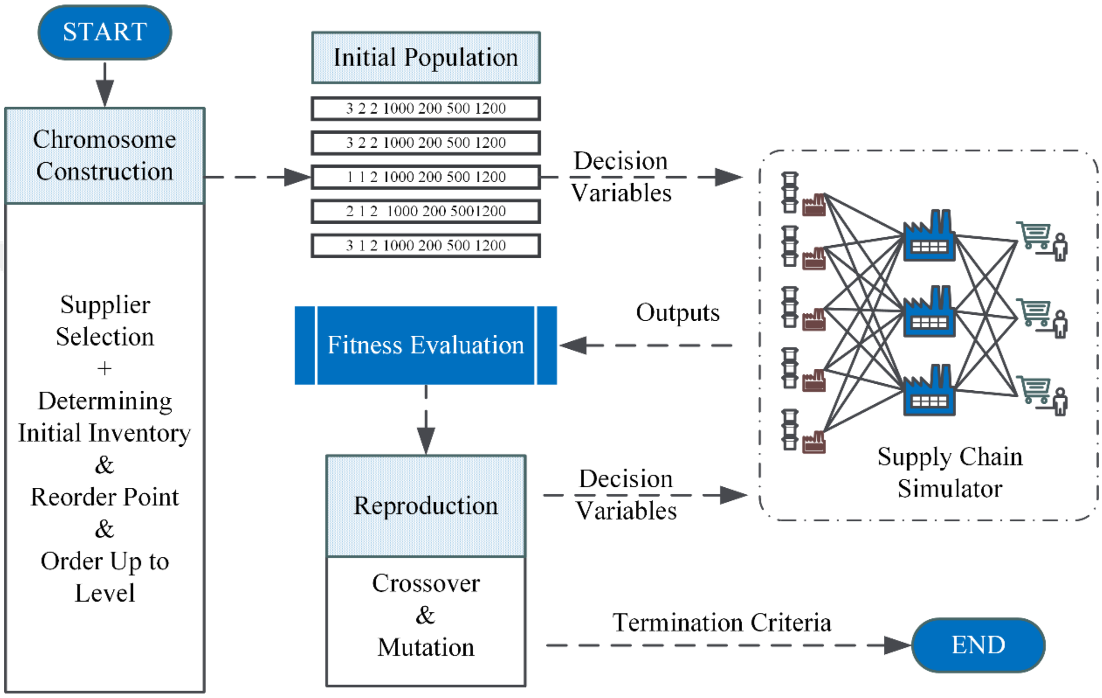


Figure 5.2. The flowchart of the proposed GA.

5.4 Results and Discussion

5.4.1 Cost based analysis for continuous (s, S) policy

SO whose convergence of the search process for continuous (s, S) policy are plotted in Figure 5.3, determined the best possible values of the initial inventory, reorder point, and order-up-to level for each DC and each Supplier. Note that convergence speed is different for each considered objective function (e.g., Model 1 (the difference between overordering cost and underordering cost) and Model 2 (TSCC)) due to their numerical values and function calculation.

To apply the most effective inventory management, the inventory control system should provide enough information to allow managers to make a decision on inventory. Hence, many researchers investigated to observe different impacts of the inventory control systems in terms of cost reduction. In this case, determining a well-selected set of suppliers makes a strategic difference to a company's ability to ensure continued improvement in control systems. Although there are plenty of studies for the supplier selection model, only limited studies focused on the inventory control systems integrated with supplier selection, especially under stochastic demand and lead times. Also, one of the repercussions of this convergence is that if inventory control parameters defined effectively with supplier selection, then the TSCC could be automatically improved.

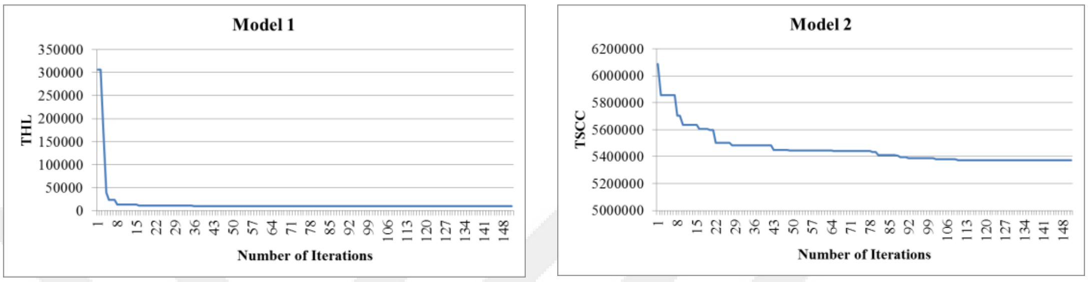


Figure 5.3 Convergence of the GA towards the best solution in both models.

Supplier1, Supplier4, and Supplier5 are selected to be the most appropriate Suppliers for satisfying DC's replenishment orders in Model 1. On the other hand, Supplier1, Supplier2, and Supplier3 are selected to be the most appropriate Suppliers for satisfying DC's replenishment orders in Model 2. Taking a glance at overall average service levels reveals that there seems no problem with DCs and Suppliers in both models (see Table 5.3). Overall average service levels of DCs with Model 1 are not as good as with Model 2 although Suppliers are almost the same with both models.

With optimal inventory control parameters, DCs and Suppliers fulfill a strategic role in achieving the SC objectives of lower costs. In this respect, the 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 TSCC including five different cost components (average holding cost, order cost per use, lost sales cost, order processing cost, and processing cost) as given in Table 5.3 and Table 5.4. Note that Model 1 minimized the difference between overordering cost and underordering cost that is taken as the objective function although it considers five different cost components to create inventory control system.

Table 5.3 Average service levels and optimal values of inventory control parameters.

SC Member	Model Type	Initial Inventory	Reorder Point (s)	Order-up-to Level (S)	Average Service Level
DC1	**Model 1**	1197	113	552	0.932
	Model 2	1973	178	493	0.993
DC2	**Model 1**	1677	166	552	0.988
	Model 2	1973	178	493	0.994
DC3	**Model 1**	1311	166	434	0.986
	Model 2	1973	175	493	0.993
Supplier1	**Model 1**	1677	182	861	0.973
	Model 2	1160	175	448	1
Supplier2	**Model 1**	-	-	-	-
	Model 2	1504	166	410	0.999
Supplier3	**Model 1**	-	-	-	-
	Model 2	1054	198	410	0.999
Supplier4	**Model 1**	1311	198	554	0.995
	Model 2	-	-	-	-
Supplier5	**Model 1**	1197	196	951	0.998
	Model 2	-	-	-	-

Table 5.4 Cost analysis of the DCs.

		Average Holding Cost		Order Cost Per Use		Lost Sales Cost		Order Processing Cost		Processing Cost	
		Model 1	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**
DC1	**Cost ($)**	10288	12871	27088	26982	110310	12703	36432	36486	4472	4726
	Share	6%	14%	14%	29%	59%	13%	19%	39%	2%	5%
DC2	**Cost ($)**	12067	12268	27065	27017	19737	10449	33439	36417	4687	4728
	Share	12%	14%	28%	30%	20%	11%	35%	40%	5%	5%
DC3	**Cost ($)**	8564	12716	26964	27024	23644	12604	36348	36521	5008	4728
	Share	8%	14%	27%	29%	24%	13%	36%	39%	5%	5%

Table 5.5 Cost analysis of the Suppliers.

		Average Holding Cost		**Order Cost Per Use**		**Lost Sales Cost**		**Order Processing Cost**		**Processing Cost**	
		Model 1	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**
Supplier1	**Cost ($)**	22454	20354	4352	3559	42441	0	5926	4769	82583	86366
	Share	14%	18%	3%	3%	27%	≈ 0%	4%	4%	52%	75%
Supplier2	**Cost ($)**	-	20535	-	3521	-	1485	-	4747	-	76320
	Share	-	19%	-	3%	-	1%	-	5%	-	72%
Supplier3	**Cost ($)**	-	18055	-	3584	-	8	-	4821	-	86688
	Share	-	16%	-	3%	-	≈ 0%		4%		77%
Supplier4	**Cost ($)**	22874	-	2596	-	7272	-	3486	-	83247	-
	Share	19%	-	2%	-	6%	-	3%	-	70%	-
Supplier5	**Cost ($)**	27756	-	2990	-	3271	-	4087	-	84929	-
	Share	23%	-	2%	-	3%	-	3%	-	69%	-

From Table 5.4, it is seen that DCs' lost sales cost is dramatically decreased with Model 2. Lost sales cost of Model 2 is approximately four times lower than Model 1. Therefore, TSCC for DCs in Model 2 is reasonably better than Model 1 and is improved approximately 28% of total cost of DCs (cost difference is $ 107873). The analysis of Model 1 demonstrated that the largest share for DC1 is the lost sales cost whose value is 59% and the largest share for DC2 and DC3 is the order processing cost whose value is 35% (DC2) and 36% (DC3), respectively.

The analysis of Model 2 demonstrated that the largest share for all DCs is the order processing cost whose value is between 39% (DC1 and DC3) and 40% (DC2). Order cost per use is also critical in Model 2 because it is approximately accounted for 29% of the total costs of DCs. Also, the share of the average holding cost (14% for all DCs) is high in Model 2.

The analysis of proposed models demonstrated that the largest share for all Suppliers is the processing cost whose value is between 52% and 77%. The share of cost components varies in accordance with the model types considered. For Suppliers, lost sales cost of Model 2 is approximately thirty-five times lower than that of Model 1 (Table 5.5). Also, TSCC for Suppliers in Model 2 is better than Model 1 and is improved approximately 16.3% of the total cost of Suppliers (cost difference is $ 65452). Note that the cost difference of DCs is significantly higher than the cost difference of Suppliers. These results show that adopting continuous review model for DCs is more critical than Suppliers since incorrect selection can be costlier for DCs. After separate analysis of SC members, we also analyzed the general structure of the whole SC. TSCC of Model 1 is improved approximately 22% with Model 2.

It is worth noting that although cost component analysis is of great importance in evaluating continuous (s, S) policy, a detailed descriptive analysis including probability-based analysis (P1 and P2), quantity-based analysis per each period (TMOQ, and 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) need to be considered up to a certain degree. P1 for both Suppliers and DCs are calculated by using Eq. (4.21). For example, if the P1 for any period is 0.997, all incoming orders are met 99.7 percent of the time within that period or in other terms incoming orders are met with 0.997 probability within that period. Calculating such a statistic allows one to obtain hidden but valuable information about the dynamics of the SC which is ignored most of the time. Also, P2 for both Suppliers and DCs are calculated by using Eq. (4.22) for comparison purposes. For example, if P2 value is 0.998 at the end of the period 2, 99.8 percent of the time (i.e., over two months) all incoming orders are met. Likewise, the same value can be interpreted as all incoming orders within the first two months are met with a 0.998 probability.

Comparing P2 with P1 provides very useful information for decision-makers. It can be quite misleading to consider just P2 values since it is being a biased indicator due to its taking initial conditions into account. Note that P1 and P2 values should be close to 1 across the periods for all SC members to have the potential to meet all incoming orders over time. In Figure 5.4 to 7, at period 1 all incoming orders are met (i.e., P1 is 1) for all DCs. The reason for period 1's being an exception is DCs' having adequate levels of initial inventories at that period. But, this is not the case for DCs at other periods. Note that P1 values are calculated just only for each period and thus can be seen just a fine-tuned version of P2 values.

TLOQ values with Model 1 vary between 11 units and 74 units. Also, NTLO values are equal to 1 order over all periods except from the first period whose value is zero. NPLO values vary between 1 order and 3 orders, and NTMO values vary between 26 orders and 29 orders at DC1. In Model 2, both TLOQ and NTLO values for DC1 are all equal to zero over all considered periods. NPLO values for DC1 are all equal to 1 order over the periods except from the first period whose value is zero. Also, NTMO values are equal to 29 orders over the periods except from the first period whose value is 30 orders with Model 2 at DC1.

Being much more realistic indicators P1 values should be relied on while making decisions. P1 is improved at least 1.6% and at most 7% and P2 is improved at least 1.6% and at most 5.9% across the periods for DC1 with Model 2. Similar things can be said with regard to both order-based analysis and quantity-based analysis. TMOQ for DC1 is improved at least 27 units and at most 165 units with Model 2. TLOQ for DC1 is improved at least 11 units and at most 74 units. PLOQ for DC1 is decreased at an average of 8 units and at most 15 units. NPLO for DC1 is improved at least 1 order and at most 2 orders. NTLO is improved at most 1 order. NTMO for DC1 is improved at least 1 order and at most 3 orders with Model 2.

In Model 1, TLOQ values for DC2 are all equal to zero except from fourth, ninth, and tenth periods whose values are 3 units. Also, NTLO values for DC2 are all equal to zero except from fourth, ninth, and tenth periods whose values are 1. NPLO values for DC2 are all equal to 1 order except from the first period whose value is zero. NTMO values vary between 28 orders and 30 orders at DC2. In Model 2, both TLOQ and NTLO values for DC2 are all equal to zero over periods. NPLO values are all equal to 1 order over the periods except from the first period whose value is zero. Also, NTMO values are all equal to 29 orders over the periods except from the first period whose value is 30 orders with Model 2 at DC2.

The analysis of PLOQ, TMOQ, P1, and P2 values for DC2 are seen in Figure 5.5. P1 is improved at most 1.6% and P2 is improved at most 0.7% across the periods for DC2 with Model 2. Similar things can be said with regard to both order based analysis and quantity based analysis. TMOQ for DC2 is improved at an average of 13 units and at most 35 units with Model 2.

TLOQ for DC2 is improved at most 3 units. PLOQ is decreased at an average of 8 units and at most 25 units with Model 2. NTLO is improved at most 1 order and NTMO is improved at most 1 order with Model 2 at DC2.

In Model 1, TLOQ values for DC3 are all equal to zero over periods except from second, fifth, and seventh periods whose values are 3 orders. Also, NTLO values for DC3 are all equal to zero over periods except from second, fifth, and seventh periods whose values are 1. NPLO values are all equal to 1 order except from the first period whose value is zero. NTMO values vary between 28 orders and 30 orders at DC3. In Model 2, both TLOQ and NTLO values for DC3 are all equal to zero over periods. NPLO values are all equal to 1 order over the periods except from the first period whose value is zero. Also, NTMO values are all equal to 29 orders over the periods except from the first period whose value is 30 orders in Model 2 at DC3.

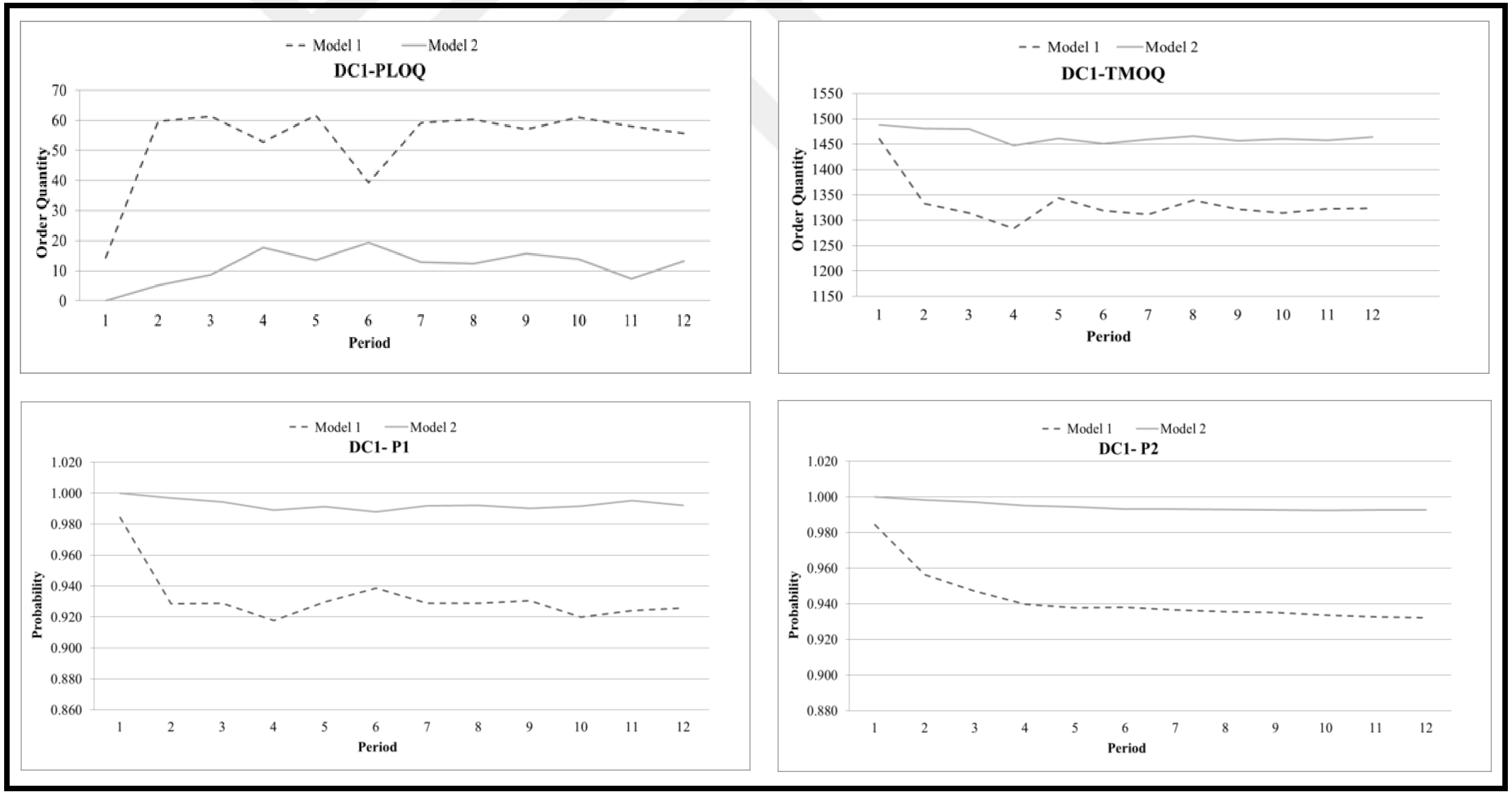


Figure 5.4 Analysis of the DC1 in Model 1 and Model 2.

The analysis of PLOQ, TMOQ, P1, and P2 for DC3 are seen in Figure 5.6. P1 is improved at most 1.8% and P2 is improved at least 0.5 and at most 1.1% across the periods for DC3 with Model 2. Similar things can be said with regard to both order-based analysis and quantity-based analysis. TMOQ for DC3 is improved at an average of 23 units and at most 69 units with Model 2. TLOQ is improved at most 3 units and PLOQ is decreased at an average of 10 units and at most 24 units with Model 2. NTLO is improved at most 1 order and NTMO is improved at most 2 orders with Model 2 at DC3.

According to quantity-based analysis, order-based analysis, and probability-based analysis, one can infer that results of continuous (s, S) policy can be improved by using Model 2 at all DCs. Note that, the magnitude of the improvements varies slightly according to DCs. The reason for this slight change may be due to stochastic order processing time, stochastic transportation time, and the levels of inventory control parameters. The strongest candidate among these is the level of inventory control parameters. After evaluating DCs, we give a detailed analysis of Suppliers. Contrary to DCs, Suppliers' total lost sales costs are extremely lower since they have shorter lead times (Suppliers' lead times do not include transportation time). Note that Supplier2 and Supplier3 are not preferred by any DC with Model 1 while Supplier4 and Supplier5 are not selected by any DC with Model 2.

Note that comparison of Suppliers for both models is a bit difficult than DCs because different Suppliers are selected for the (s, S) policy and just only Supplier1 remains the same.

In Model 1, TLOQ and NTLO values for Supplier1 are all equal to zero across periods. NPLO is at most 2 orders for Supplier1. NTMO for Supplier1 varies between 2 orders and 4 orders. It is worth noting that P1 and P2 values with Model 2 are all equal to 1 across the periods for Supplier1 which indicates that Supplier1 meets all incoming orders over time. TLOQ, NTLO, PLOQ and NPLO values for Supplier1 are all zero across the periods and NTMO is at most 5 orders with Model 2.

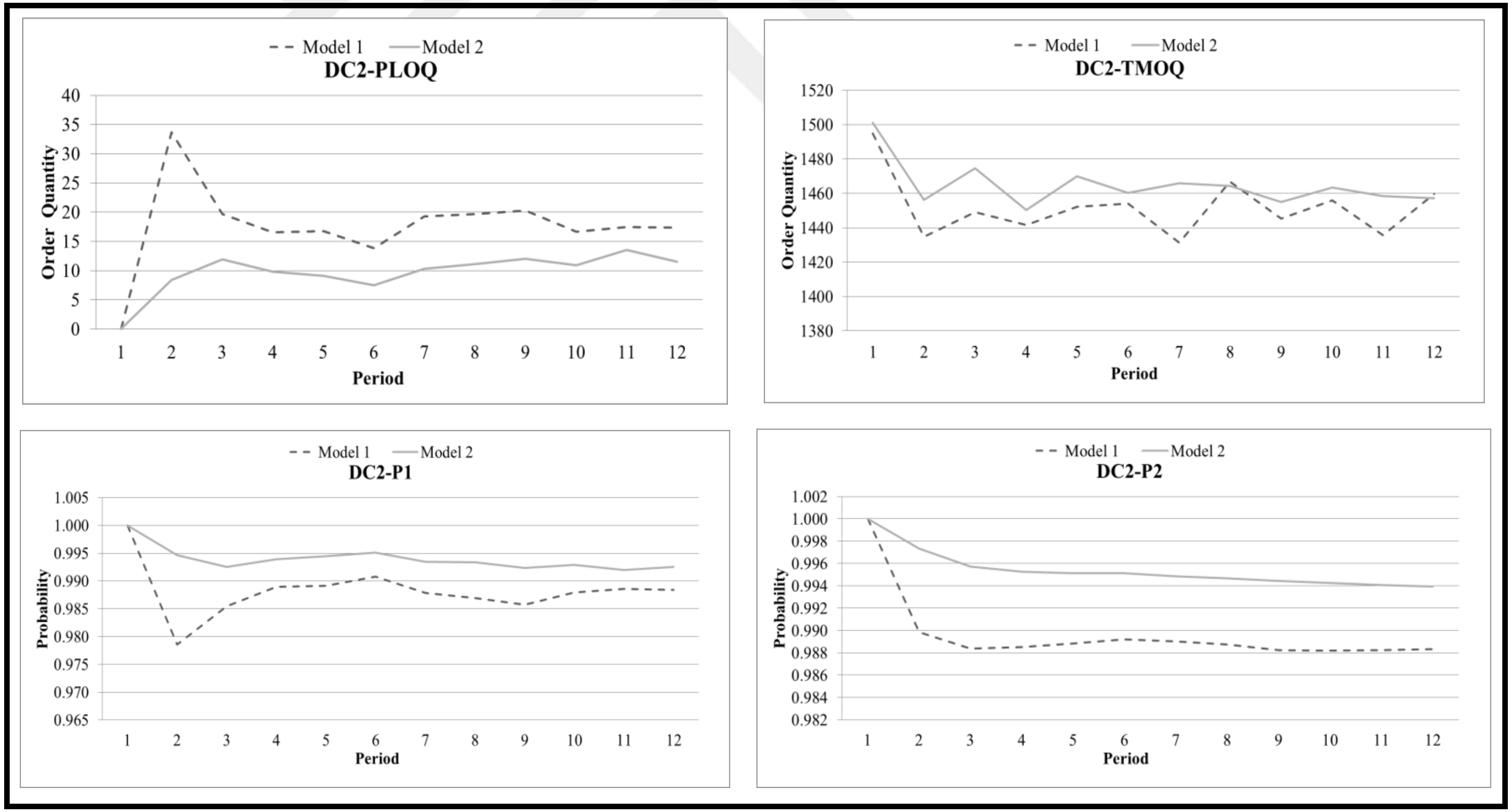


Figure 5.5 Analysis of the DC2 in Model 1 and Model 2.

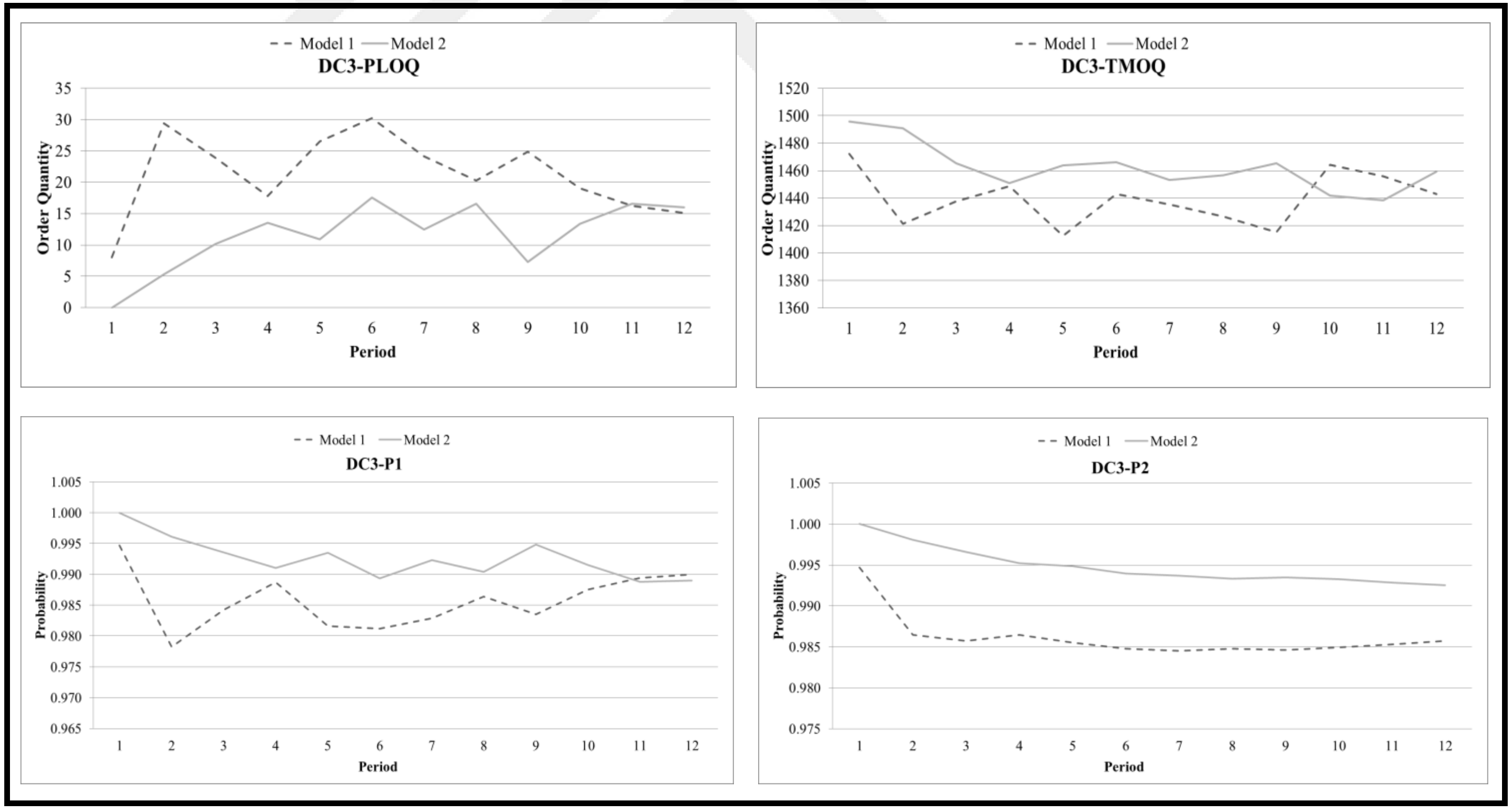


Figure 5.6 Analysis of the DC3 in Model 1 and Model 2.

The analysis of PLOQ, TMOQ, P1, and P2 for Supplier1 are seen in Figure 5.7. P1 is improved at most 2.9% and P2 is improved at most 2.2% across the periods for Supplier1 with Model 2. TMOQ for Supplier1 is improved at an average of 270 units and at most 442 units with Model 2. PLOQ for Supplier1 is decreased at an average of 39 units and at most 50 units and NPLO is improved at most 2 orders with Model 2. NTMO for Supplier1 is improved at most 1 order with Model 2.

Although both PLOQ and NPLO values are generally zero across the periods with Supplier4 and Supplier5, in period 2 DC's replenishment order has been unmet. Also, both TLOQ and NTLO are all zero across the periods in both Suppliers. It is noticeable that TMOQ and NTMO can be said to be uniformly distributed across the periods among Supplier4 and Supplier5 except from period 1. Also, P1 and P2 are uniformly distributed across the periods with Supplier4 and Supplier5 as seen in Table 5.6.

Both PLOQ and NPLO values are all zero across the periods with Supplier3. Although PLOQ and NPLO are generally zero across the periods with Supplier2, in period 3 DC's replenishment orders have been unmet. Also, both TLOQ and NTLO are all zero across the periods in both Suppliers. It is noticeable that TMOQ and NTMO can be said to be uniformly distributed across the periods among Supplier2 and Supplier3 except from period 1. Also, P1 and P2 are uniformly distributed across the periods with Supplier2 as seen in Table 5.7. Both P1 and P2 are equal to 1 across the periods with Supplier3. Thus, all incoming orders are satisfied by Supplier3 with Model 2.

Due to the increased competition in the SC 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 SC members' structural properties, and evaluating proposed models are very important in lost sales environment.

Hence, statistical analysis including cost components analysis, quantity-based analysis, order-based analysis, probability-based analysis, and lead time-based analyses are given to show the differences between Model 1 and Model 2. It should be noted that selection of the model mainly depends on the companies' objectives. Also, increasing diversity in customer expectations can be easily satisfied using our proposed models since it has an ability to offer a high level of service at the lowest possible cost in each SC member.

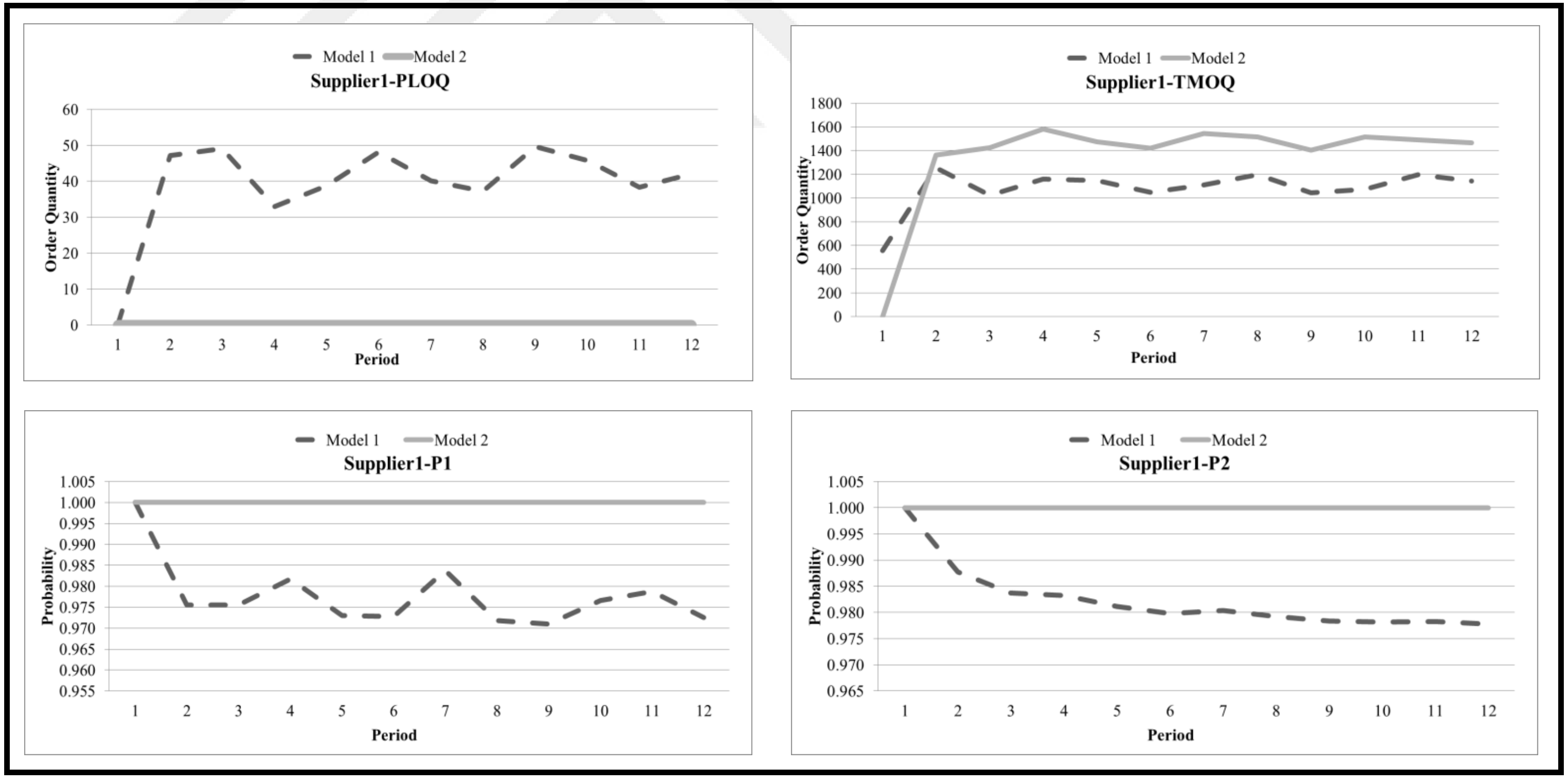


Figure 5.7 Analysis of the Supplier1 for both models.

Table 5.6 Analysis of the Supplier4 and Supplier5 for Model 1.

PM*	Supplier	Periods											
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
		QUANTITY-BASED ANALYSIS											
PLOQ	Supplier4	0	80	0	0	0	0	0	0	0	0	0	0
	Supplier5	0	36	0	0	0	0	0	0	0	0	0	0
TMOQ	Supplier4	484	1193	1393	1383	1351	1477	1348	1428	1374	1394	1349	1420
	Supplier5	143	1112	1619	1371	1521	1500	1395	1537	1488	1479	1499	1440
PM	**Supplier**	**ORDER-BASED ANALYSIS**											
NPLO	Supplier4	0	1	0	0	0	0	0	0	0	0	0	0
	Supplier5	0	1	0	0	0	0	0	0	0	0	0	0
NTMO	Supplier4	1	3	3	3	3	3	3	3	3	3	3	3
	Supplier5	0	3	4	3	4	4	3	4	4	4	4	4
PM	**Supplier**	**PROBABILITY-BASED ANALYSIS**											
P1	Supplier4	1.000	0.954	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	Supplier5	1.000	0.979	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
P2	Supplier4	1.000	0.977	0.985	0.988	0.991	0.992	0.993	0.994	0.995	0.995	0.996	0.996
	Supplier5	1.000	0.990	0.993	0.995	0.996	0.997	0.997	0.997	0.998	0.998	0.998	0.998

*Performance Metrics

Table 5.7 Analysis of the Supplier2 and Supplier3 for Model 2.

PM*	Supplier	Periods											
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
		QUANTITY-BASED ANALYSIS											
PLOQ	Supplier2	0	0	16	0	0	0	0	0	0	0	0	0
	Supplier3	0	0	0	0	0	0	0	0	0	0	0	0
TMOQ	Supplier2	0	1379	1406	1549	1478	1470	1525	1501	1408	1586	1433	1493
	Supplier3	0	1354	1462	1536	1475	1479	1490	1506	1492	1475	1440	1503
PM	**Supplier**	**ORDER-BASED ANALYSIS**											
NPLO	Supplier2	0	0	1	0	0	0	0	0	0	0	0	0
	Supplier3	0	0	0	0	0	0	0	0	0	0	0	0
NTMO	Supplier2	0	4	4	5	4	4	4	4	4	5	4	4
	Supplier3	0	4	4	5	4	4	4	4	4	4	4	4
PM	**Supplier**	**PROBABILITY-BASED ANALYSIS**											
P1	Supplier2	1.000	1.000	0.994	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	Supplier3	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
P2	Supplier2	1.000	1.000	0.998	0.999	0.999	0.999	0.999	0.999	0.999	0.999	0.999	0.999
	Supplier3	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

*Performance Metrics

5.4.2 Lead time-based analysis for continuous (s, S) policy

Most of the companies realize the importance of lead time as a competitive weapon. By controlling lead time, they can lower the lost sales and also improve the service level so as to increase the competitive edge in the market place. Therefore, the purpose of this section is to analyze the lead time-based analysis more in depth to provide more useful information for continuous (s, S) policy.

Note that order met probabilities per lead time for Suppliers are always 1 or close to 1 in all periods.

Table 5.8 Order met probabilities over replenishment lead time-based analysis for DCs.

		DC1		DC2		DC3	
		Model 1	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**
Order Met Probabilities	**Mean**	0.6721	0.9510	0.9383	0.9497	0.95052	0.9607
	Median	0.6725	0.9758	0.9494	0.9772	0.96331	0.9712
	Range	0.5877	0.9041	0.5457	0.9103	0.44969	0.5500
	IQR*	0.0478	0.0219	0.0212	0.0168	0.01544	0.0190

***Interquartile Range**

From Table 5.8, it is clearly seen that order met probabilities per lead time period in Model 2 is higher than Model 1. The worst order met probability per lead time period is at DC1 and 67.21% on average which means that an average of 32.79% incoming orders is lost at DC1 during replenishment lead time period. In Table 5.8, range and interquartile range (IQR) are also given to measure the variability of order met probabilities. It is seen that IQR is lower than range because IQR eliminates the effect of extreme values. IQR can be worthwhile for statistical analysis when the extremes are of less interest and more consideration of the middle part of the distribution is required. These results show that in general, Model 1 has a higher variability and extreme values.

Table 5.9 Statistics related with the length of the lead time for DCs.

		DC1		DC2		DC3	
		Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Lead Time (hours)	**Mean**	68.350	64.38	67.44	63.29	63.639	64.369
	Median	69.141	65.41	68.87	65.46	63.877	65.034
	Range	34.701	64.94	50.80	65.24	35.037	45.788
	IQR*	3.282	3.66	3.56	4.45	3.207	5.753

***Interquartile Range**

Table 5.10 Statistics related with the length of the lead time for Suppliers.

		Supplier1		Supplier2	Supplier3	Supplier4	Supplier5
		Model 1	Model 2	Model 2	Model 2	Model 1	Model 1
Lead Time (hours)	**Mean**	71.392	27.778	28.328	27.966	37.54	67.12
	Median	71.593	28.508	28.722	28.518	38.76	68.41
	Range	3.834	26.231	15.303	28.877	44.12	48.63
	IQR*	0.229	0.520	0.483	0.417	0.48	0.70

***Interquartile Range**

It is clear that longer lead time periods (see Table 5.9-Table 5.10) together with lower average inventory holding unit (see Table 5.11-Table 5.12) will result in lower order met probabilities during lead time period or vice versa (i.e., 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 Eq. 4.23).

Table 5.11 Average holding unit of DCs over replenishment lead time.

		DC1		DC2		DC3	
		Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Average holding unit	**Mean**	44	103	92	104	96	103
	Median	44	106	94	107	97	104
	Range	30	108	56	105	52	66
	IQR*	5	8	6	7	6	7

***Interquartile Range**

Table 5.12 Average holding unit of Suppliers over replenishment lead time.

		Supplier1		Supplier2	Supplier3	Supplier4	Supplier5
		Model 1	**Model 2**	**Model 2**	**Model 2**	**Model 1**	**Model 1**
Average holding unit	**Mean**	4	104	65	65	82	119
	Median	2	106	65	67	88	129
	Range	46	125	68	67	96	137
	IQR*	2	6	6	6	5	9

***Interquartile Range**

In summary, once we place an order, replenishment lead time elapses before the order is available for satisfying demands. Therefore, we want to place a replenishment order when the inventory level is still enough to protect us over replenishment lead time. In this case, finding optimal values of inventory control parameters is essential to meet the demand during lead time. In addition, the decrease in the lost sales per replenishment lead time is offset by the increase in average holding cost. This is a counterintuitive result that highlights the importance of inventory decisions over lead time.

5.5 Comparison of Continuous and Periodic Review (s, S) policies

In this section, four SO models have been compared, each having its own advantages and disadvantages. P-Model 1 denotes periodic review model whose objective function is TSCC. P-Model 2 specifies periodic review model whose objective function is THL. C-Model 1 denotes continuous review model whose objective function is TSCC. C-Model 2 specifies continuous review model whose objective function is THL. The convergence results for SO models are plotted in Figure 5.8.

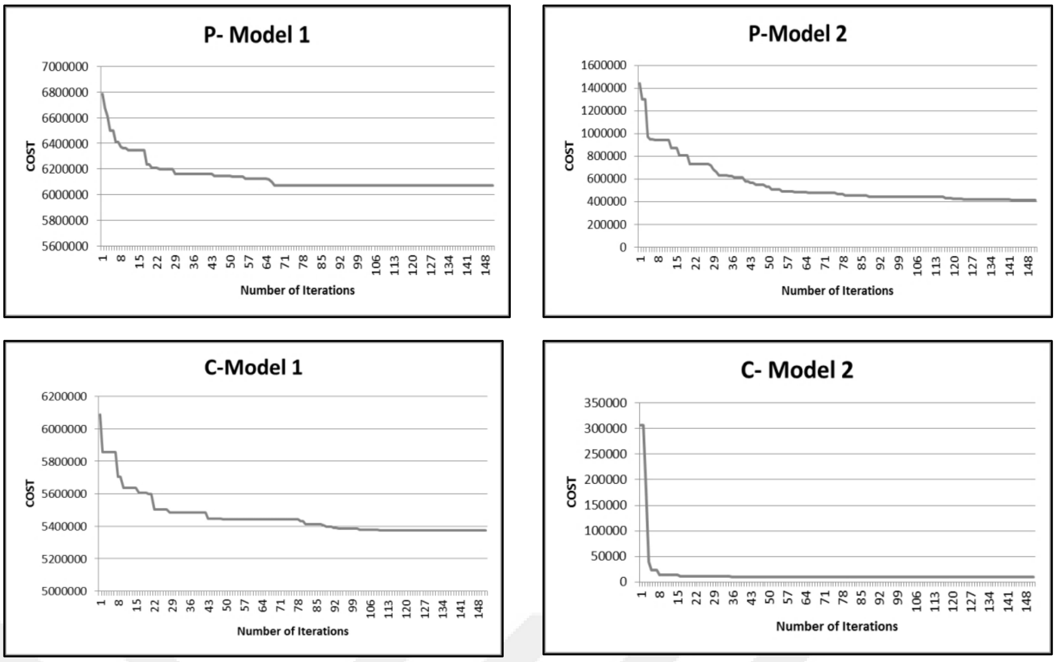


Figure 5.8 The convergence results for periodic review and continuous review policies.

Table 5.13 Comparison of optimal values of inventory control parameters for all review policies.

SC Component	Model Type	Initial Inventory	Reorder Point (s)	Order-up-to Level (S)	Average Service Level
DC1	P*-Model 1	1897	82	656	0.789633
	P-Model 2	1658	197	679	0.862634
	C*-Model 1	1973	178	493	0.932
	C-Model 2	1197	113	552	**0.993**
DC2	P-Model 1	1897	82	503	0.69926
	P-Model 2	1949	197	679	0.859089
	C-Model 1	1973	178	493	0.988
	C-Model 2	1677	166	552	**0.994**
DC3	P-Model 1	1985	82	503	0.704517
	P-Model 2	1949	197	679	0.862492
	C-Model 1	1973	175	493	0.986
	C-Model 2	1311	166	434	**0.993**
Supplier1	P-Model 2	1949	197	679	0.996588
	C-Model 1	1160	175	448	0.973
	C-Model 2	1677	182	861	**1**
Supplier2	C-Model 1	1504	166	410	0.999
Supplier3	P-Model 1	1880	144	679	0.996853
	C-Model 1	1054	198	410	**0.999**
Supplier4	P-Model 1	936	193	576	0.993674
	P-Model 2	1915	197	679	0.991571
	C-Model 2	1311	198	554	**0.995**
Supplier5	P-Model 1	1667	193	652	0.993619
	P-Model 2	1915	197	679	0.997495
	C-Model 2	1197	196	951	**0.998**

P*: Periodic review model, C*: Continuous review model.

Different Suppliers are selected to satisfy DCs replenishment orders by continuous and periodic review models as given in Table 5.13. When TSCC and lost sales cost for DCs are considered, C-Model 1 is significantly better than other models as seen in Figure 5.9.

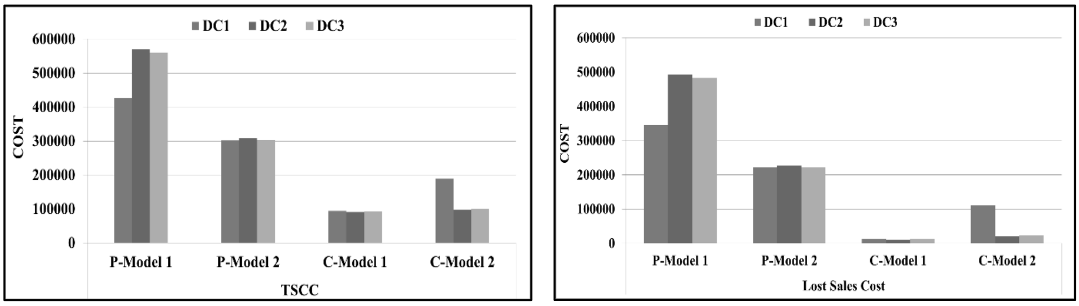


Figure 5.9 The comparison of TSCC and lost sales cost for DCs.

Table 5.14 Quantity-based analysis for DC1.

Period	PLOQ				TLOQ				TMOQ			
	P-Model 1	P-Model 2	C-Model 1	C-Model 2	P-Model 1	P-Model 2	C-Model 1	C-Model 2	P-Model 1	P-Model 2	C-Model 1	C-Model 2
1	0	0	0	14	0	0	0	11	1488	1488	1488	1460
2	53	43	5	60	350	154	0	48	1040	1253	1481	1333
3	45	50	9	61	295	229	0	43	1135	1169	1480	1315
4	50	48	18	53	325	179	0	74	1091	1210	1447	1284
5	52	37	14	62	263	192	0	47	1128	1210	1462	1344
6	42	48	19	39	321	203	0	57	1085	1195	1451	1319
7	39	48	13	59	302	189	0	52	1119	1218	1460	1311
8	44	44	12	60	278	173	0	48	1129	1232	1466	1339
9	48	43	16	57	312	142	0	50	1089	1265	1456	1321
10	43	45	14	61	277	170	0	60	1122	1230	1460	1314
11	53	36	7	58	320	165	0	55	1088	1248	1458	1322
12	51	50	13	56	269	167	0	57	1131	1244	1464	1323

Table 5.15 Order-based analysis for DC1.

Period	NPLO				NTLO				NTMO			
	P-Model 1	P-Model 2	C-Model 1	C-Model 2	P-Model 1	P-Model 2	C-Model 1	C-Model 2	P-Model 1	P-Model 2	C-Model 1	C-Model 2
1	0	0	0	1	0	0	0	0	30	30	30	29
2	2	2	0	2	7	7	0	1	21	25	30	27
3	2	2	1	3	6	6	0	1	23	23	29	26
4	2	2	1	3	6	6	0	1	22	24	29	26
5	2	2	1	3	5	5	0	1	23	24	29	27
6	2	2	1	2	6	6	0	1	22	24	29	27
7	2	2	1	3	6	6	0	1	22	24	29	27
8	2	2	1	2	6	6	0	1	23	25	29	27
9	2	2	1	3	6	6	0	1	22	25	29	26
10	2	2	1	3	6	6	0	1	23	25	29	26
11	2	2	1	2	6	6	0	1	22	25	29	26
12	2	2	1	3	5	5	0	1	23	25	29	26

Table 5.16 Probability-based analysis for DC1.

Period	P1				P2			
	P-Model 1	P-Model 2	C-Model 1	C-Model 2	P-Model 1	P-Model 2	C-Model 1	C-Model 2
1	1,000	1,000	1,000	0,984	1,000	1,000	1,000	0,984
2	0,737	0,864	0,997	0,928	0,869	0,932	0,998	0,956
3	0,774	0,812	0,994	0,929	0,837	0,892	0,997	0,947
4	0,752	0,846	0,989	0,918	0,816	0,881	0,995	0,940
5	0,788	0,848	0,991	0,930	0,810	0,874	0,994	0,938
6	0,758	0,831	0,988	0,939	0,802	0,867	0,993	0,938
7	0,772	0,844	0,992	0,929	0,797	0,864	0,993	0,937
8	0,787	0,858	0,992	0,929	0,796	0,863	0,993	0,936
9	0,762	0,875	0,990	0,930	0,792	0,864	0,993	0,935
10	0,784	0,856	0,992	0,920	0,791	0,863	0,993	0,934
11	0,755	0,865	0,995	0,924	0,788	0,864	0,993	0,933
12	0,786	0,857	0,992	0,926	0,788	0,863	0,993	0,932

C-Model 1 can be used to increase responsiveness and customer satisfaction in today's competitive environment. In addition to the analysis of TSCC and lost sales cost, a comprehensive analysis including order-based analysis per each period (NTLO and NPLO), probability-based analysis (P1 and P2), and quantity-based analysis per each period (TMOQ, TLOQ, PLOQ) are taken into consideration.

For DC1 it is observed that the TLOQ value of C-Model 1 is equal to zero on average while its value is 276, 164, and 50 on average for P-Model 1, P-Model 2, and C-Model 2, respectively. Also, PLOQ and TMOQ values on average for DC1 are given in Figure 5.10.

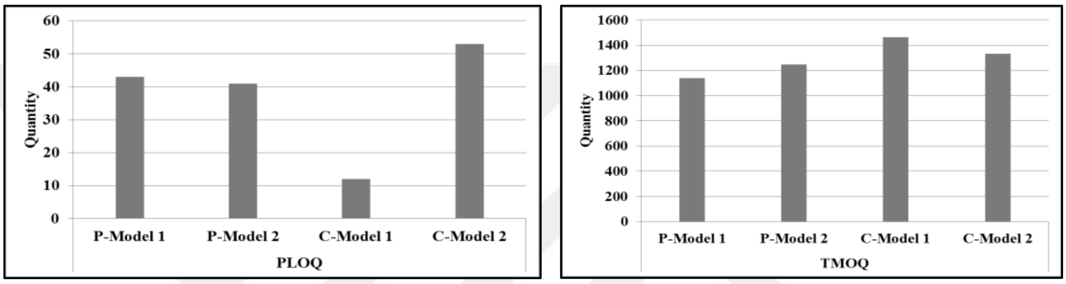


Figure 5.10 PLOQ and TMOQ values for DC1

According to the order-based analysis, the value of NPLO for DC1 with all review models considered is found to be 1 order on average. NTLO values for DC1 are generally zero in continuous review models while in periodic review models NTLO is observed to be 6 orders on average.

Note that if the values of P1 and P2 are close to 1, DCs/Suppliers have the potential to satisfy all incoming demands over periods. According to the probability-based analysis, P1 values with C-Model 1 for DC1 improve at an average of 26 %, 15 %, and 7 % with respect to P-Model 1, P-Model 2, and C-Model 2, respectively. P2 values with C-Model 1 for DC1 improve at an average of 21 %, 12 %, and 6 % with respect to P-Model 1, P-Model 2, and C-Model 2, respectively.

For DC2 it is observed that the TLOQ value of C-Model 1 is equal to zero on average while its value is 410, 168, and 1 on average for P-Model 1, P-Model 2, and C-Model 2, respectively. Also, average values of PLOQ and TMOQ for DC2 are given in Figure 5.11.

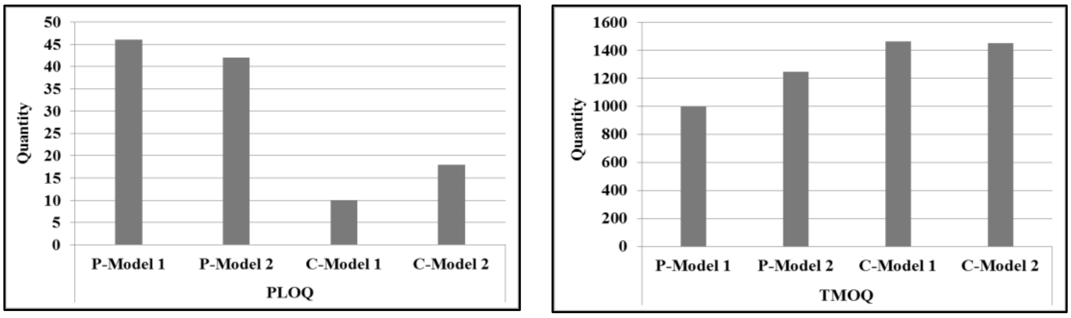


Figure 5.11 PLOQ and TMOQ values for DC2.

According to the order-based analysis, the value of NPLO for DC2 is 1 order on average in continuous review models while on average its value is 2 orders in periodic review models. NTLO values for DC2 are zero in continuous review models while in P-Model 1 and P-Model 2 NTLO is observed to be 9 orders and 3 orders on average, respectively.

According to the probability-based analysis, P1 values with C-Model 1 for DC2 improve at an average of 43 %, 16 %, and 1 % with respect to P-Model 1, P-Model 2, and C-Model 2, respectively. P2 values with C-Model 1 for DC2 improve at an average of 32 %, 13 %, and 1 % with respect to P-Model 1, P-Model 2, and C-Model 2, respectively.

Table 5.17 Quantity-based analysis for DC2.

Period	PLOQ				TLOQ				TMOQ			
	P-Model 1	P-Model 2	C-Model 1	C-Model 2	P-Model 1	P-Model 2	C-Model 1	C-Model 2	P-Model 1	P-Model 2	C-Model 1	C-Model 2
1	0	0	0	0	0	0	0	0	1501	1501	1501	1495
2	56	47	8	34	449	191	0	0	944	1213	1456	1435
3	54	48	12	20	473	198	0	3	911	1207	1475	1449
4	42	48	10	17	437	179	0	0	951	1246	1450	1442
5	51	46	9	17	449	162	0	0	955	1240	1470	1452
6	49	44	8	14	455	201	0	0	957	1208	1460	1454
7	47	47	10	19	436	193	0	0	965	1209	1466	1431
8	55	38	11	20	443	186	0	0	967	1201	1464	1467
9	55	37	12	20	453	171	0	3	947	1242	1455	1445
10	51	51	11	17	442	171	0	3	953	1249	1463	1456
11	50	51	14	18	438	185	0	0	979	1224	1458	1436
12	43	48	12	17	448	178	0	0	945	1218	1457	1460

Table 5.18 Order-based analysis for DC2.

Period	NPLO				NTLO				NTMO			
	P-Model 1	P-Model 2	C-Model 1	C-Model 2	P-Model 1	P-Model 2	C-Model 1	C-Model 2	P-Model 1	P-Model 2	C-Model 1	C-Model 2
1	0	0	0	0	2	0	0	0	30	30	30	30
2	2	2	1	1	10	4	0	0	19	24	29	29
3	2	2	1	1	10	4	0	1	18	24	29	28
4	2	2	1	1	9	4	0	0	19	25	29	29
5	2	2	1	1	9	3	0	0	19	25	29	29
6	2	2	1	1	10	4	0	0	19	24	29	29
7	2	2	1	1	9	4	0	0	19	24	29	29
8	2	2	1	1	9	4	0	0	19	24	29	29
9	2	2	1	1	10	4	0	1	19	25	29	28
10	2	2	1	1	9	3	0	1	19	25	29	28
11	2	2	1	1	9	4	0	0	19	24	29	29
12	2	2	1	1	9	4	0	0	19	24	29	29

Table 5.19 Probability-based analysis for DC2.

Period	P1				P2			
	P-Model 1	**P-Model 2**	**C-Model 1**	**C-Model 2**	**P-Model 1**	**P-Model 2**	**C-Model 1**	**C-Model 2**
1	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000
2	0,663	0,839	0,995	0,979	0,831	0,920	0,997	0,990
3	0,648	0,835	0,993	0,985	0,770	0,891	0,996	0,988
4	0,677	0,849	0,994	0,989	0,747	0,881	0,995	0,989
5	0,671	0,862	0,994	0,989	0,732	0,877	0,995	0,989
6	0,665	0,835	0,995	0,991	0,721	0,870	0,995	0,989
7	0,675	0,839	0,993	0,988	0,714	0,865	0,995	0,989
8	0,672	0,848	0,993	0,987	0,709	0,863	0,995	0,989
9	0,661	0,857	0,992	0,986	0,704	0,862	0,994	0,988
10	0,676	0,854	0,993	0,988	0,701	0,862	0,994	0,988
11	0,676	0,845	0,992	0,989	0,699	0,860	0,994	0,988
12	0,671	0,847	0,993	0,988	0,696	0,859	0,994	0,988

For DC3 it is observed that the TLOQ value of C-Model 1 is equal to zero on average while its value is 402, 162, and 1 on average for P-Model 1, P-Model 2, and C-Model 2, respectively. Also, PLOQ and TMOQ values on average for DC3 are given in Figure 5.12. According to the order-based analysis, the value of NPLO for DC3 is 1 order on average in continuous review models while on average its value is 2 orders in periodic review models. NTLO values for DC3 are zero in continuous review models while in P-Model 1 and P-Model 2 NTLO is observed to be 8 orders, and 3 orders on average, respectively. According to the probability-based analysis, P1 values with C-Model 1 for DC3 improve at an average of 41 %, 15 %, and 1 % with respect to P-Model 1, P-Model 2, and C-Model 2, respectively. P2 values with C-Model 1 for DC3 improve at an average of 30 %, 12 %, and 1 % with respect to P-Model 1, P-Model 2, and C-Model 2, respectively.

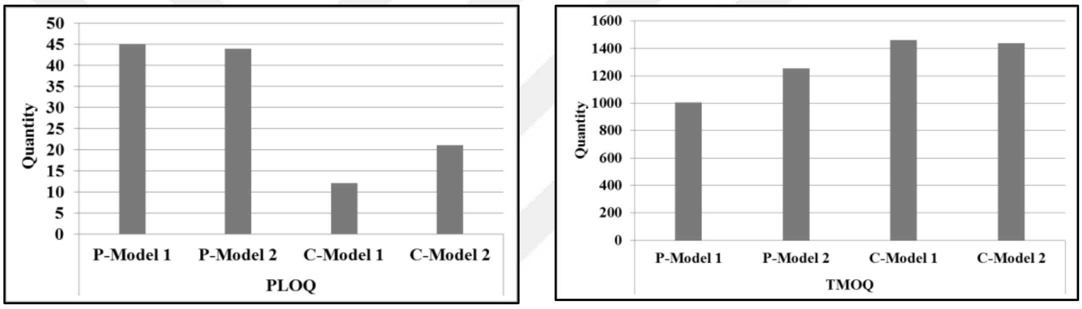


Figure 5.12 The value of PLOQ and TMOQ for DC3.

Table 5.20 Quantity-based analysis for DC3.

Period	PLOQ				TLOQ				TMOQ			
	P-Model 1	P-Model 2	C-Model 1	C-Model 2	P-Model 1	P-Model 2	C-Model 1	C-Model 2	P-Model 1	P-Model 2	C-Model 1	C-Model 2
1	0	0	0	8	0	0	0	0	1496	1496	1496	1472
2	43	44	5	29	372	147	0	3	1021	1264	1491	1421
3	56	51	10	24	421	181	0	0	977	1216	1466	1438
4	44	46	14	18	457	223	0	0	955	1208	1451	1449
5	55	54	11	27	443	161	0	3	951	1240	1464	1413
6	48	44	18	30	458	175	0	0	939	1240	1466	1443
7	52	47	12	24	437	180	0	3	974	1227	1453	1435
8	48	49	17	20	440	147	0	0	959	1245	1457	1426
9	50	55	7	25	458	174	0	0	938	1235	1465	1415
10	52	51	13	19	441	184	0	0	959	1226	1442	1464
11	45	46	17	16	461	183	0	0	945	1225	1438	1456
12	49	39	16	15	443	191	0	0	965	1229	1459	1443

Table 5.21 Order-based analysis for DC3

Period	NPLO				NTLO				NTMO			
	P-Model 1	P-Model 2	C-Model 1	C-Model 2	P-Model 1	P-Model 2	C-Model 1	C-Model 2	P-Model 1	P-Model 2	C-Model 1	C-Model 2
1	0	0	0	0	0	0	0	0	30	30	30	30
2	2	2	0	1	7	3	0	1	21	25	30	28
3	2	2	1	1	9	4	0	0	20	24	29	29
4	2	2	1	1	9	4	0	0	19	24	29	29
5	2	2	1	1	9	3	0	1	19	25	29	28
6	2	2	1	1	9	4	0	0	19	25	29	29
7	2	2	1	1	9	4	0	1	19	25	29	28
8	2	2	1	1	9	3	0	0	19	25	29	29
9	2	2	1	1	9	4	0	0	19	25	29	29
10	2	2	1	1	9	4	0	0	19	24	29	29
11	2	2	1	1	9	4	0	0	19	24	29	29
12	2	2	1	1	9	4	0	0	19	24	29	29

Table 5.22 Probability-based analysis for DC3.

Period	P1				P2			
	P-Model 1	P-Model 2	C-Model 1	C-Model 2	P-Model 1	P-Model 2	C-Model 1	C-Model 2
1	1,000	1,000	1,000	0,995	1,000	1,000	1,000	0,995
2	0,724	0,871	0,996	0,978	0,862	0,935	0,998	0,986
3	0,680	0,844	0,994	0,984	0,801	0,905	0,997	0,986
4	0,666	0,824	0,991	0,989	0,767	0,885	0,995	0,986
5	0,670	0,859	0,993	0,982	0,748	0,879	0,995	0,985
6	0,663	0,855	0,989	0,981	0,734	0,875	0,994	0,985
7	0,678	0,853	0,992	0,983	0,726	0,872	0,994	0,985
8	0,676	0,869	0,990	0,986	0,719	0,872	0,993	0,985
9	0,658	0,847	0,995	0,984	0,713	0,869	0,993	0,985
10	0,672	0,844	0,991	0,988	0,709	0,867	0,993	0,985
11	0,665	0,844	0,989	0,989	0,705	0,864	0,993	0,985
12	0,675	0,846	0,989	0,990	0,702	0,863	0,993	0,986

In DCs, if the company has to use the periodic review model, P-Model 2 is better than P-Model 1.The percentage of improvement depending on TSCC, lost sales cost, probability-based analysis, quantity-based analysis per each period, and order-based analysis per each period is given in Figure 5.13. The value of NPLO is same for both periodic review models. Although NTLO value at DC1 is same for both models, the difference between models is five on average for DC2 and DC3.

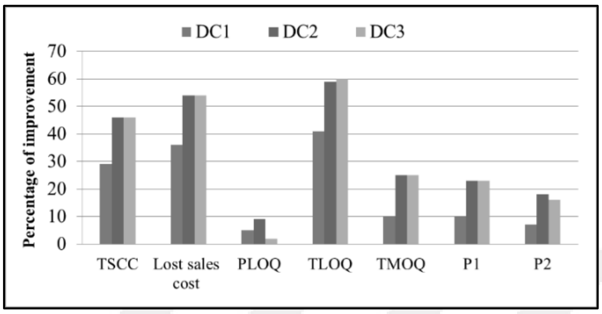


Figure 5.13 Percentage of improvement with P-Model 2 in DCs with respect to P-Model 1.

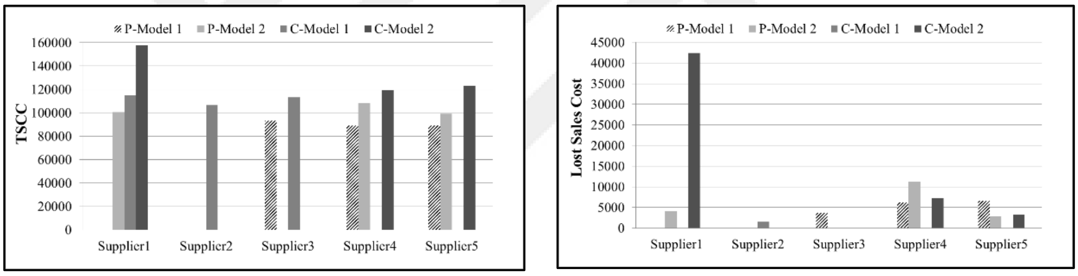


Figure 5.14 The comparison of TSCC and lost sales cost for Suppliers.

The magnitude of the decrease of the lost sales cost is not as high with the DCs as seen in Figure 5.14 where TSCC for each Supplier is also given. According to the quantity-based analysis, PLOQ is zero for C-Model 1 and is 39 units on average for C-Model 2 while its value is 2 units on average with P-Model 2 for Supplier1. TLOQ is zero with continuous review models while its value is 42 units on average for P-Model 2. The average value of P1, P2, and TMOQ for Supplier1 is given in Figure 5.15.

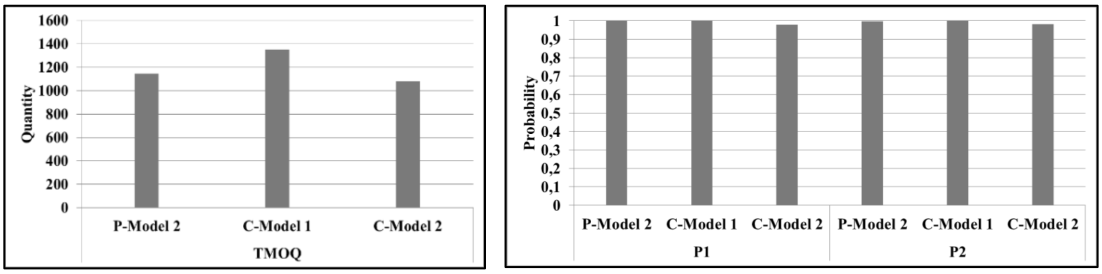


Figure 5.15 The analysis of Supplier1 for each model.

Table 5.23 Quantity-based analysis for Supplier1

Period	PLOQ			TLOQ			TMOQ		
	P-Model 2	C-Model 1	C-Model 2	P-Model 2	C-Model 1	C-Model 2	P-Model 2	C-Model 1	C-Model 2
1	0	0	0	0	0	0	0	0	557
2	0	0	47	0	0	0	1242	1361	1256
3	19	0	49	499	0	0	1237	1423	1025
4	0	0	33	0	0	0	1284	1582	1161
5	0	0	39	0	0	0	1201	1475	1149
6	0	0	48	0	0	0	1295	1420	1048
7	0	0	40	0	0	0	1289	1545	1110
8	0	0	37	0	0	0	1233	1514	1196
9	0	0	50	0	0	0	1224	1405	1043
10	0	0	46	0	0	0	1284	1515	1072
11	0	0	38	0	0	0	1228	1489	1197
12	0	0	42	0	0	0	1264	1465	1142

Table 5.24 Order-based analysis and probability-based analysis for Supplier1.

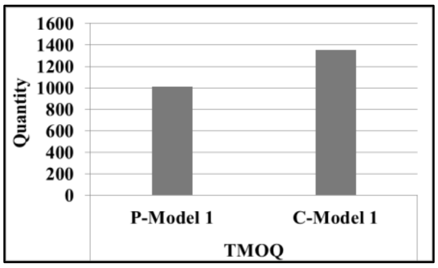
Period	NPLO			NTLO			NTMO			P1			P2		
	P-Model 2	C-Model 1	C-Model 2	P-Model 2	C-Model 1	C-Model 2	P-Model 2	C-Model 1	C-Model 2	P-Model 2	C-Model 1	C-Model 2	P-Model 2	C-Model 1	C-Model 2
1	0	0	0	0	0	0	0	0	2	1,000	1,000	1,000	1,000	1,000	1,000
2	0	0	1	0	0	0	2	4	4	1,000	1,000	0,976	1,000	1,000	0,988
3	1	0	2	1	0	0	2	4	4	0,985	1,000	0,976	0,995	1,000	0,984
4	0	0	1	0	0	0	2	5	4	1,000	1,000	0,982	0,996	1,000	0,983
5	0	0	1	0	0	0	2	4	4	1,000	1,000	0,973	0,997	1,000	0,981
6	0	0	2	0	0	0	2	4	4	1,000	1,000	0,973	0,998	1,000	0,980
7	0	0	1	0	0	0	2	5	4	1,000	1,000	0,984	0,998	1,000	0,980
8	0	0	1	0	0	0	2	4	4	1,000	1,000	0,972	0,998	1,000	0,979
9	0	0	2	0	0	0	2	4	4	1,000	1,000	0,971	0,998	1,000	0,978
10	0	0	2	0	0	0	2	4	4	1,000	1,000	0,977	0,999	1,000	0,978
11	0	0	1	0	0	0	2	4	4	1,000	1,000	0,979	0,999	1,000	0,978
12	0	0	1	0	0	0	2	4	4	1,000	1,000	0,972	0,999	1,000	0,978

Note that Supplier2 is only used by C-Model 1 and therefore the comparison is not available for this SC member.

Table 5.25 The analysis of Supplier2.

Period	PLOQ	TLOQ	TMOQ	NPLO	NTLO	NTMO	P1	P2
1	0	0	0	0	0	0	1,000	1,000
2	0	0	1379	0	0	4	1,000	1,000
3	16	0	1406	1	0	4	0,994	0,998
4	0	0	1549	0	0	5	1,000	0,999
5	0	0	1478	0	0	4	1,000	0,999
6	0	0	1470	0	0	4	1,000	0,999
7	0	0	1525	0	0	4	1,000	0,999
8	0	0	1501	0	0	4	1,000	0,999
9	0	0	1408	0	0	4	1,000	0,999
10	0	0	1586	0	0	5	1,000	0,999
11	0	0	1433	0	0	4	1,000	0,999
12	0	0	1493	0	0	4	1,000	1,000

According to the order-based analysis, NPLO value for Supplier3 is zero for C-Model 1 while its value is 1 order on average for P-Model 1. NTLO values are zero for both models for Supplier3. According to the quantity-based analysis, PLOQ is zero for C-Model 1 while its value is 3 units on average for P-Model 1. For Supplier3, TLOQ is zero for both models. The analysis of TMOQ, P1, and P2 values on average for Supplier3 is given in Figure 5.16.



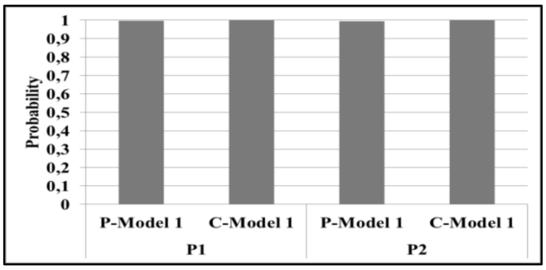


Figure 5.16 The analysis of Supplier3 for each model.

Table 5.26 Quantity-based analysis, order-based analysis and probability-based analysis for Supplier3.

Period	PLOQ		TLOQ		TMOQ		NPLO		NTLO		NTMO		P1		P2	
	P-Model 1	C-Model 1	P-Model 1	C-Model 1	P-Model 1	C-Model 1	P-Model 1	C-Model 1	P-Model 1	C-Model 1	P-Model 1	C-Model 1	P-Model 1	C-Model 1	P-Model 1	C-Model 1
1	0	0	0	0	0	0	0	0	0	0	0	0	1,000	1,000	1,000	1,000
2	0	0	0	0	835	1354	0	0	0	0	1	4	1,000	1,000	1,000	1,000
3	40	0	0	0	673	1462	1	0	0	0	1	4	0,973	1,000	0,991	1,000
4	0	0	0	0	1273	1536	0	0	0	0	2	5	0,995	1,000	0,992	1,000
5	0	0	0	0	1150	1475	0	0	0	0	2	4	1,000	1,000	0,994	1,000
6	0	0	0	0	1110	1479	0	0	0	0	2	4	1,000	1,000	0,995	1,000
7	0	0	0	0	1138	1490	0	0	0	0	2	4	1,000	1,000	0,995	1,000
8	0	0	0	0	1161	1506	0	0	0	0	2	4	1,000	1,000	0,996	1,000
9	0	0	0	0	1259	1492	0	0	0	0	2	4	1,000	1,000	0,996	1,000
10	0	0	0	0	1154	1475	0	0	0	0	2	4	1,000	1,000	0,997	1,000
11	0	0	0	0	1189	1440	0	0	0	0	2	4	1,000	1,000	0,997	1,000
12	0	0	0	0	1180	1503	0	0	0	0	2	4	1,000	1,000	0,997	1,000

Table 5.27 Quantity-based analysis for Supplier4.

Period	PLOQ			TLOQ			TMOQ		
	P-Model 1	P-Model 2	C-Model 2	P-Model 1	P-Model 2	C-Model 2	P-Model 1	P-Model 2	C-Model 2
1	0	0	0	0	0	0	0	0	484
2	70	0	80	0	0	0	503	1318	1193
3	0	67	0	0	58	0	1006	1091	1393
4	0	0	0	0	0	0	1006	1253	1383
5	0	0	0	0	0	0	1006	1305	1351
6	0	0	0	0	0	0	1006	1291	1477
7	0	0	0	0	0	0	1006	1291	1348
8	0	0	0	0	0	0	1006	1264	1428
9	0	0	0	0	0	0	1006	1273	1374
10	0	0	0	0	0	0	1006	1275	1394
11	0	0	0	0	0	0	1006	1275	1349
12	0	0	0	0	0	0	1006	1323	1420

Table 5.28 Order-based analysis and probability-based analysis for Supplier4.

Period	NPLO			NTLO			NTMO			P1			P2		
	P-Model 1	P-Model 2	C-Model 2	P-Model 1	P-Model 2	C-Model 2	P-Model 1	P-Model 2	C-Model 2	P-Model 1	P-Model 2	C-Model 2	P-Model 1	P-Model 2	C-Model 2
1	0	0	0	0	0	0	0	0	1	1,000	1,000	1,000	1,000	1,000	1,000
2	1	0	1	0	0	0	1	2	3	0,977	1,000	0,954	0,989	1,000	0,977
3	0	1	0	0	1	0	2	2	3	0,958	0,953	1,000	0,978	0,985	0,985
4	0	0	0	0	0	0	2	2	3	1,000	1,000	1,000	0,984	0,989	0,988
5	0	0	0	0	0	0	2	2	3	1,000	1,000	1,000	0,987	0,991	0,991
6	0	0	0	0	0	0	2	2	3	1,000	1,000	1,000	0,989	0,993	0,992
7	0	0	0	0	0	0	2	2	3	1,000	1,000	1,000	0,991	0,994	0,993
8	0	0	0	0	0	0	2	2	3	1,000	1,000	1,000	0,992	0,994	0,994
9	0	0	0	0	0	0	2	2	3	1,000	1,000	1,000	0,993	0,995	0,995
10	0	0	0	0	0	0	2	2	3	1,000	1,000	1,000	0,994	0,996	0,995
11	0	0	0	0	0	0	2	2	3	1,000	1,000	1,000	0,994	0,996	0,996
12	0	0	0	0	0	0	2	2	3	1,000	1,000	1,000	0,995	0,996	0,996

Table 5.29 Quantity-based analysis for Supplier5

Period	PLOQ			TLOQ			TMOQ		
	P-Model 1	P-Model 2	C-Model 2	P-Model 1	P-Model 2	C-Model 2	P-Model 1	P-Model 2	C-Model 2
1	0	0	0	0	0	0	0	0	143
2	0	0	36	0	0	0	985	1295	1112
3	0	31	0	0	0	0	927	965	1619
4	0	0	0	0	0	0	1006	1269	1371
5	0	0	0	0	0	0	1002	1277	1521
6	0	0	0	0	0	0	1006	1262	1500
7	0	0	0	0	0	0	1006	1241	1395
8	0	0	0	0	0	0	979	1230	1537
9	0	0	0	0	0	0	1006	1243	1488
10	0	0	0	0	0	0	1006	1257	1479
11	0	0	0	0	0	0	1006	1298	1499
12	0	0	0	0	0	0	1006	1311	1440

Table 5.30 Order-based analysis and probability-based analysis for Supplier5.

Period	NPLO			NTLO			NTMO			P1			P2		
	P-Model 1	P-Model 2	C-Model 2	P-Model 1	P-Model 2	C-Model 2	P-Model 1	P-Model 2	C-Model 2	P-Model 1	P-Model 2	C-Model 2	P-Model 1	P-Model 2	C-Model 2
1	0	0	0	0	0	0	0	0	0	1,000	1,000	1,000	1,000	1,000	1,000
2	0	0	1	0	0	0	2	2	3	1,000	1,000	0,979	1,000	1,000	0,990
3	0	1	0	0	0	0	2	2	4	0,979	0,982	1,000	0,993	0,993	0,993
4	0	0	0	0	0	0	2	2	3	0,990	1,000	1,000	0,992	0,995	0,995
5	0	0	0	0	0	0	2	2	4	0,992	1,000	1,000	0,992	0,996	0,996
6	0	0	0	0	0	0	2	2	4	1,000	1,000	1,000	0,994	0,996	0,997
7	0	0	0	0	0	0	2	2	3	1,000	1,000	1,000	0,994	0,997	0,997
8	0	0	0	0	0	0	2	2	4	0,990	1,000	1,000	0,994	0,997	0,997
9	0	0	0	0	0	0	2	2	4	1,000	1,000	1,000	0,995	0,998	0,998
10	0	0	0	0	0	0	2	2	4	1,000	1,000	1,000	0,995	0,998	0,998
11	0	0	0	0	0	0	2	2	4	1,000	1,000	1,000	0,996	0,998	0,998
12	0	0	0	0	0	0	2	2	4	1,000	1,000	1,000	0,996	0,998	0,998

According to the order-based analysis, NPLO for Supplier4 is 1 order on average for used models. NTLO is zero for P-Model 1 and C-Model 2 while its value is 1 order for P-Model 2. According to the quantity-based analysis, PLOQ is 6 units on average for used models. TLOQ is zero with P-Model 1 and C-Model 2 while its value is 5 units on average for P-Model 2. The analysis of TMOQ, P1, and P2 for Supplier4 values on average is given in Figure 5.17.

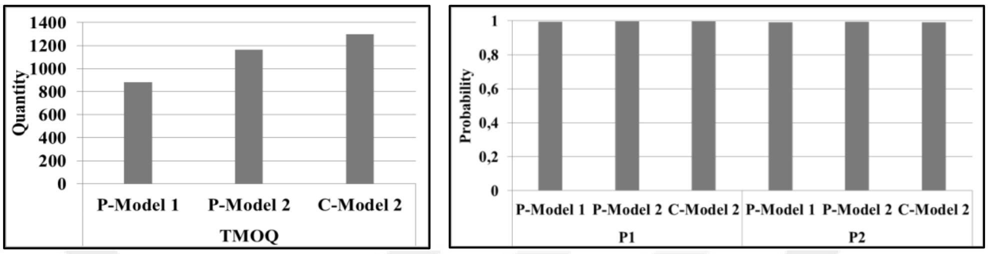


Figure 5.17 The analysis of Supplier4 for each model.

According to the order-based analysis, NPLO for Supplier5 is 1 order on average for P-Model 2 and C-Model 2 while its value is zero for P-Model 1. For Supplier5, NTLO is zero for used models. According to the quantity-based analysis, PLOQ is 3 units on average for P-Model 2 and C-Model 2 while its value is zero for P-Model 1. TLOQ is zero for used models for Supplier5. The analysis of TMOQ, P1 and P2 values on average for Supplier5 is given in Figure 5.18.

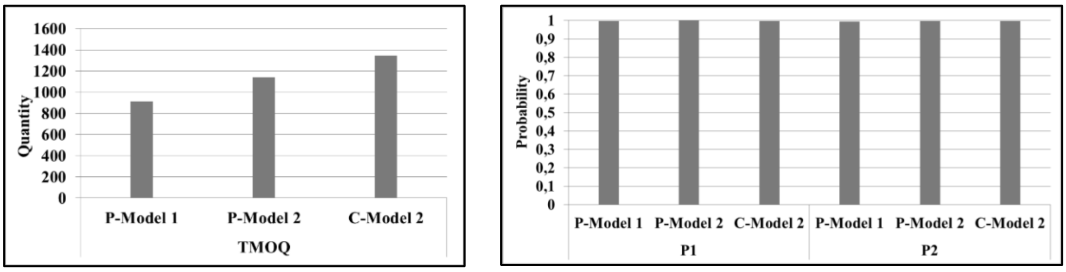


Figure 5.18 The analysis of Supplier5 for each model.

Each company is unique and includes many different inventory control systems. For example, a detailed analysis on continuous (s, S) inventory control systems can be found in Göçken et al. (2017b). Defining which review model to use depends on the properties of the company. Therefore, extensive analysis of review models is performed to provide the manager with more information about the optimal review model. Proposed continuous review (s, S) policies and periodic review (s, S) policies obtained in this study can provide a guideline on what companies need to do in order to increase their performance.

5.6 Conclusion

Understanding of the whole SC perfectly is needed to select an effective model because every company has different processes and different forms of strategies. Inventory control is the one of the most important factors and its improvement is crucial for sustaining continuous improvement in companies. Therefore, many approaches have been proposed to compute optimal or near-optimal inventory levels for continuous (s, S) policy and periodic (R, s, S) policy with different environment of interests. Each approach has its own strengths and limitations under different situations. Also, there is a strong need to further improve the performance and effectiveness of inventory control and supplier selection approaches in SC in order to act effectively in different environments. Therefore, many different analysis including cost-based analysis and customer satisfaction-based analysis should be used to evaluate proposed models. The results of this study show that managers can increase company's competitiveness and responsiveness by using SO models.

The results of this study show that managers can increase company's competitiveness and responsiveness by using SO models. The lost sales cost of review models can be improved at least 46 % and at most 98 % on average for DCs with C-Model 1. If company must use the periodic review model, the lost sales cost can be reduced at least 36 % and at most 54 % on average with P-Model 2 for DCs. The TSCC of P-Model 1, P-Model 2 and C-Model 2 can be improved at an average of 66 %, 50 % and 22 %, respectively with C-Model 1. For periodic review models, the TSCC of P-Model 1 can also be improved at an average of 33 % with P-Model 2.

In same manner, TMOQ is increased at most 165 units and TLOQ is improved at most 74 units. NPLO is improved at most 2 orders, NTLO is improved at most 1 order and NTMO is improved at most 3 orders with continuous review policy and objective function as total cost. Similar conclusions can be drawn related to P1 and P2. Both P1 (i.e., at most 7%) and P2 (i.e., at most 6%) can be further improved by using continuous review policy. Note that comparison of Suppliers by considering proposed models is a bit difficult when compared with DCs. DC's replenishment order is supplied by a different Supplier which is determined after the optimization phase among the candidate Suppliers. Only Supplier1 is selected by both models. Therefore, according to the results of the Supplier1, TMOQ is increased at most 442 units and also NTMO is improved at most 1 order with Model 2. PLOQ is improved at most 50 units and also NPLO is improved at most 2 orders. P1 is improved at most 2.9% and P2 is improved at most 2.2% across the periods for Supplier1 with continuous review policy.

Extensive statistical analyses also showed that managers can increase company's competitiveness by using SO models while maintaining or even improving responsiveness. In addition, integration of inventory control system and supplier selection is an important task for managing and controlling inventories under different environments.

CHAPTER 6

CLOSED LOOP SUPPLY CHAIN PROBLEM AND COMPUTATIONAL RESULTS

In this part of the thesis, SO approach is developed by combining simulation and genetic algorithm to solve a CLSC problem. Two different simulation models are created for two different inventory review systems, namely periodic and continuous. In proposed models, optimal values of inventory control parameters and facilities to be opened are determined simultaneously for periodic review and continuous review system, respectively. Furthermore, single product and multi-components of CLSC network are optimized considering two different objective functions of review system to gain a sustainable competitive advantage for companies. We seek to offer valuable insights for creating robust and user-friendly CLSC network where the forward network includes suppliers, plants, retailers, and customers, and the reverse network includes collection centers, disassembly centers, refurbishing centers, and disposal centers. The results of this study demonstrated that four SO models have a significant potential to satisfy the customer's needs since average service level of the models is at least 81.8%. The TCC can be improved at least 3% and at most 22% on average with proposed continuous review model whose objective is to minimize differences between the total overordering cost and the total underordering cost (C-D). Furthermore, the total lost sales cost can be improved at least 15% and at most 89% on average with C-D model.

6.1 Introduction

Over the past years, companies are facing the ongoing challenge to evaluate and organize their strategies due to the waste and pollution management, government policy and environmental protection, organizational and customer pressures.

Many companies need to take a renewed interest in the concept of reverse logistics in SCM to remain competitive and manage their business effectively. Reverse logistics include all the activities related to the conversion and the flows of goods and services with their information from original sources to final consumers (Ramezani et al., 2013a). Review of the related literature shows that reverse logistics can be divided into recovery network and closed-loop network. The first case fully concentrates on recovery activities (Melo et al., 2009). In the second case, forward and reverse networks are integrated to avoid the sub-optimality resulting from separated design (Pishvaee et al., 2009). The focus of the present study is to propose a CLSC network and to provide recommendations on the management of a closed-loop network. CLSC can be defined as “the design, control, and operation of a system to maximize value creation over the entire life cycle of a product with the dynamic recovery of value from different types and volumes of returns over time” (Guide and Van Wassenhove, 2009).

Companies are seriously exploring the correct strategy to manage complex, multifaceted, and nuanced issues in CLSC. Although each SC has its own characteristics, proposed methods should provide satisfying information to solve the problem of each SC. Adaptable and generic methods, which are reasonably detailed and accurate in representing the complexity and uncertainty, are the core of complex CLSC problems. There is a need to use them in order to overcome the challenges of satisfying the rapidly changing needs. In this context, companies forces researchers to create generic and adaptable SC. Note that adaptability can be defined as an ability of an SC to vary the behavior of SC to preserve, improve, or obtain the new characteristics for satisfying the SC goal in the conditions of environment changing in time, the aprioristic information about which is incomplete (Ivanov et al., 2010). The generic modelling specifies a structured approach that renders high-quality models with short run times, short maintenance time, short development time, robustness, compact size, accuracy and a single software application (Albertyn and Kruger, 2003).

In this study, we proposed a generic and adaptable simulation optimization (SO) to overcome the challenges of today’s and tomorrow’s CLSC problems. SO is an umbrella term for methods used to handle all the dynamically change of CLSC variables (Amaran et al., 2014). A comprehensive review of SO methods is available in Amaran et al. (2014). In addition, we analyzed some SO methods in forward network, reverse network, and CLSC network due to the limited number of studies that specifically address SO methods in CLSC (Table 6.1). It should be noted that the number of papers published in CLSC should be increased to provide a basis and guidelines for researchers and practitioners to link SO with real-world applications.

Table 6.1 A brief review of SO models related to forward chain, reverse chain, and CLSC.

Network Type	**SCM Issues**	***OM**	**Author&Years**
Forward Network	Production, Stocking, Transportation	MILP	Almeder et al. (2009)
Forward Network	Supply Chain Coordination	Opt	Eskandari et al. (2010)
Forward Network	Production-Distribution	MILP	Nikolopoulou and Ierapetritou (2012)
Forward Network	Production-Distribution	GA, SA	Rooeinfar et al. (2016)
Forward Network	Inventory Management	RSM	Ye and You (2016)
Reverse Logistics	Production Planning	ILP	Lourenço and Soto (2002)
Reverse Logistics	Network Configuration	GA	Swarnkar and Harding (2009)
Reverse Logistics	Emergency Scheduling	GA	Zhou and Xue (2011)
Reverse Logistic	Designing Sustainable Recovery Network	Opt	Shokohyar and Mansour (2013)
Reverse Logistics	Network Design of a Third-Party Logistics Provider	MIP	Suyabatmaz et al. (2014)
Reverse Logistics	Inventory Management	HVNS	Zolfagharinia et al. (2014)
CLSC Network	Inventory Management	MOEA	Godichaud and Amodeo (2013)
CLSC Network	Asset Management	Mode	Bottani et al. (2015)
CLSC Network	Supplier Selection and Order Allocation	Goal	Moghaddam (2015)
CLSC Network	Inventory Management	MOEA	Godichaud and Amodeo (2015)
CLSC Network	Inventory Management and Facility Selection	GA	Proposed method

*OM represents optimization method, MILP is mixed-integer linear programming, GA is genetic algorithm, SA is simulated annealing, RSM is region-wise surrogate modeling method, Opt is OptQuest optimization software, ILP is integer linear programming model, MIP is mixed integer programming, HVNS is hybrid variable neighborhood search, MOEA is multi-objective evolutionary algorithm, Mode is ModeFRONTIER™ software, Goal denotes goal programming methods.

Aware of the importance of developing SO method to improve the performance of the companies, we created CLSC network including four SC members in forward direction (i.e. raw material suppliers, plants, retailers, and customers) and four SC members in reverse direction (i.e. collection centers, disassembly centers, refurbishing centers, and final disposal locations) using SO method. A proposed SO method consists of two phases: an optimization phase that searches to determine optimal solution and a simulation phase that evaluates the performance of candidate solutions. In the optimization phase, GA is used to guide the search direction. There is no clear methodology available about proposed SO method whose objective is to determine how many and which plants/retailers should be open, and how the optimal parameters of periodic/continuous review system are determined in CLSC problem. To manage, set and meet expectations about today's CLSC problem, proposed SO model can easily be used as a complementary tool under stochastic environment and lost sales option.

The remainder of this chapter is organized as follows. The problem definition is stated in Section 6.2. Section 6.3 presents the proposed SO methodology. A detailed analysis of the proposed CLSC network is given in Section 6.4. Conclusions are expressed in Section 6.5.

6.2 Problem Definition

The suppliers are responsible for providing the components to the plants. Plants produce end-products based on returned components (i.e., purchased from refurbishing centers) and new components (i.e., purchased from suppliers). Also, collection centers send a percentage of products directly to plants. Note that the plants in the CLSC network produce a homogeneous end-products, the output of one plant cannot be distinguished from the others. Thus, there is no perceived quality depreciation of end-products made from retuned and new components as well. Then, end-products are sent from plants to retailers on demand. In the next part of the network, they are carried to customers.

SO model is used to know which plant/retailer should be opened based on the defined objective function. Furthermore, the proposed model is utilized to optimize the inventory control parameters of plants and retailers where each plant and each retailer has their own initial inventory, reorder point, and order-up-to level values, separately. The inventory level in each plant and each retailer is controlled using periodic and continuous (s, S) policy where (s) denotes reorder point and S represents the order-up-to level. In periodic (s, S) policy, inventory levels of all plants and all retailers are all inspected at every R time units where R is a fixed constant and assumed to be 5 days. In continuous (s, S) policy, a replenishment order is placed to increase the product’s inventory level to the order-up-to level (S) when this inventory level reaches or drops below the reorder point (s). If a customer order is lower than the current inventory level of the retailer, it is fully satisfied. Due to the limited storage capacities of retailers, some orders are either satisfied partially or never satisfied. Thus, unsatisfied demands are lost. The same principle is applied to satisfy replenishment orders of plants and retailers.

Push-type and pull-type can be used to control the reverse flow. With the pull-type strategy, products are processed on demand. With a push-type strategy, recovered products are processed from their entry in the reverse logistics system to meet subsequent needs (Aït-Kadi et al., 2012). In this paper, components are sequentially pushed into plants, synchronizing with the occurrence of the reverse. Therefore, returned products and remanufactured products would be kept as inventory in plants. Also, inventory is not considered for reverse network.

The distribution of the customer order quantity at retailers has a Poisson distribution with a rate parameter of 50. Also, we assumed that customer arrival at retailers is 1 per day. The other parameter values related to retailers and plants are all given in Table 6.2. In addition, transportation cost is proportional to the unit transportation cost, the transportation time, and the order quantity at each shipment (see Appendix A) for each SC member. Unit transportation cost is assumed to be $ Uniform (0.75, 3.00).

Table 6.2 The parameter values related with SC members.

Plants	**Retailers**
Fixed Cost: $ Uniform(3000, 5000)	Fixed Cost: $ Uniform(2000, 3000)
Order Cost Per Use: $ Uniform(50,100)	Order Cost Per Use: $ Uniform(50,100)
Unit Lost Sales Cost: $ Uniform(80, 100)	Unit Lost Sales Cost: $ Uniform(80, 100)
Order Holding Cost Rate: $ Uniform(5,10)	Order Holding Cost Rate: $ Uniform(5,10)
Cost per Use: $ Uniform(10,20)	Cost per Use: $ Uniform(10,20)
Processing Cost Rate: $ Uniform(5,10)	Processing Cost Rate: $ Uniform(5,10)
Average Holding Cost: $ Uniform(2,5)	Average Holding Cost: $ Uniform(2,5)
Purchasing Cost (From Suppliers): $ Uniform(40,50)	Processing Time: Triangular(1,2,3) minutes
Purchasing Cost (From Refurbishing): $ Uniform(8,10)	Order Processing Time: Uniform(2,5) hours
Purchasing Cost (From Collection): $ Uniform(5,8)	
Processing Time: Triangular(3,5,7) minutes	
Order Processing Time: Uniform(2,5) hours	
Collection centers, Disassembly centers & Refurbishing centers	
Processing Time: Triangular(1,2,3) minutes	
Collection/Disassembly/Refurbishing Cost: $ Uniform(2,5)	
Processing Cost Rate: $ Uniform(5,10)	

In proposed CLSC network, two different objective functions are used to optimize four SO model. First SO model represents periodic review model whose objective is to minimize the total CLSC cost and is called (P-T). Second SO model represents periodic review model whose objective is to minimize the difference between overordering cost and underordering cost and called (P-D). Third SO model represents continuous review model whose objective is to minimize TCC and called (C-T). Fourth SO model represents continuous review model whose objective is to minimize the difference between overordering cost and underordering cost and called (C-D).

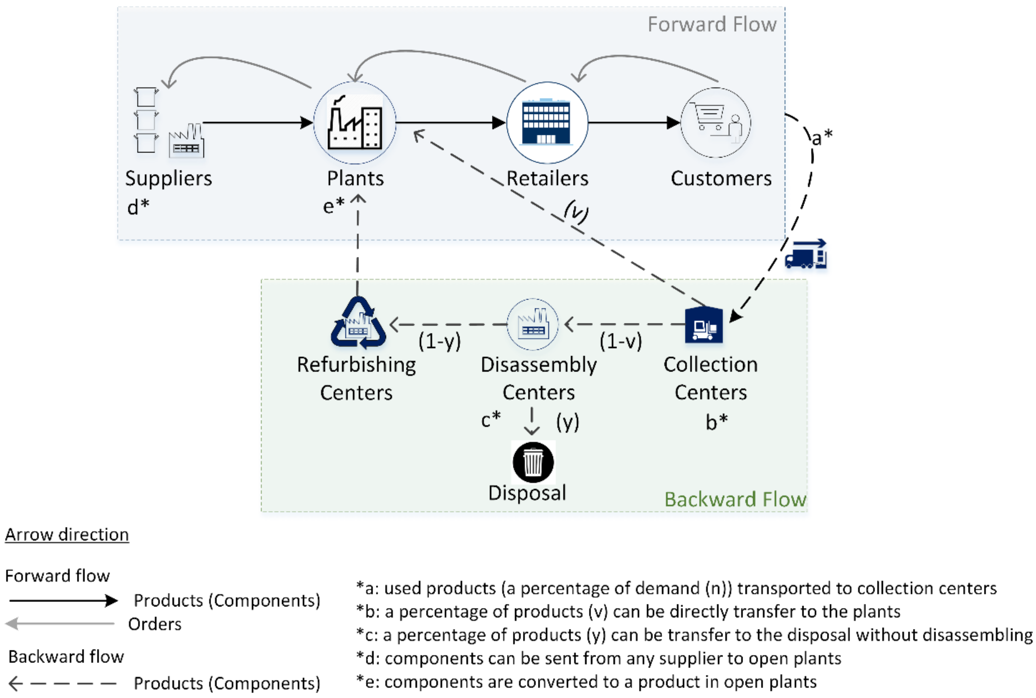


Figure 6.1 The proposed CLSC network.

The general structure of the proposed system is given in Figure 6.1. The returned products from customers are collected in collection centers. Products have a triangular recovery ratio at collection centers with endpoints (0.25, 0.35) and mode at 0.30. After testing and inspecting in collection centers, some of them are sent to plants and all others are shipped to disassembly centers where the components are grouped into reusable and unusable components. Products have a triangular transfer ratio from collection centers to disassembly centers with endpoints (0.65, 0.75) and mode at 0.70. At this point, remaining products (triangular distribution with endpoints (0.35, 0.25) and mode at 0.30) are transported from collection centers to plants. Products have a triangular transfer ratio from disassembly centers to refurbishing centers with endpoints (0.75, 0.85) and mode at 0.80. Also, remaining products (triangular distribution with endpoints (0.25, 0.15) and mode at 0.20) are transported from disassembly centers to disposal center that is outside of CLSC. Reusable components are transported to refurbishing facilities to be inspected and refurbished. Finally, they are transferred to plants.

6.3 Simulation Optimization

In this study, a simulation model is coupled with GA to optimize designs and operations of forward and reverse flow in the SC. The procedure of GA is initialized by defining chromosome structure to represent a set of parameters.

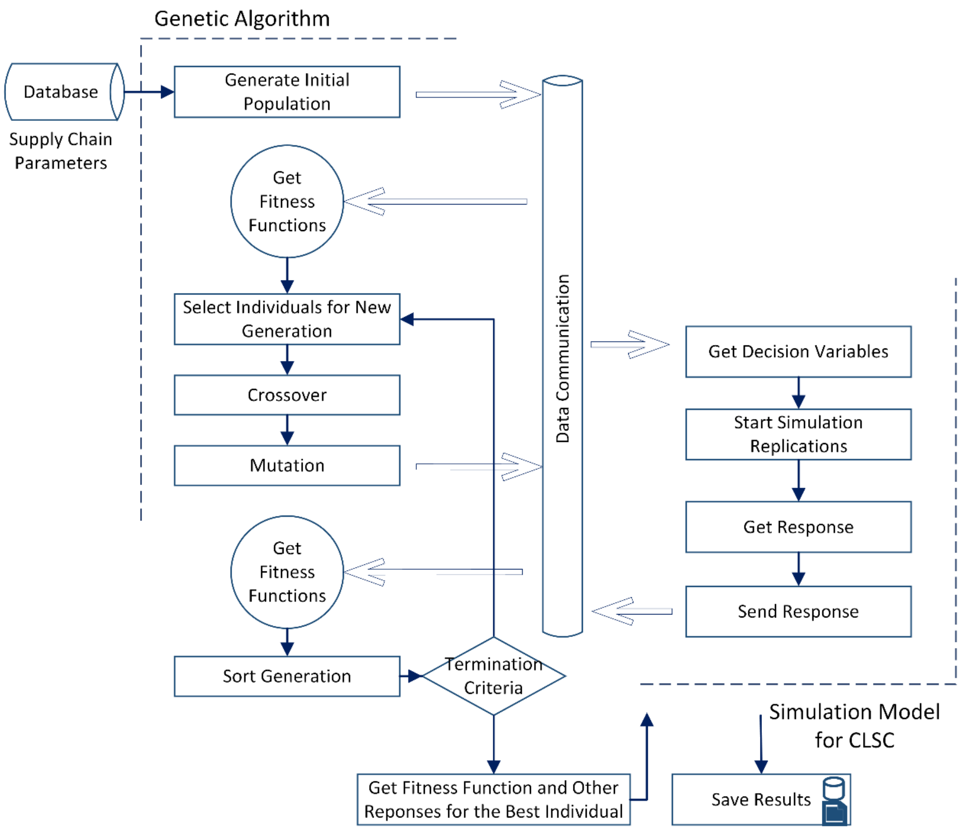


Figure 6.2 General structure of the proposed model.

In GA, selection, crossover, and mutation operators are repeatedly applied to form new chromosomes. In the GA, after preliminary runs the values of population size, the number of iterations, crossover rate, and mutation rate is set to be 20, 200, 0.8, and 0.05, respectively. The tournament is used as selection operator in proposed GA. It is better than other selection operators because it does not use fitness function directly. The working principle of tournament selection and a clear description of its advantages can be found in Miller and Goldberg (1995).

In SO model, GA alters decision variables to explore the solution space and the simulation model evaluates the performance of each solution. The proposed model is initialized by running GA to determine the optimal parameters in CLSC network. GA generates a new set of solutions and feedbacks these to the simulation model. This process of generating and evaluating solutions continues until predetermined termination criteria are satisfied. The general structure of the proposed SO model is depicted in Figure 6.2.

Briefly, the characteristics of our simulation model are summarized as follows:

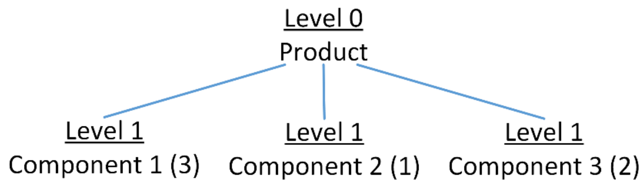


Figure 6.3 Bill of materials of a product.

1. Single product flows through the chain. The product consists of three components that have different utilization rates. It includes three units of the first component, one unit of the second component, and two units of the third component (Figure 6.3).
2. The model considers multi-period.
3. The proposed model is used to determine how many and which plants/retailers should be opened. However, the locations of SC members are known and fixed.
4. The amounts of returned products through reverse flow in each time period are stochastic.
5. The remanufactured products and the new products are indistinguishable to the customer. There is no perceived quality depreciation of end-products made from returned and new components as well.
6. If the demand quantity exceeds the current inventory level of SC members, possible order fulfillment takes place and unmet demand is lost.
7. Periodic review system or continuous review system is used to control inventory level of plants and retailers.
8. Inventory is not allowed at reverse flow.
9. It is assumed that all transfer times are stochastic.

Model is run for one year that is composed of twelve periods (month). Also, one simulation run consists of 20 replications. Computational results are given as the averages of 20 replications.

6.4 Results and Discussions

To be capable of handling real problems in CLSC, various methods that include many different factors transforming forward/reverse SC into a critical and important subject in SCM have been developed in the literature. In this study, we presented that designing and modeling of CLSC problem can be efficiently achieved using SO models since a large number of properties are easily incorporated into the model to cope with uncertainty in decision-making environment. The proposed SO model determines the appropriate plant/retailer to achieve more profits and higher customer service level together. In addition, the inventory control parameters of plants and retailers are optimized to minimize lost sales in the forward network. Note that inventory of reverse network is not considered due to the push-type strategy. The scale of this study is as follows: four suppliers, four plants, four retailers, five customers, two collection centers, two disassembly centers, two refurbishing centers. Selected plant and retailer for each model and theirs optimized initial inventory, reorder point, and order-up-to levels are given in Table 6.3. Note that the order-up-to levels of the most of the SC members are significantly less for C-D model.

Suppliers have the responsibility to manage the inventories of the plants, given that the information about inventory level of components is accessible. Suppliers decide about the plant's replenishment quantity and replenishment point. Plant's replenishment time is determined according to the inventory level of component 1. A replenishment order is placed to increase the inventory level of components including component 1, component 2, and component 3 when inventory level of component 1 reaches or drops below the point that is determined by proposed models as given in Table 6.3. Note that component 1, component 2, and component 3 can be considered for this purpose since there is no matter in which component is selected. After replenishment order is placed, replenishment quantity for component 1, component 2, and component 3 is determined using uniformly distributed number between 0 and 500.

Table 6.3 Optimal values of inventory control parameters for SO models.

SC member	Inventory control policy	Inventory Level of Component 1	Initial Inventory	Reorder Point	Order-up to Level	Average service level
Plant 1	**P-T**	1032	963	277	2267	0,968
	P-D	1108	1549	393	2059	0,985
	C-T	539	1008	209	1518	0,986
	C-D	568	904	208	1133	0,995
Plant 2	**P-D**	1308	1485	227	1566	0,978
	C-T	679	1547	244	1518	0,996
	C-D	742	1901	386	800	0,998
Plant 3	**P-T**	1007	1761	303	2433	0,971
	C-D	548	1961	179	680	0,929
Plant 4	**P-T**	1309	1384	325	1300	0,963
	P-D	1549	1297	104	1248	0,951
Retailer 1	**P-T**	-	1839	188	1300	0,818
	P-D	-	1504	227	1629	0,971
Retailer 2	**P-T**	-	1384	319	1175	0,992
	P-D	-	1485	271	2085	0,883
	C-T	-	1464	319	1814	0,986
	C-D	-	1559	334	560	1,000
Retailer 3	**P-D**	-	1504	271	2003	0,992
	C-T	-	1662	231	1815	0,991
	C-D	-	1930	228	647	1,000
Retailer 4	**P-T**	-	1988	325	1329	0,829
	C-D	-	1559	303	1437	1,000

To remain competitive in today's condition, companies forces themselves to meet customer needs better than their competitors. At this point, the average service level that can be easily used to evaluate companies is frequently incorporated into the decision making process. At most of the SC members highest average service levels are achieved by using C-D models (see Table 6.3).

To help the shaping of future policy for companies, controlling cost components affecting CLSC network is important. The values and shares of cost components are summarized in Table 6.4. According to the cost analysis, TCC difference between P-T model and P-D model is 488073. The TCC difference between C-T model and C-D model is 95446. Both P-T model and P-D model have higher TCC s than those of C-T model and C-D model. C-D model has the lowest TCC cost while P-T model has the highest TCC. The largest share of TCC for P-T model is the lost sales cost. The largest share of TCC for P-D model, C-T model, and C-D model is the purchasing cost from suppliers. These differences may arise from the determination of plants and retailers because each model has its own selected plants and retailers.

According to the cost analysis the TCC performance of C-D model outperforms all the other considered models. The TCC of P-T model can be improved approximately 11%, 20%, and 22% with P-D model, C-T model, and C-D model, respectively. In addition, the TCC of P-D model can be improved approximately 10% and 12% with C-T model and C-D model, respectively. The TCC of C-T model can be improved approximately 3% with C-D model.

6.4.1 Forward Network Analysis

Plants buy components from both suppliers and refurbishing centers and products from collection centers. The total quantity of products (components) and the total number of incoming orders from each member are given in Table 6.5 where the share of incoming products (components)/orders is also specified. From Table 6.5 it is seen that suppliers have the highest share of total quantity while the share of total number with suppliers is the lowest for all plants.

For a more detailed performance analysis of SC members, probability-based analysis (P1 and P2), quantity-based analysis per each period (TMOQ, TLOQ, and PLOQ), order-based analysis per each period (NTMO, NTLO, and NPLO) are also analyzed.

P1 and P2 values of Plant 1 with P-T Model can be said to be uniformly distributed over the periods except from period 1 and period 2 as seen from Figure 6.4. The analysis of Plant 1 with P-T Model showed that the largest share in the pie chart is the lost sales cost (64%) and the smallest share in the pie chart is the order cost per use (1%). Thus, the shortage is the most strategic cost component among various cost types involved in Plant 1. From Figure 6.5, it can be said that one order is partially lost at each period and the PLOQ performance of Plant 1 varies between 24 and 38 over the periods 3-12. Note that, period 1 and period 2 have higher PLOQ values than the other periods. This behavior of PLOQ performance can be attributed to the initial inventory level of Plant 1 with P-T Model.

Table 6.4 The values of cost components for CLSC.

Cost Components	P-T		P-D		C-T		C-D	
	Cost ($)	Share (%)	Cost ($)	Share (%)	Cost ($)	Share (%)	Cost ($)	Share (%)
Total Average Holding Cost	142566	3,13	178849	4,39	135073	3,68	136970	3,84
Total Order Cost Per Use	138344	3,03	137708	3,38	139047	3,79	150619	4,22
Lost Sales Cost	1331522	29,20	736991	18,10	164918	4,50	140731	3,94
Total Order Processing Cost	186767	4,10	185716	4,56	187973	5,13	203447	5,70
Total Processing Cost	27289	0,60	38140	0,94	51044	1,39	51690	1,45
Total Order Processing Cost for Reverse Flow	401406	8,80	401634	9,86	401523	10,95	400982	11,23
Total Processing Cost for Reverse Flow	10826	0,24	10823	0,27	10822	0,30	10826	0,30
Total Collection Cost	97343	2,13	97428	2,39	97540	2,66	97329	2,73
Total Disassembly Cost	59840	1,31	59849	1,47	59796	1,63	59835	1,68
Total Refurbishing Cost	59363	1,30	59393	1,46	59323	1,62	59430	1,66
Total Transportation Cost	981861	21,53	919228	22,58	998855	27,24	959846	26,88
Total Purchasing Cost From Collection Centers	60170	1,32	60137	1,48	60225	1,64	60064	1,68
Total Purchasing Cost From Refurbishing Centers	153333	3,36	153369	3,77	153196	4,18	153419	4,30
Total Purchasing Cost From Suppliers	889991	19,52	1013020	24,88	1134400	30,94	1066680	29,87
Total Fixed Cost for Plants	11998	0,26	12047	0,30	8156	0,22	12092	0,34
Total Fixed Cost for Retailers	7306	0,16	7519	0,18	4835	0,13	7319	0,20

Table 6.5 Analysis of incoming products for plants.

		Total quantity of incoming products				Total number of incoming orders			
		C1 and C2	**R1 and R2**	**Suppliers**	**Total**	**C1 and C2**	**R1 and R2**	**Suppliers**	**Total**
Plant 1	**P-T**	3064	5695	19697	28457	595	595	39	1229
	Share	11	20	69	100	48	48	3	100
	P-D	3005	5631	38236	46872	584	587	76	1248
	Share	6	12	82	100	47	47	6	100
	C-T	4553	8407	22750	35710	885	879	46	1809
	Share	13	24	64	100	49	49	3	100
	C-D	3043	5603	26717	35363	592	585	53	1230
	Share	9	16	76	100	48	48	4	100
Plant 2	**P-D**	3067	5586	9022	17675	596	584	18	1198
	Share	17	32	51	100	50	49	2	100
	C-T	4592	8406	39430	52429	891	878	79	1848
	Share	9	16	75	100	48	48	4	100
	C-D	3062	5623	25033	33718	595	587	50	1233
	Share	9	17	74	100	48	48	4	100
Plant 3	**P-T**	3036	5585	9126	17747	590	583	18	1191
	Share	17	31	51	100	50	49	2	100
	C-D	3040	5620	6601	15261	589	587	13	1190
	Share	20	37	43	100	50	49	1	100
Plant 4	**P-T**	3049	5550	19498	28096	592	581	39	1211
	Share	11	20	69	100	49	48	3	100
	P-D	3068	5617	8286	16971	596	587	17	1200
	Share	18	33	49	100	50	49	1	100

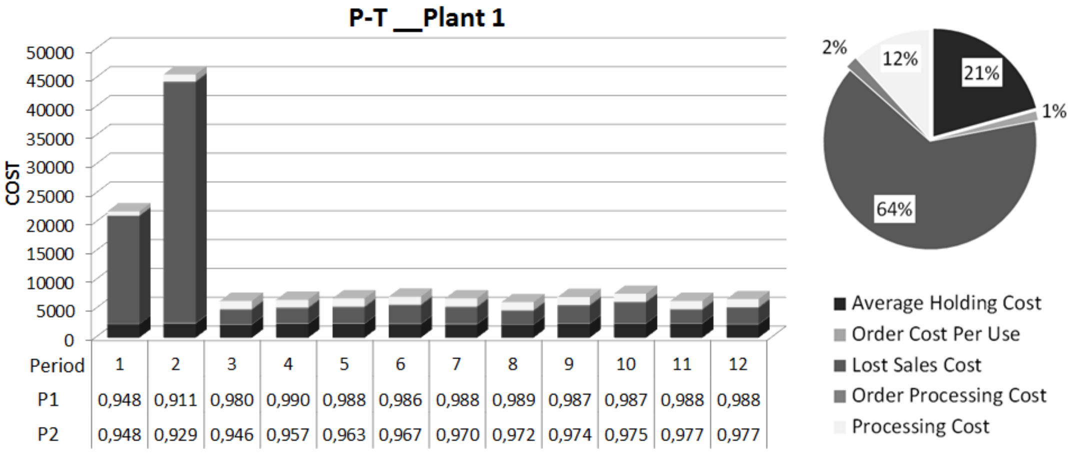


Figure 6.4 Cost based analysis and probability based analysis of Plant 1 for P-T Model.

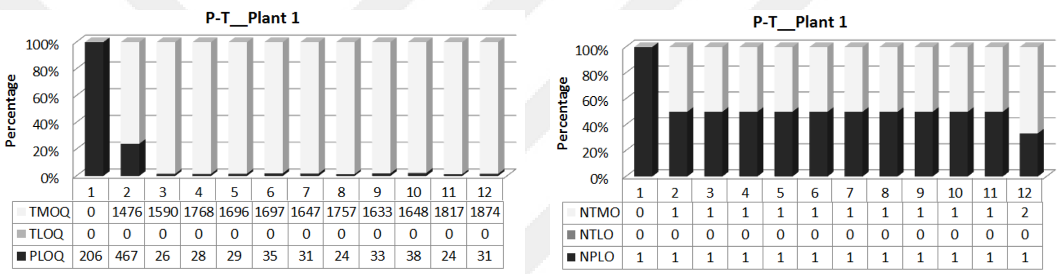


Figure 6.5 Quantity-based analysis and order-based analysis of Plant 1 for P-T Model.

P1 and P2 performances of Plant 1 vary slightly over the periods as seen in Figure 6.6. The largest share in the pie chart is the lost sales cost (59%) and the smallest share in the pie chart is the order cost per use (1%). Note that period 1 is not shown visually as a bar in Figure 6.6 due to having extremely high lost sales cost at that period (i.e., including period 1 into Figure 6.6 leads scale problems (shrinks the bars of other periods)). However, it should be noted that period 1 is considered while performing the analysis of Plant 1. In period 1, the values of average holding cost, order cost per use, lost sales cost, order processing cost, and processing cost are 2214.92, 149.4, 68058.6, 203.76, and 1276.55, respectively. From Figure 6.7, only one order is partially lost at period 1 and period 2. The NTMO value of Plant 1 with P-D Model varies between 1 order and 2 orders. Except from period 1 and period 2, it can be said that all incoming orders to Plant 1 with P-D Model are met.

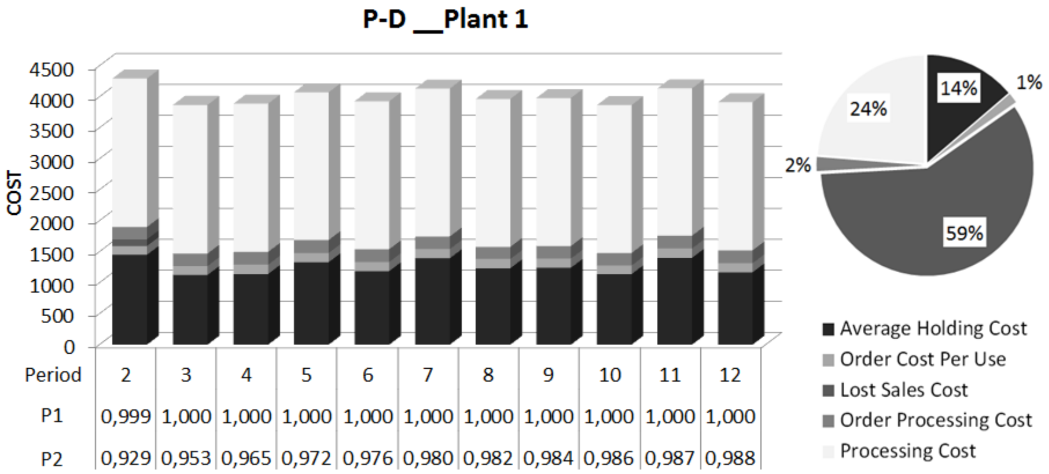


Figure 6.6 Cost based analysis and probability based analysis of Plant 1 with P-D Model.

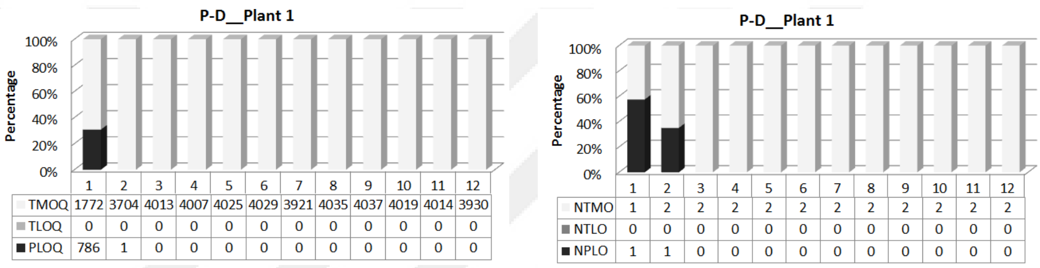


Figure 6.7 Quantity-based analysis and order-based analysis of Plant 1 with P-D Model.

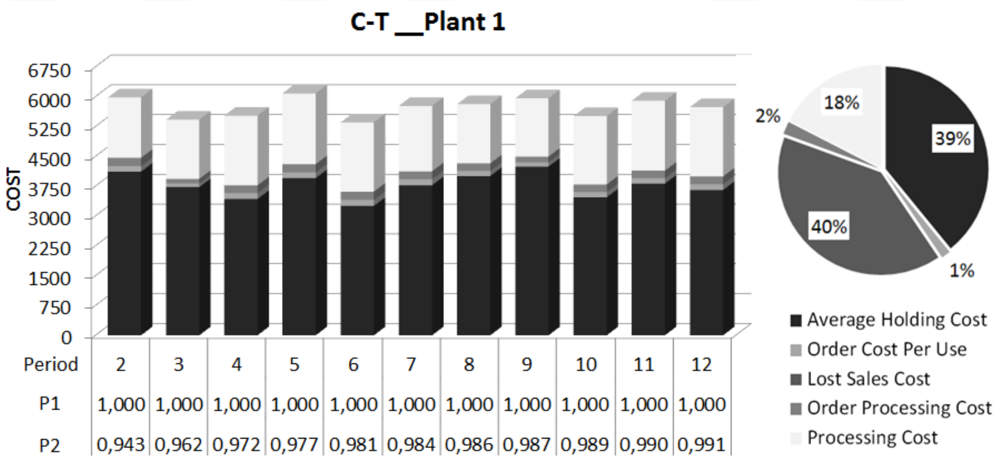
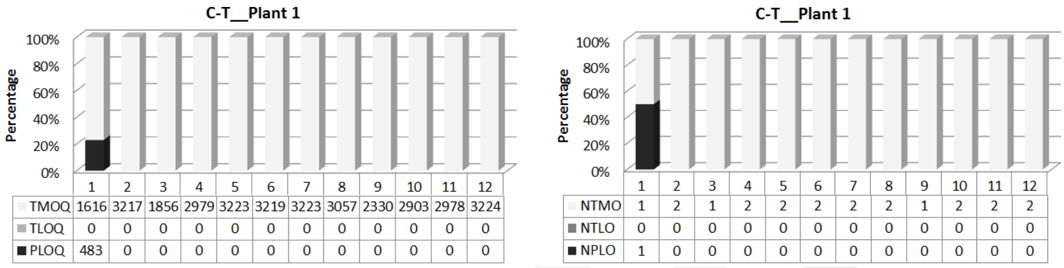


Figure 6.8 Cost based analysis and probability based analysis of Plant 1 with C-T Model.

In Figure 6.8, the largest share in the pie chart is still the lost sales cost (40%) but the share of average holding cost is also high (39%) and the smallest share in the pie chart is the order cost per use (1%). Note that period 1 is not shown visually as a bar in Figure 6.8 due to having extremely high lost sales cost at that period (i.e., including period 1 into Figure 6.8 leads scale problems (shrinks the bars of other periods)).

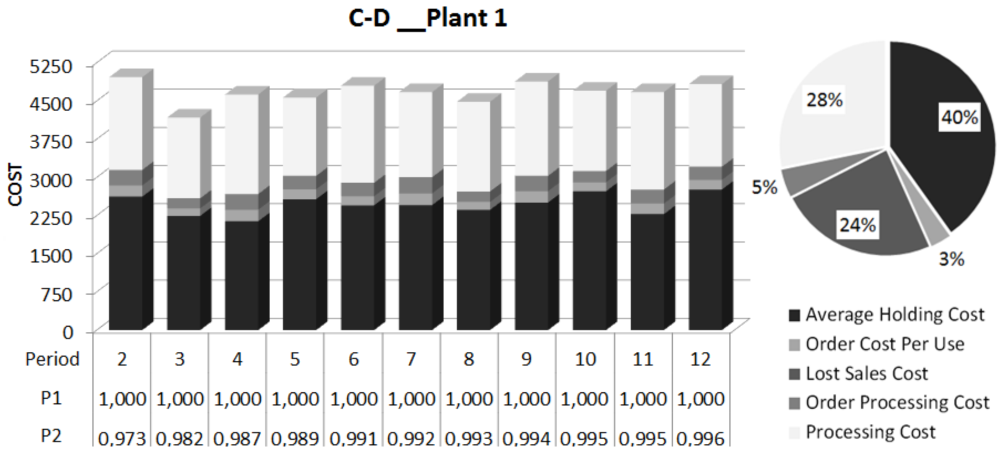
However, it should be noted that period 1 is considered while performing the analysis of Plant 1. At period 1, the values of average holding cost, order cost per use, lost sales cost, order processing cost, and processing cost are 2684.5, 139.9, 45126.42, 203.08, and 1591.02, respectively. From Figure 6.9, only one order is partially lost at period 1. The NTMO value varies between 1 order and 2 orders. Except from period 1, all incoming orders are met by using C-T Model for Plant 1.



	1	2	3	4	5	6	7	8	9	10	11	12
TMOQ	1616	3217	1856	2979	3223	3219	3223	3057	2330	2903	2978	3224
TLOQ	0	0	0	0	0	0	0	0	0	0	0	0
PLOQ	483	0	0	0	0	0	0	0	0	0	0	0

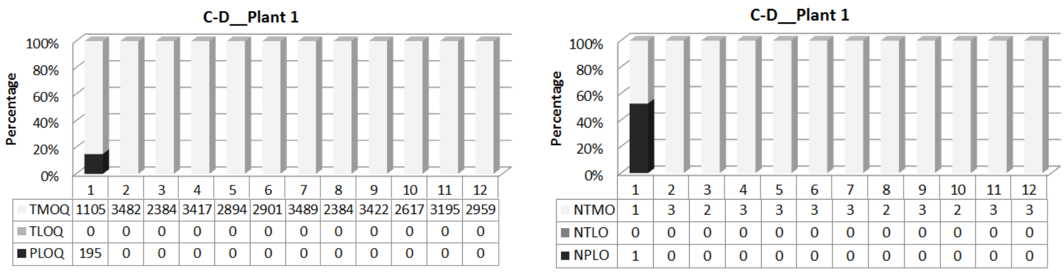
	1	2	3	4	5	6	7	8	9	10	11	12
NTMO	1	2	1	2	2	2	2	2	1	2	2	2
NTLO	0	0	0	0	0	0	0	0	0	0	0	0
NPLO	1	0	0	0	0	0	0	0	0	0	0	0

Figure 6.9 Quantity-based analysis and order-based analysis of Plant 1 with C-T Model.



Period	2	3	4	5	6	7	8	9	10	11	12
P1	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000
P2	0,973	0,982	0,987	0,989	0,991	0,992	0,993	0,994	0,995	0,995	0,996

Figure 6.10 Cost based analysis and probability based analysis of Plant 1 with C-D Model.



	1	2	3	4	5	6	7	8	9	10	11	12
TMOQ	1105	3482	2384	3417	2894	2901	3489	2384	3422	2617	3195	2959
TLOQ	0	0	0	0	0	0	0	0	0	0	0	0
PLOQ	195	0	0	0	0	0	0	0	0	0	0	0

	1	2	3	4	5	6	7	8	9	10	11	12
NTMO	1	3	2	3	3	3	3	2	3	2	3	3
NTLO	0	0	0	0	0	0	0	0	0	0	0	0
NPLO	1	0	0	0	0	0	0	0	0	0	0	0

Figure 6.11 Quantity-based analysis and order-based analysis of Plant 1 with C-D Model.

In Figure 6.10, the largest share in the pie chart is the average holding cost (40%) and the smallest share in the pie chart is the order cost per use (3%). Note that period 1 is not shown visually as a bar in Figure 6.10 due to having extremely high lost sales cost at that period (i.e., including period 1 into Figure 6.10 leads scale problems (shrinks the bars of other periods)). However, it should be noted that period 1 is considered while performing the analysis of Plant 1. In period 1, the values of average holding cost, order cost per use, lost sales cost, order processing cost, and processing cost are 2214.66, 159.15, 17613.35, 198.53, and 1415.75, respectively. From Figure 6.11, only one order is partially lost at period 1. The NTMO value varies between 1 order and 3 orders. Except from period 1, all incoming orders are met by using C-D Model for Plant 1.

Note that the share of lost sales cost with P-T model is improved at least 5% with P-D model and at most 40% with C-D model for Plant 1. Although both the values of TLOQ and NTLO are zero with all models at Plant 1, PLOQ and NPLO performances of Plant 1 can be improved with C-D model.

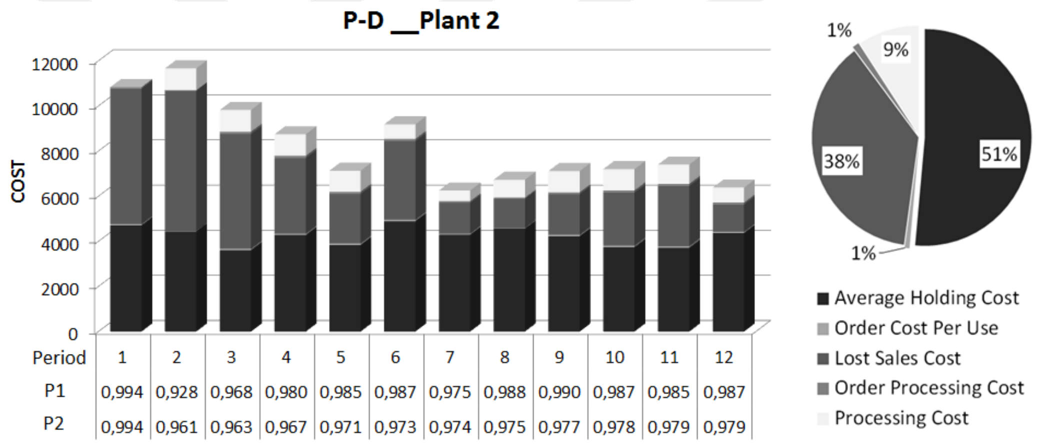


Figure 6.12 Cost based analysis and probability based analysis of Plant 2 with P-D Model.

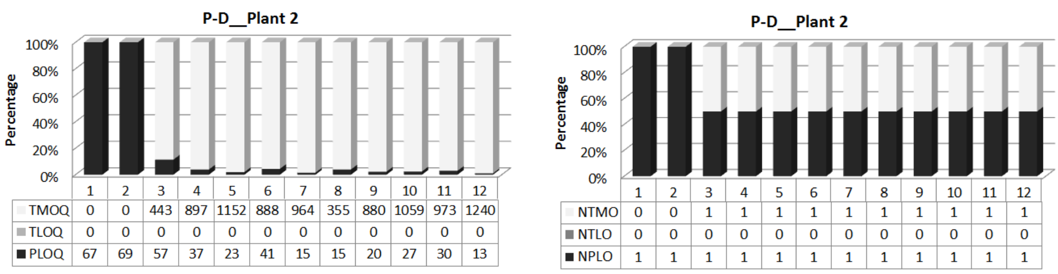


Figure 6.13 Quantity-based analysis and order-based analysis of Plant 2 with P-D Model.

The analysis of Plant 2 with P-D Model (Figure 6.12) showed that the largest share in the pie chart is the average holding cost (51%) and the smallest share in the pie chart is the order cost per use (1%) and order processing cost (1%). From Figure 6.13, it can be said that one order is partially lost at all periods and PLOQ performance of Plant 2 varies over the periods. The values of TMOQ at period 1 and period 2 are both zero. Thus, incoming orders can only be met partially at those periods. The reason can be initial inventory level of Plant 2 with P-D Model and other stochastic parameters.

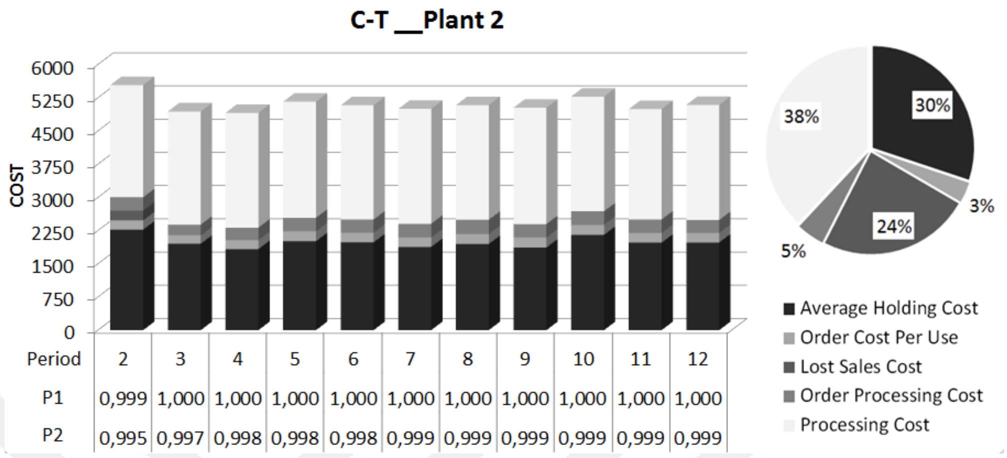


Figure 6.14 Cost based analysis and probability based analysis of Plant 2 with C-T Model.

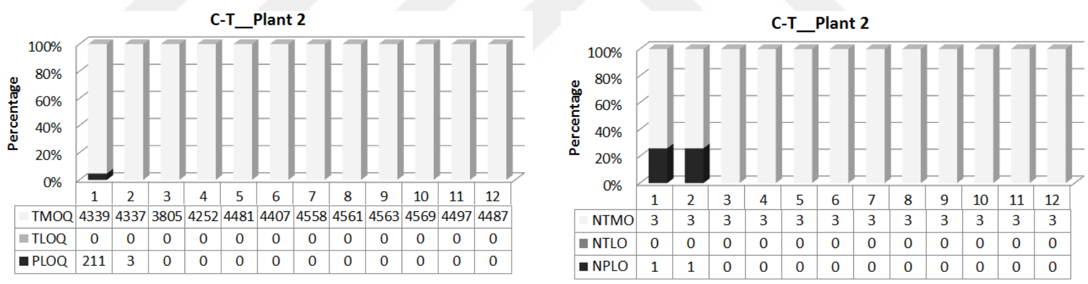


Figure 6.15 Quantity-based analysis and order-based analysis of Plant 2 with C-T Model.

In Figure 6.14, the largest share in the pie chart is the processing cost (38%) and the smallest share in the pie chart is the order cost per use (3%). Note that period 1 is not shown visually as a bar in Figure 6.14 due to having extremely high lost sales cost at that period (i.e., including period 1 into Figure 6.14 leads scale problems (shrinks the bars of other periods)). However, it should be noted that period 1 is considered while performing the analysis of Plant 1. In period 1, the values of average holding cost, order cost per use, lost sales cost, order processing cost, and processing cost are 2300.14, 236.83, 19151.58, 308.38, and 2113.94, respectively. From Figure 6.15, it can be said that by using C-T Model all incoming orders are met at Plant 2 except from period 1 and period 2.

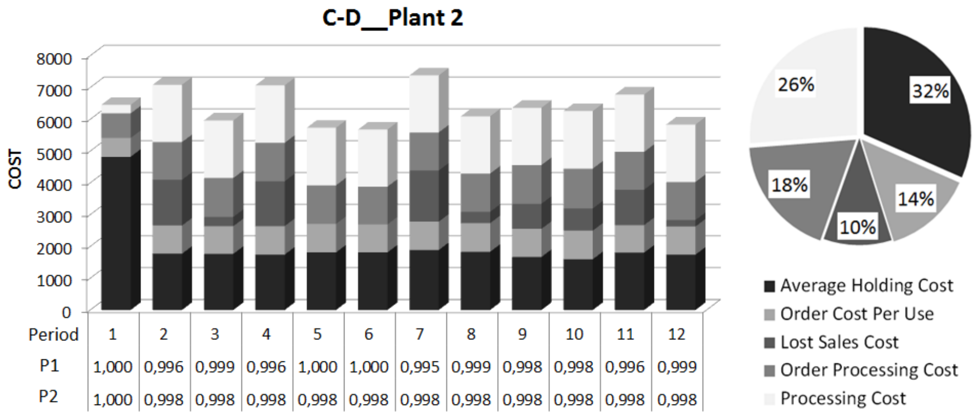


Figure 6.16 Cost based analysis and probability based analysis of Plant 2 in C-D Model.

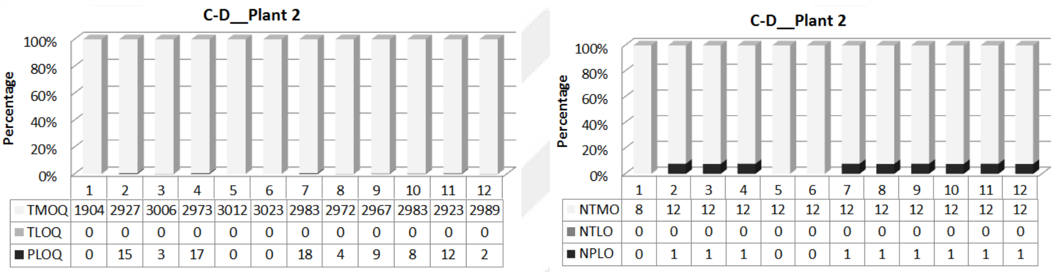


Figure 6.17 Quantity-based analysis and order-based analysis of Plant 2 in C-D Model.

The analysis of Plant 2 with C-D Model (Figure 6.16) shows that the largest share in the pie chart is the average holding cost (32%) and the smallest share in the pie chart is the lost sales cost (10%). The NTMO value of Plant 2 with C-D Model varies between 8 orders and 12 orders (Figure 6.17). Incoming orders of Plant 2 with C-D Model are either totally met or partially met since TLOQ and NTLO values are zero over all periods.

Note that the share of lost sales cost with P-D model is improved at least 14% with C-T model and at most 28% with C-D model for Plant 2. In addition, the share of average holding cost with P-D model is improved at least 19% with C-D model and at most 21% with C-T model for Plant 2.

The analysis of Plant 3 with P-T Model (Figure 6.18) showed that the largest share in the pie chart is the average holding cost (45%) but the lost sales cost (43%) is also high. Also, the smallest share in the pie chart is the order cost per use (1%). From Figure 6.19, it can be said that at most one order is partially lost and PLOQ value varies over the periods. The NTMO values vary between 1 order and 2 orders. Incoming orders of Plant 3 with P-T Model are either totally met or partially met since TLOQ and NTLO values are both zero over all periods.

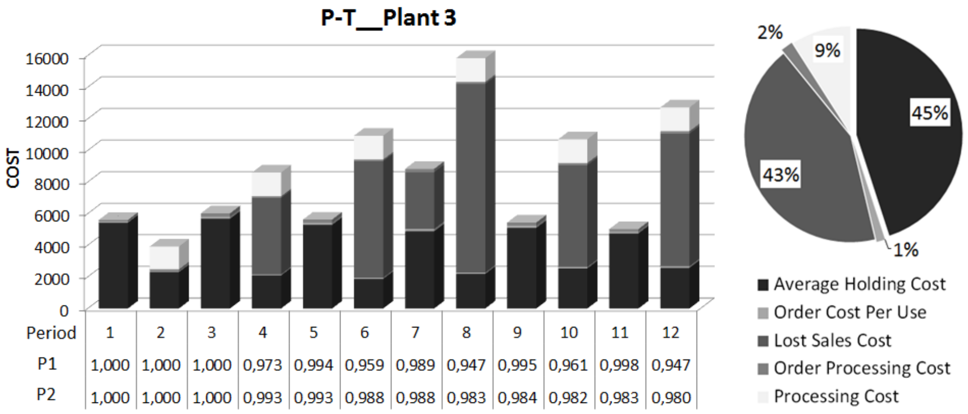


Figure 6.18 Cost based analysis and probability based analysis of Plant 3 with P-T Model.

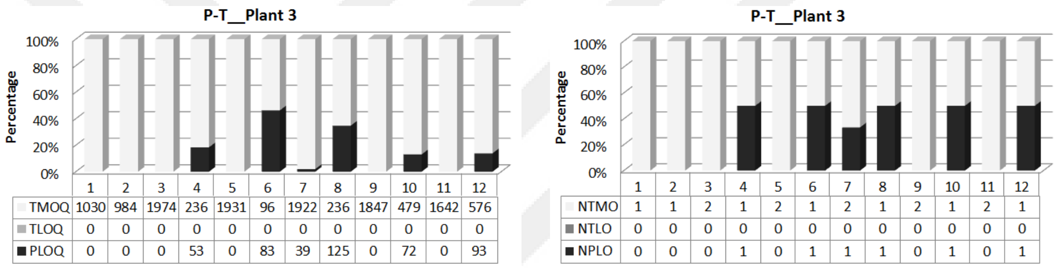


Figure 6.19 Quantity-based analysis and order-based analysis of Plant 3 with P-T Model.

P1 and P2 values of Plant 3 with C-D Model vary between 0.923 and 1 as seen in Figure 6.20. The analysis of Plant 3 with C-D Model showed that the largest share in the pie chart is the lost sales cost (74%) and the smallest share in the pie chart is the order cost per use (2%) and order processing cost (2%).

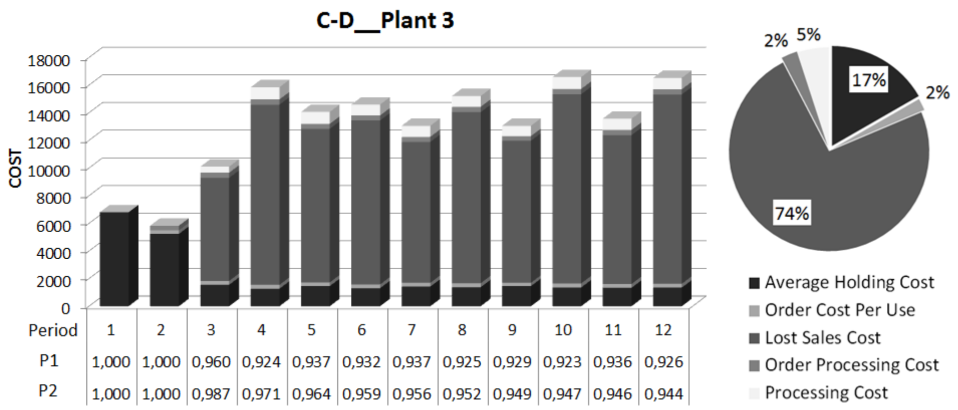


Figure 6.20 Cost based analysis and probability based analysis of Plant 3 with C-D Model.

From Figure 6.21, NTMO value varies between 0 order and 3 orders and NPLO value varies between 0 order and 2 orders.

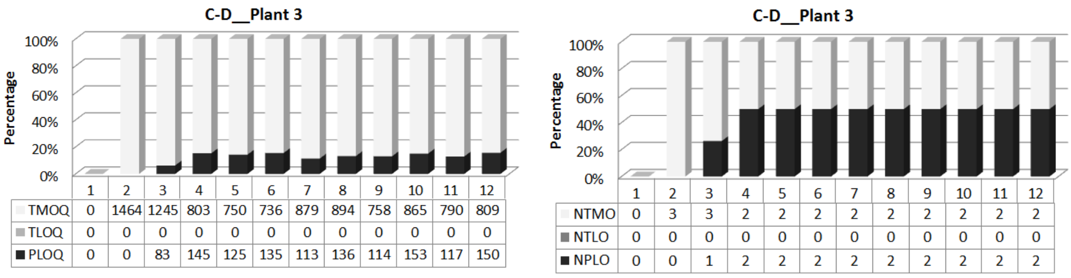


Figure 6.21 Quantity-based analysis and order-based analysis of Plant 3 with C-D Model.

The share of lost sales cost with C-D model is improved 31% with P-T model for Plant 3. Although the values of TLOQ and NTLO are both zero for C-D model and P-T model at Plant 3, total values of PLOQ and NPLO can be improved with P-T model.

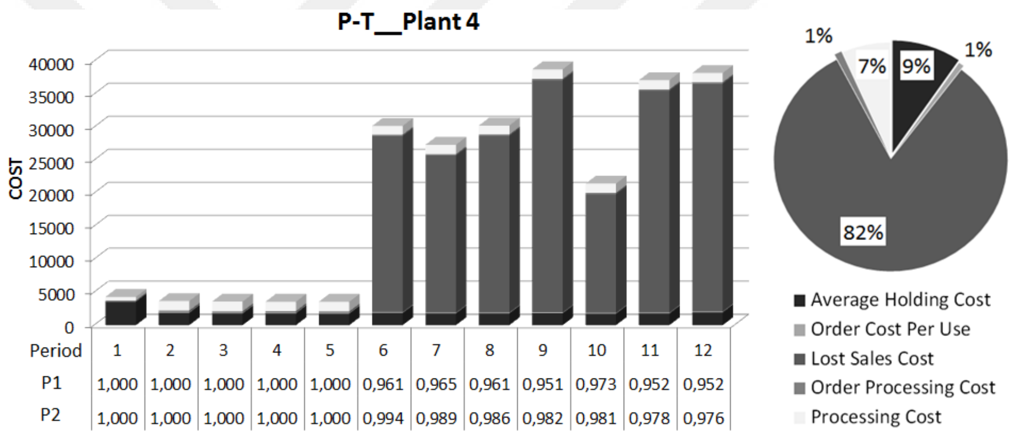


Figure 6.22 Cost based analysis and probability based analysis of Plant 4 with P-T Model.

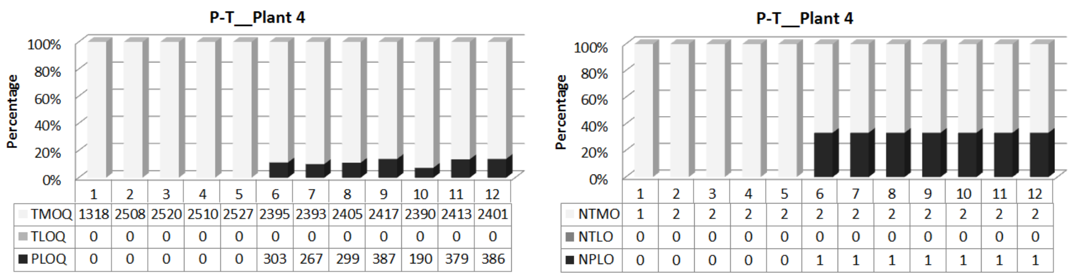


Figure 6.23 Quantity-based analysis and order-based analysis of Plant 4 with P-T Model.

As seen in Figure 6.22, the largest share in the pie chart is the lost sales cost (82%) and the smallest share in the pie chart is the order cost per use (1%) and order processing cost (1%). The share of the lost sales cost is dramatically higher than the others. From

Figure 6.23, NTMO value varies between 1 order and 2 orders. All incoming orders are met until period 5 however one order is partially lost after period 5 (Figure 6.23).

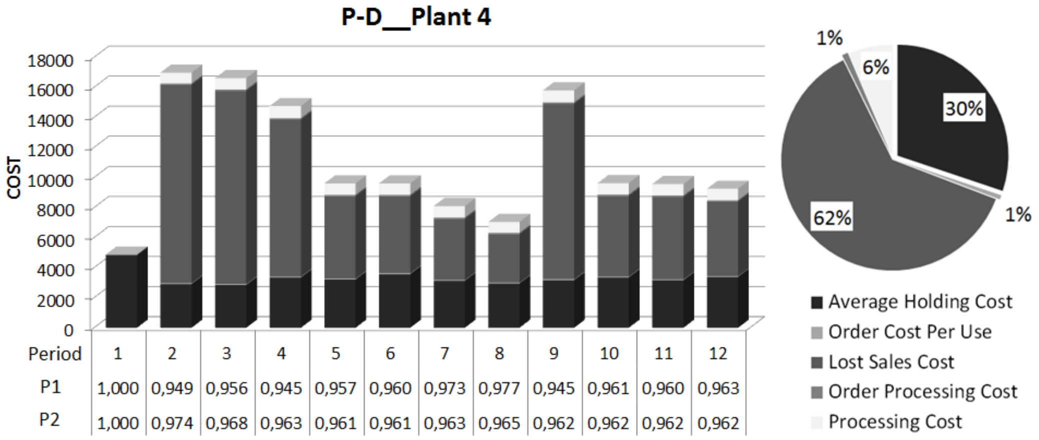


Figure 6.24 Cost based analysis and probability based analysis of Plant 4 with P-D Model.

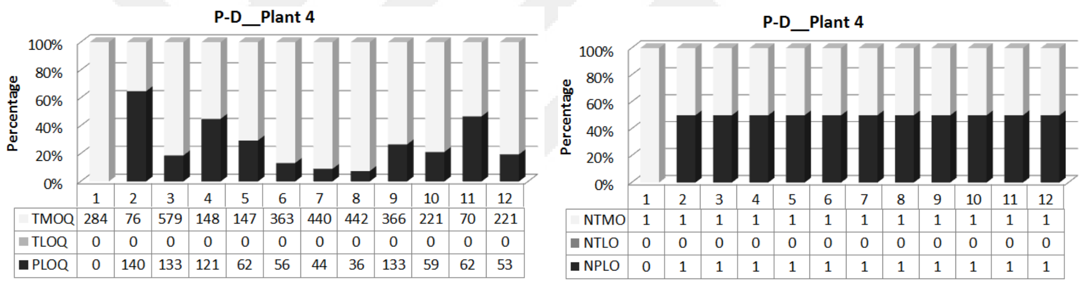


Figure 6.25 Quantity-based analysis and order-based analysis of Plant 4 with P-D Model.

P1 and P2 values of Plant 4 with P-D Model vary over the periods as seen in Figure 6.24. The analysis of Plant 4 with P-D Model showed that the largest share in the pie chart is the lost sales cost (62%) and the smallest share in the pie chart is the order cost per use (1%) and order processing cost (1%). From Figure 6.25, it can be said that all incoming orders are met at period 1. In addition, one order is totally met over the periods and TMOQ value varies over the periods.

The share of lost sales cost with P-T model is improved 20% with P-D model for Plant 4. Although the values of TLOQ and NTLO are both zero for P-T model and P-D model in Plant 4, total value of PLOQ can be improved with P-D model.

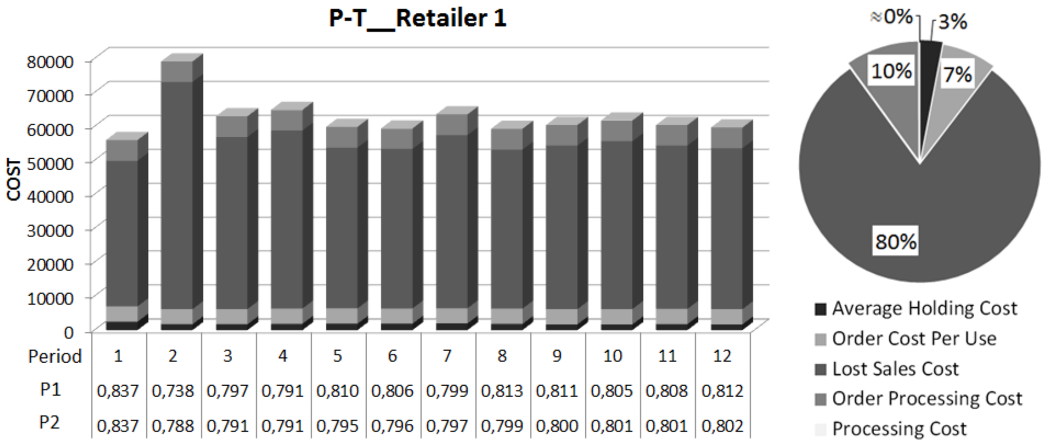


Figure 6.26 Cost based analysis and probability based analysis of Retailer 1 with P-T Model.

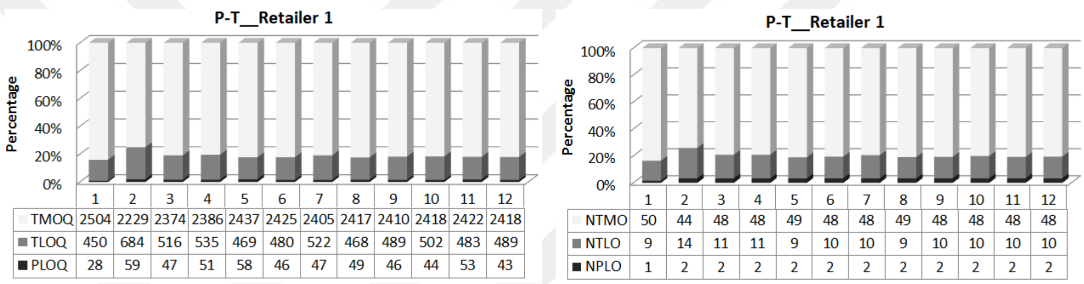


Figure 6.27 Quantity-based analysis and order-based analysis of Retailer 1 with P-T Model.

P1 and P2 values of Retailer 1 with P-T Model vary over the periods as seen in Figure 6.26. The analysis of Retailer 1 with P-T Model showed that the largest share in the pie chart is the lost sales cost (80%) and the smallest share in the pie chart is the processing cost (≈0). In Figure 6.27, NTLO values are higher than NPLO values. Therefore, the shortage can be considered as the most strategic issue of Retailer 1 with P-T Model.

In Figure 6.28, the largest share in the pie chart is the lost sales cost (33%) and the smallest share in the pie chart is the processing cost (≈0). For Retailer 1, P-D model can be used to decrease the lost sales cost since the share of lost sales cost with P-T model is improved 47% with P-D model for Retailer 1. Furthermore, compared with P-T Model, P-D model reduces the values of TLOQ and PLOQ of Retailer 1. In Figure 6.29, compared with the values of NTLO and NPLO the values of NTMO are extremely high.

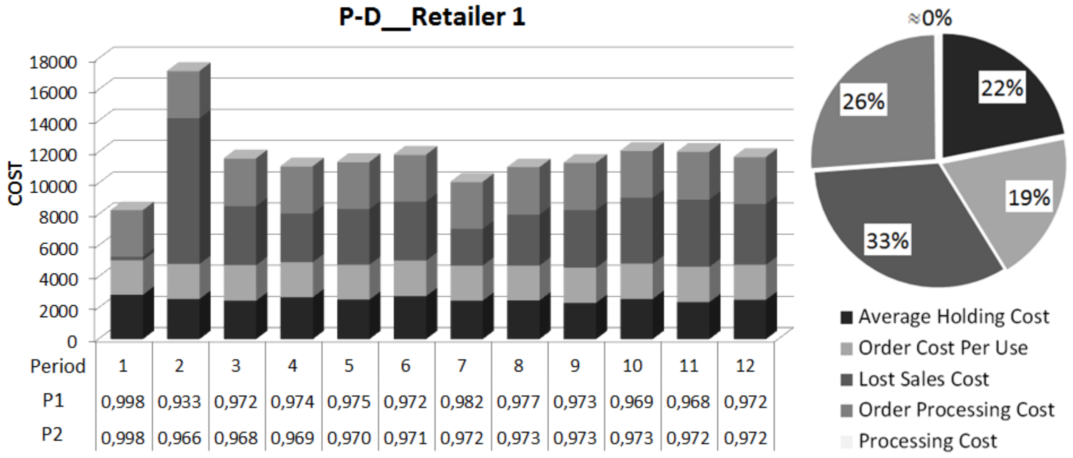


Figure 6.28 Cost based analysis and probability based analysis of Retailer 1 with P-D Model.

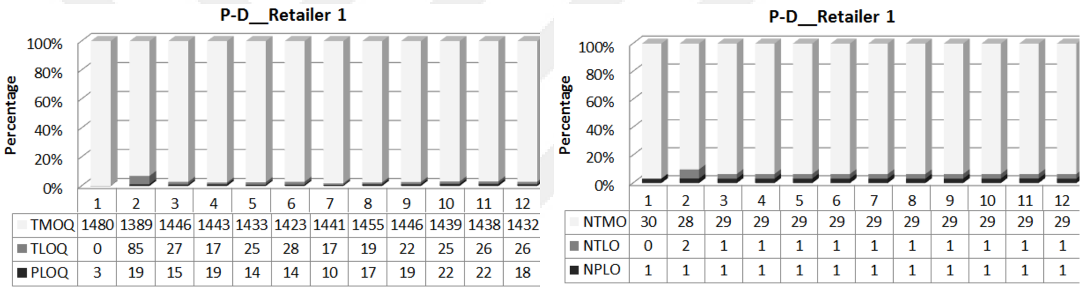


Figure 6.29 Quantity-based analysis and order-based analysis of Retailer 1 with P-D Model.

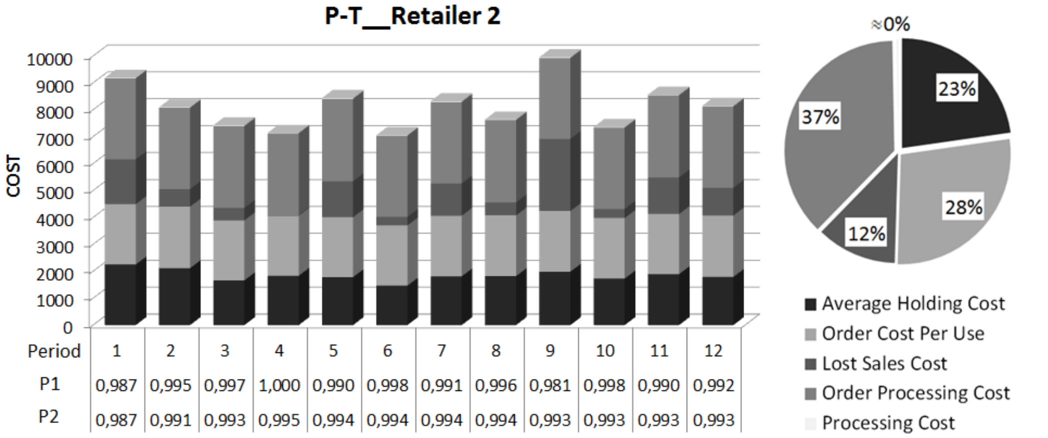
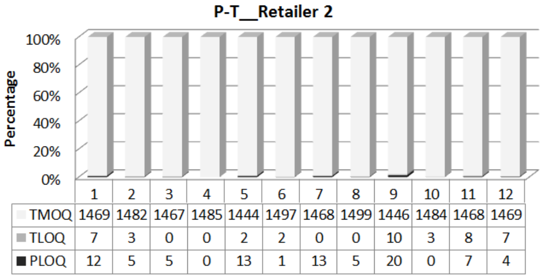


Figure 6.30 Cost based analysis and probability based analysis of Retailer 2 with P-T Model.



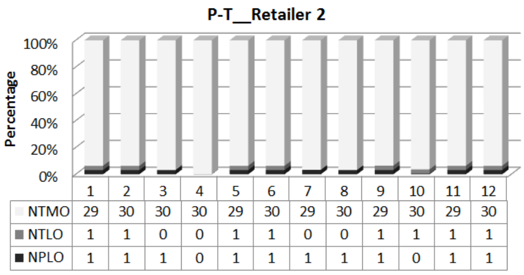


Figure 6.31 Quantity-based analysis and order-based analysis of Retailer 2 with P-T Model.

In Figure 6.30, the largest share in the pie chart is the order processing cost (37%) and the smallest share in the pie chart is the processing cost (≈0). From Figure 6.31, NTMO value varies between 29 orders and 30 orders. All incoming orders of Retailer 2 with P-T Model are met at period 4.

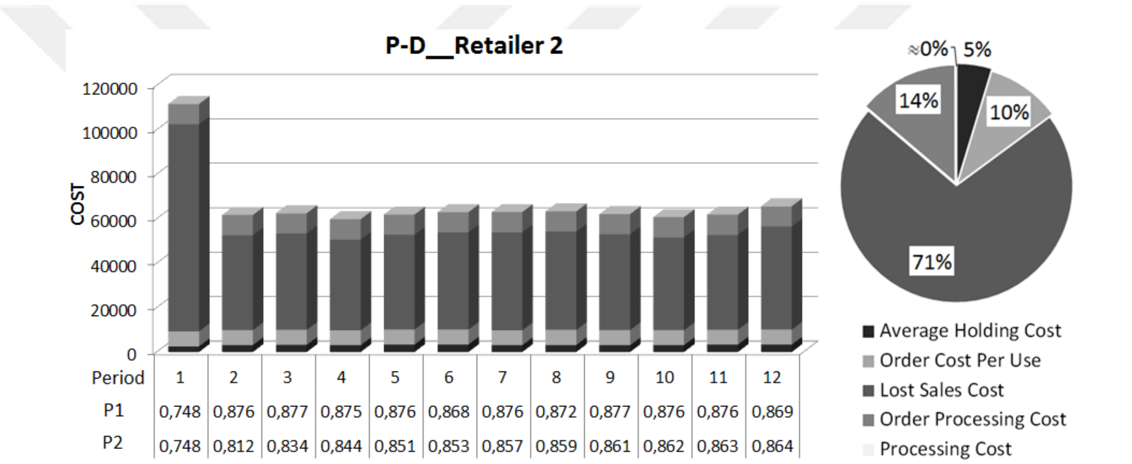
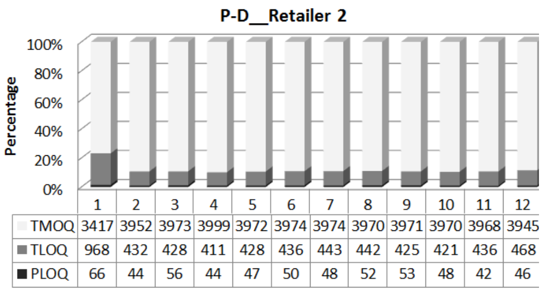


Figure 6.32 Cost based analysis and probability based analysis of Retailer 2 with P-D Model.



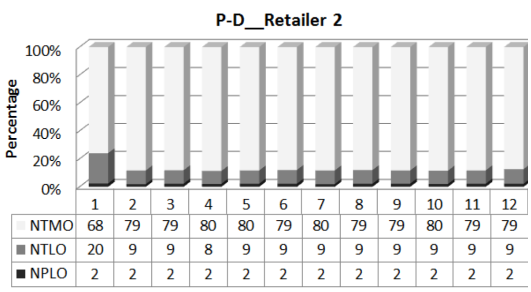


Figure 6.33 Quantity-based analysis and order-based analysis of Retailer 2 with P-D Model.

In Figure 6.32, the largest share in the pie chart is the lost sales cost (71%) and the smallest share in the pie chart is the processing cost (≈0). From Figure 6.33, NTMO value of Retailer 2 in P-D Model varies between 68 orders and 80 orders. The values of NTLO and NPLO are uniformly distributed over the periods except from the first period. The reason can be initial inventory level of Retailer 2 with P-D Model.

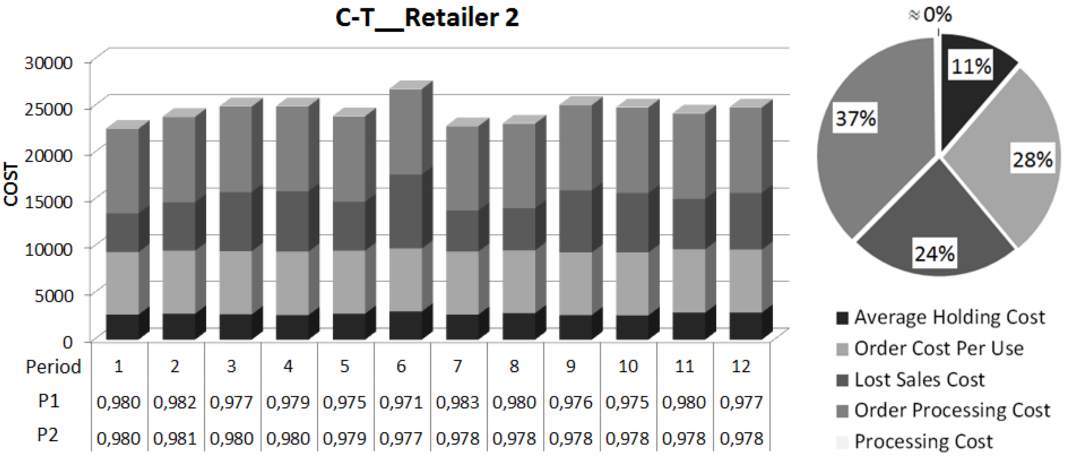


Figure 6.34 Cost based analysis and probability based analysis of Retailer 2 with C-T Model.

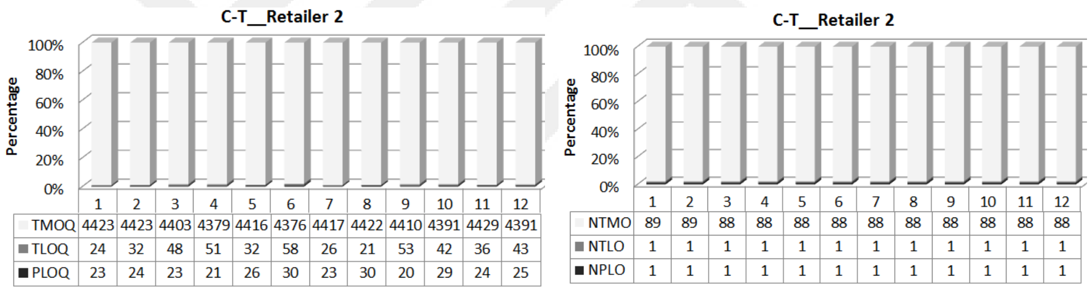


Figure 6.35 Quantity-based analysis and order-based analysis of Retailer 2 with C-T Model.

In Figure 6.34, the largest share in the pie chart is the order processing cost (37%) and the smallest share in the pie chart is the processing cost (≈0). From Figure 6.35, NTMO value of Retailer 2 with C-T Model varies between 88 orders and 89 orders. The values of NTLO and NPLO of Retailer 2 with C-T Model are both uniformly distributed over the periods.

In Figure 6.36, the largest share in the pie chart is the order processing cost (52%) and the smallest share in the pie chart is the lost sales cost (≈0). From Figure 6.37, NTMO value of Retailer 2 with C-D Model is 60 orders. The values of NTLO and NPLO of Retailer 2 with C-D Model are both zero over the periods except from period 7 whose value is one.

The share of lost sales cost with P-D model is improved at least 47% with C-T model and at most 71% with C-D model for Retailer 2. C-D model can be successfully used for Retailer 2 to improve responsiveness.

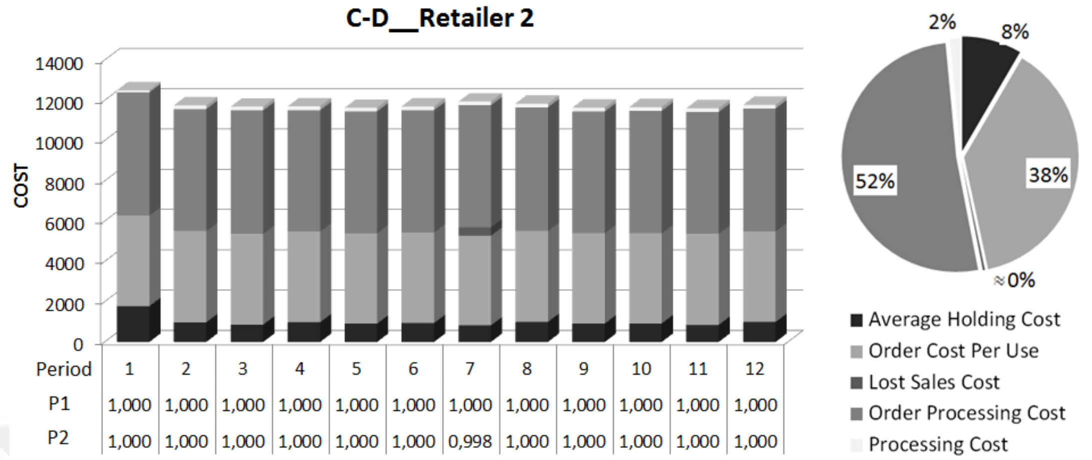


Figure 6.36 Cost based analysis and probability based analysis of Retailer 2 with C-D Model.

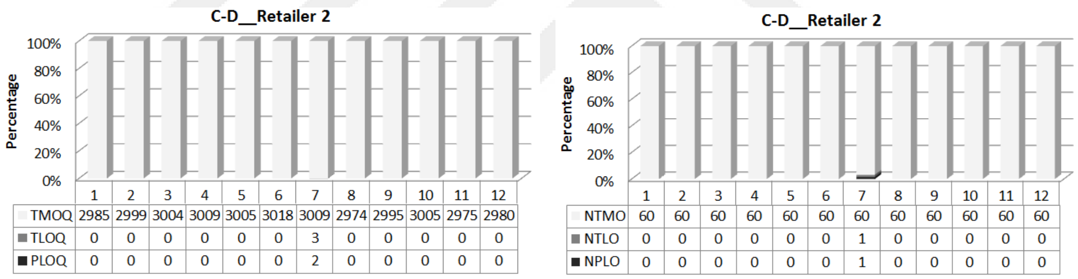


Figure 6.37 Quantity-based analysis and order-based analysis of Retailer 2 with C-D Model.

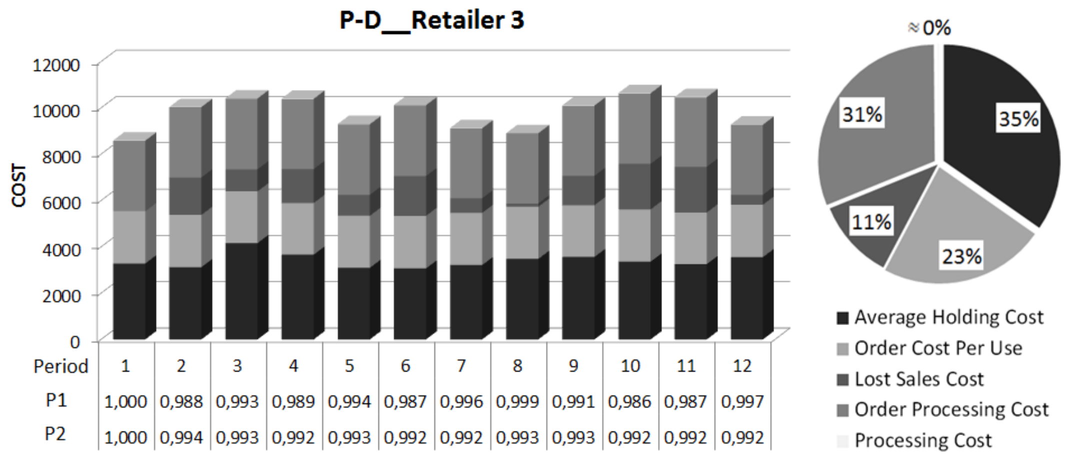


Figure 6.38 Cost based analysis and probability based analysis of Retailer 3 with P-D Model.

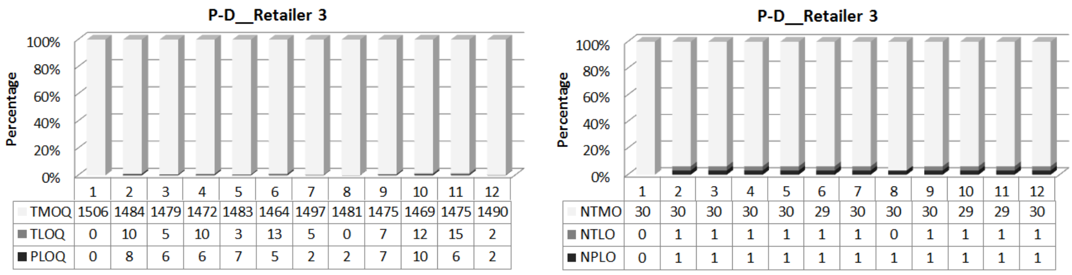


Figure 6.39 Quantity-based analysis and order-based analysis of Retailer 3 with P-D Model.

In Figure 6.38, P1 and P2 values of Retailer 3 with P-D Model can be said to be uniformly distributed over the periods. The largest share in the pie chart is the average holding cost (35%) and the smallest share in the pie chart is the processing cost (≈0). From Figure 6.39, NTMO values of Retailer 3 with P-D Model vary between 29 orders and 30 orders.

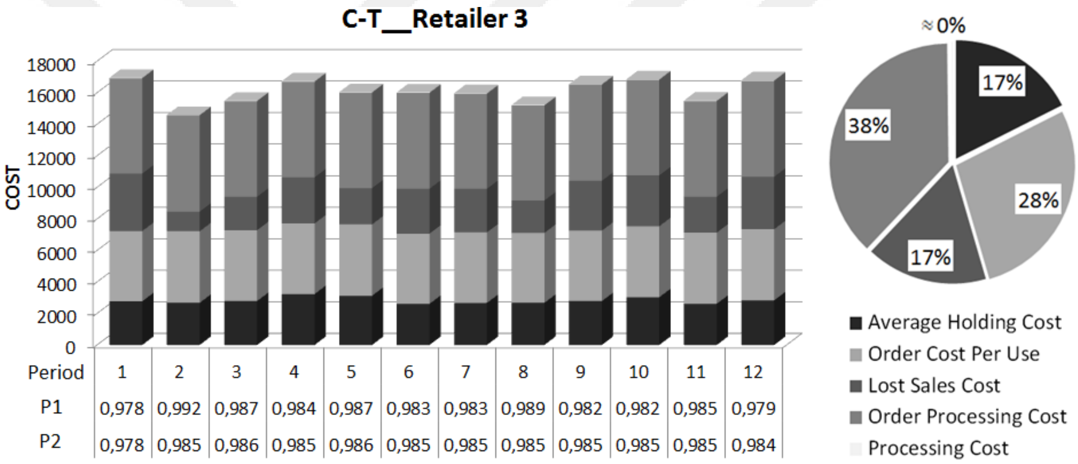


Figure 6.40 Cost based analysis and probability based analysis of Retailer 3 with C-T Model.

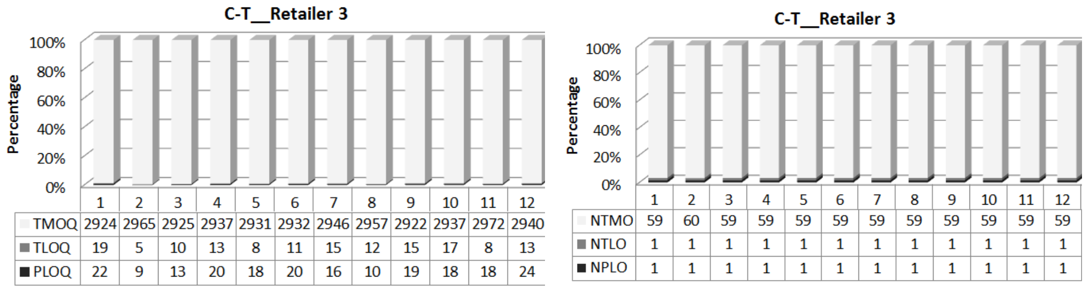


Figure 6.41 Quantity-based analysis and order-based analysis of Retailer 3 with C-T Model.

In Figure 6.40, the largest share in the pie chart is the order processing cost (38%) and the smallest share in the pie chart is the processing cost (≈0). From Figure 6.41, NTMO values of Retailer 3 with C-T Model vary between 59 orders and 60 orders.

The values of NTLO and NPLO of Retailer 3 with C-T Model is one over the periods but the values of TLOQ and PLOQ vary according to the periods.

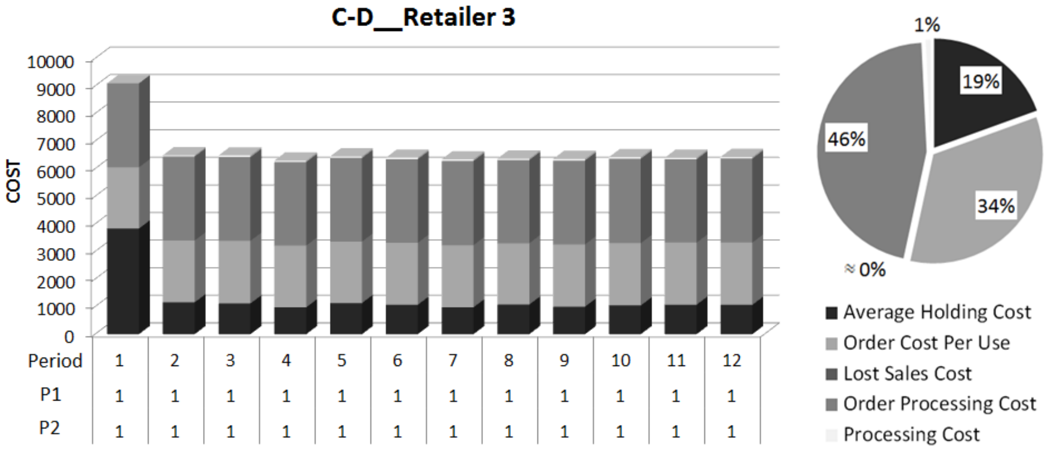


Figure 6.42 Cost based analysis and probability based analysis of Retailer 3 with C-D Model.

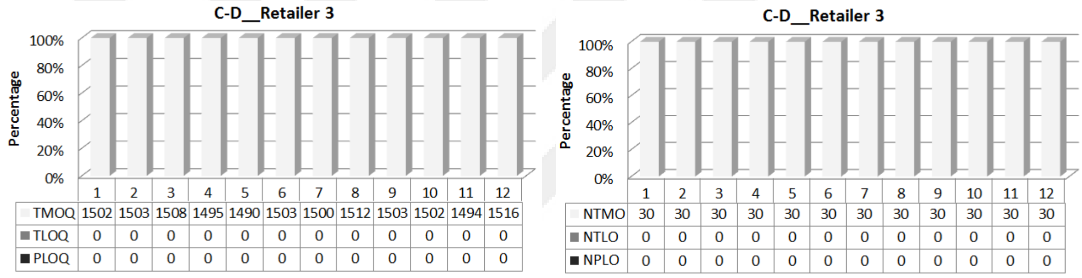


Figure 6.43 Quantity-based analysis and order-based analysis of Retailer 3 with C-D Model.

In Figure 6.42, the largest share in the pie chart is the order processing cost (46%) and the smallest share in the pie chart is the lost sales cost (≈0). From Figure 6.43, NTMO values of Retailer 3 with C-T Model are all 30 orders over the periods. All incoming orders are met and therefore the values of TLOQ, PLOQ, NTLO, and NPLO are all zero. Also, both P1 and P2 values are 1 for Retailer 3 with C-D Model.

The share of lost sales cost with C-T model is improved at least 6% with P-D model and at most 17% with C-D model for Retailer 3. C-D model can be successfully used for Retailer 3 to meet the all incoming orders.

In Figure 6.44, the largest share in the pie chart is the lost sales cost (79%) and the smallest share in the pie chart is the processing cost (≈0). From Figure 6.45, NTMO values of Retailer 4 with P-T Model vary between 46 orders and 53 orders over the periods. The values of TLOQ, PLOQ, NTLO, and NPLO with P-T Model are high when compared with C-D model for Retailer 4. Therefore, C-D model can be used to decrease partially and totally lost orders of Retailer 4.

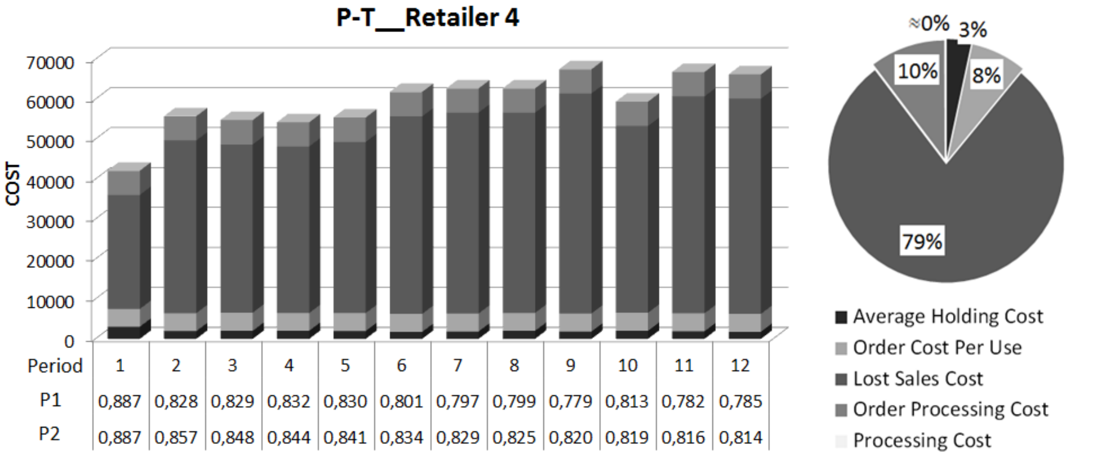


Figure 6.44 Cost based analysis and probability based analysis of Retailer 4 with P-T Model.

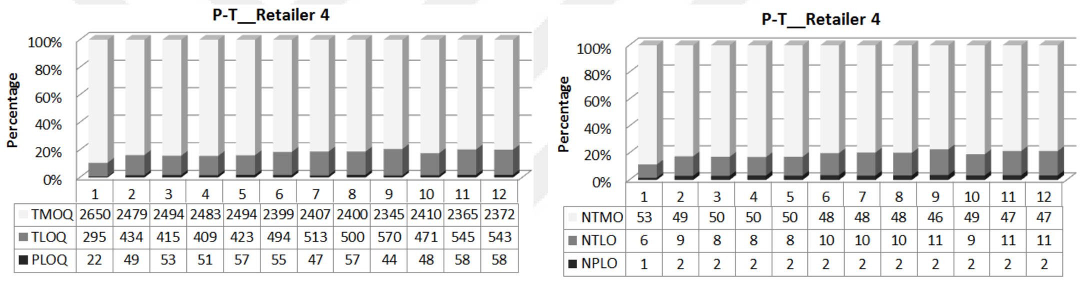


Figure 6.45 Quantity-based analysis and order-based analysis of Retailer 4 with P-T Model.

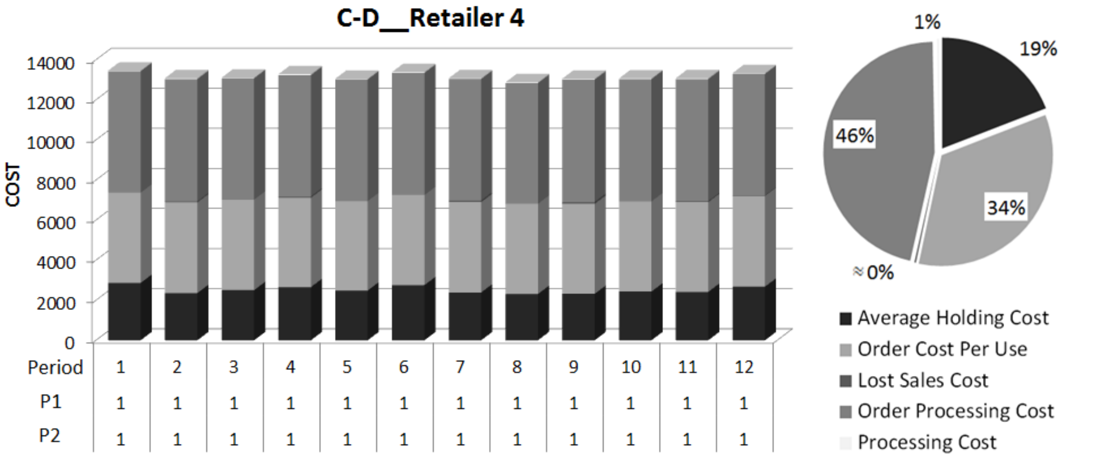


Figure 6.46 Cost based analysis and probability based analysis of Retailer 4 with C-D Model.

In Figure 6.45, the largest share in the pie chart is the order processing cost (46%) and the smallest share in the pie chart is the lost sales cost (≈0). From Figure 6.46, NTMO values of Retailer 4 with C-D Model are all 60 orders over the periods. All incoming orders are met and therefore the values of TLOQ, PLOQ, NTLO, and NPLO are all zero. Also, both P1 and P2 values are 1 for Retailer 4 with C-D Model.

The share of lost sales cost with P-T model is improved 79% with C-D model for Retailer 4. Thus, C-D model can be successfully used for Retailer 4 to meet the all incoming orders.

6.4.2 Reverse Network Analysis

The growing need for product recovery due to the increasing economic gains while protecting the environment requires companies to consider a reverse network in their SCs. In our proposed SC, the reverse network begins with collection center that is used to collect the returned products from customers. Since customer demands are stochastic, the occurrence of returned products is stochastic.

The analysis of collection center 1 (C1) and collection center 2 (C2) including a number of incoming products per period and the quantity of incoming products per period are given in Table 6.6 and Table 6.7. It is seen that the number and the quantity of incoming products over twelve periods vary with respect to model types and collection centers. The total number of incoming products is at least 893 units (C-D model for C2) and at most 902 units (C-D model for C1). Also, the total quantity of incoming products is at least 13821 units (C-D model for C2) and at most 14003 units (C-D model for C1).

The analysis of disassembly center 1 (D2) and disassembly center 2 (D2) including number of incoming products per period, quantity of incoming products per period, and quantity of disposed products per period are given in Table 6.8, Table 6.9 and Table 6.10 respectively. The total number of incoming orders is at least 886 units (C-D model for D1) and at most 899 units (C-D model for D2). Also, the total quantity of incoming products is at least 8486 units (C-D model for D1) and at most 8610 units (C-D model for D2). The total quantity of disposed products varies between 2463 and 2499 units.

Table 6.6 Number of incoming products for C1 and C2.

Period	P-T		P-D		C-T		C-D	
	C1	C2	C1	C2	C1	C2	C1	C2
1	74	71	72	73	72	74	73	72
2	74	76	77	73	74	77	77	74
3	74	76	76	74	75	75	76	74
4	77	74	75	75	76	74	73	77
5	73	77	75	75	74	76	77	74
6	76	74	75	75	74	76	76	74
7	77	73	74	76	75	75	74	76
8	76	75	74	76	75	75	74	76
9	73	77	76	74	77	74	77	73
10	74	76	75	75	74	75	75	75
11	75	75	76	74	75	75	77	73
12	76	74	74	75	75	75	74	76

Table 6.7 Quantity of incoming products for C1 and C2.

Period	P-T		P-D		C-T		C-D	
	C1	C2	C1	C2	C1	C2	C1	C2
1	1149	1102	1116	1128	1110	1131	1138	1109
2	1157	1183	1192	1134	1144	1187	1187	1141
3	1154	1158	1185	1146	1163	1156	1187	1141
4	1186	1139	1154	1165	1170	1139	1137	1187
5	1135	1196	1158	1165	1139	1186	1187	1140
6	1178	1147	1163	1168	1141	1184	1171	1152
7	1183	1148	1146	1190	1165	1166	1151	1185
8	1171	1156	1153	1168	1167	1157	1147	1179
9	1129	1195	1181	1152	1194	1134	1196	1129
10	1147	1177	1162	1154	1153	1167	1167	1156
11	1176	1152	1184	1146	1173	1161	1184	1131
12	1182	1148	1158	1170	1157	1167	1151	1171

Table 6.8 Number of incoming products for D1 and D2.

Period	P-T		P-D		C-T		C-D	
	D1	D2	D1	D2	D1	D2	D1	D2
1	70	66	68	67	68	68	67	68
2	73	76	75	75	76	74	74	77
3	75	75	76	75	74	76	75	75
4	73	77	75	75	73	77	74	77
5	74	77	76	74	74	76	75	74
6	74	75	76	75	75	76	73	76
7	75	75	76	74	74	76	72	79
8	74	76	76	74	76	74	75	75
9	76	73	75	74	77	73	77	73
10	75	75	74	77	74	76	74	76
11	75	76	72	78	74	76	74	76
12	78	72	76	75	77	73	76	74

Table 6.9 Quantity of incoming products for D1 and D2.

Period	P-T		P-D		C-T		C-D	
	D1	D2	D1	D2	D1	D2	D1	D2
1	672	629	652	644	648	645	638	659
2	707	729	719	715	722	715	708	735
3	717	713	723	711	704	729	717	715
4	696	740	720	714	698	729	705	735
5	708	736	726	711	712	724	725	709
6	709	717	725	715	716	725	702	731
7	722	719	723	709	710	725	690	761
8	705	729	732	710	727	709	715	715
9	728	705	723	711	738	694	740	695
10	717	716	697	732	711	728	711	728
11	718	727	695	745	714	725	709	716
12	743	689	724	717	732	702	726	711

Table 6.10 Quantity of disposed products for D1 and D2.

Period	P-T		P-D		C-T		C-D	
	D1	D2	D1	D2	D1	D2	D1	D2
1	196	182	190	187	188	188	186	191
2	206	213	208	207	209	207	204	214
3	210	206	209	206	205	212	208	209
4	202	215	209	206	203	212	205	214
5	204	212	211	207	207	211	210	204
6	207	209	210	208	208	210	204	213
7	210	210	210	206	207	211	201	220
8	204	212	214	205	212	206	208	207
9	211	204	209	206	214	201	215	203
10	209	207	204	211	205	210	205	212
11	208	212	200	217	207	210	206	209
12	218	201	209	207	213	205	211	205

Incoming products are disassembled in D1 and D2 according to the BOM structure that is given in Figure 6.3, and then reusable components are sent to refurbishing center 1 (R1) and refurbishing center 2 (R2) where components are tested and refurbished. Analysis of refurbishing centers is given in Table 6.11 and Table 6.12 where the number of incoming components per period and the quantity of incoming components per period are given. The total number of incoming components over periods varies between 880 units and 893 units while the total quantity of incoming components over periods varies between 50550 units and 51294 units. Note that, 50550 components composed of the components A, B, and C in accordance with the ratios given in BOM structure. Also, some additional statistics for reverse flow are given in Appendix B.

Table 6.11 Number of incoming components for R1 and R2.

Period	P-T		P-D		C-T		C-D	
	R1	R2	R1	R2	R1	R2	R1	R2
1	63	59	61	61	61	61	61	62
2	75	76	76	75	76	74	74	77
3	73	76	75	75	74	76	76	74
4	73	77	75	75	74	76	73	77
5	74	77	75	75	74	77	75	75
6	75	75	76	74	75	75	75	75
7	75	75	76	74	74	76	71	79
8	73	77	76	73	75	75	74	76
9	77	73	75	75	77	72	77	73
10	75	75	74	76	75	75	74	76
11	76	75	71	79	74	76	76	75
12	77	72	75	75	76	74	75	75

Table 6.12 Quantity of incoming components for R1 and R2.

Period	P-T		P-D		C-T		C-D	
	R1	R2	R1	R2	R1	R2	R1	R2
1	3654	3384	3516	3504	3498	3486	3468	3576
2	4314	4332	4356	4254	4356	4284	4230	4422
3	4230	4350	4320	4278	4212	4368	4332	4260
4	4176	4428	4308	4296	4224	4368	4212	4416
5	4248	4404	4332	4314	4230	4404	4314	4266
6	4296	4284	4380	4266	4308	4302	4272	4338
7	4284	4338	4344	4266	4278	4350	4122	4560
8	4218	4398	4416	4206	4314	4308	4278	4380
9	4410	4206	4302	4314	4446	4140	4428	4146
10	4278	4326	4248	4344	4320	4326	4248	4368
11	4356	4296	4128	4488	4278	4380	4332	4260
12	4416	4128	4326	4338	4320	4236	4314	4302

6.4.3 Lead Time-Based Analysis

The purpose of this section is to analyze the lead time related statistics more in-depth to provide more useful information. 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 these statistics. Note that, at some periods there will be no replenishment orders for both Plants and Retailers and denoted as “-” in following sections.

6.4.3.1 Analysis of Average Holding Unit

Table 6.13-Table 6.14 summarizes the average holding unit that is held at both Plants and Retailers during the lead time periods. Considering all Plants with all types of models the average holding unit varies between 10 units and 348 units. However, the average holding unit of Retailers varies between 0 unit and 217 units. The minimum value of total average holding unit over periods is observed at Plant 3 with C-D Model (i.e., 115 units) and the maximum value of total average holding unit over periods is observed at Plant 2 with C-D Model (i.e., 3993 units).

Also, the minimum amount of average holding unit is observed at Retailer 1 with P-T model (i.e., 53 units) and the maximum value is observed at Retailer 2 with C-D Model (i.e., 2527 units).

Table 6.13 Plants’ average holding units over periods.

Period	Plant 1				Plant 2			Plant 3		Plant 4	
	P-T	P-D	C-T	C-D	P-D	C-T	C-D	P-T	C-D	P-T	P-D
1	-	95	50	50	-	143	348	-	-	-	-
2	90	227	127	88	100	173	326	180	-	237	84
3	112	225	168	93	100	178	334	96	10	191	86
4	110	228	166	91	113	172	330	92	12	210	87
5	116	235	161	99	129	180	333	-	12	207	80
6	107	229	154	97	142	193	336	93	11	218	73
7	124	228	151	89	109	185	326	52	13	198	79
8	106	233	160	93	126	178	336	104	12	197	82
9	111	224	168	101	139	179	333	-	11	210	78
10	115	232	159	101	131	174	326	96	12	188	78
11	110	240	153	93	121	179	326	78	12	197	79
12	120	232	162	96	128	179	338	99	10	219	74

Table 6.14 Retailers' average holding units over periods.

Period	Retailer 1		Retailer 2				Retailer 3			Retailer 4	
	P-T	P-D	P-T	P-D	C-T	C-D	P-D	C-T	C-D	P-T	C-D
1	0	129	61	0	160	212	170	124	-	0	211
2	4	12	101	13	171	210	3	143	156	13	205
3	6	67	99	9	167	213	85	128	156	9	209
4	4	44	107	9	162	205	96	125	155	11	204
5	4	42	102	8	183	214	128	133	161	7	217
6	7	53	86	7	160	210	95	126	157	4	208
7	3	60	102	7	177	207	150	132	153	4	200
8	5	50	127	6	171	217	121	131	153	3	202
9	5	52	96	7	170	214	123	118	153	2	208
10	3	37	123	8	167	205	115	119	156	4	212
11	6	40	95	10	155	210	107	133	155	7	206
12	6	47	113	7	164	208	137	127	153	2	211

6.4.3.2 Analysis of Lead Time Over Periods

The minimum length of the lead time period for Plants is observed at Plant 3 with P-T Model (i.e., 0.43 hours of related review period) and the maximum length of lead time is observed at Plant 2 with C-T Model (i.e., 205.56 hours of related review period) (Table 6.15). Also, the minimum length of the lead time period for Retailers is observed at Retailer 2 with C-D Model (i.e., 37.69 hours of related review period) and the maximum length of the lead time period is observed at Retailer 2 with P-T Model (i.e., 71.62 hours of related review period) (Table 6.16). The total length of lead time over 12 periods for Plants varies between 474.3 hours (P-D Model for Plant 2) and 2167.14 hours (C-T Model for Plant 2). For Retailers, the total length of lead time over 12 periods vary between 484.27 hours (Retailer 2 with C-D Model) and 833.96 hours (Retailer 2 with P-T Model). Such a large gap between minimum and maximum values shows the importance of taking stochastic behavior of the system into account.

Table 6.15 Average lead time lengths for Plants.

Period	Plant 1				Plant 2			Plant 3		Plant 4	
	P-T	**P-D**	**C-T**	**C-D**	**P-D**	**C-T**	**C-D**	**P-T**	**C-D**	**P-T**	**P-D**
1	-	86.75	179.28	139.38	-	205.56	38.19	-	-	-	-
2	68.060	91.64	168.44	109.85	70.34	171.58	45.73	109.14	-	53.80	69.97
3	107.42	91.75	163.97	125.91	33.39	188.74	48.71	2.8800	56.46	55.83	79.79
4	101.09	97.89	159.89	122.42	44.96	169.56	47.51	104.02	64.78	52.33	43.53
5	102.23	89.60	151.89	126.13	41.43	187.80	48.05	-	63.56	34.99	76.82
6	101.96	91.77	156.37	120.81	46.87	161.95	46.74	99.410	65.75	44.66	80.00
7	101.63	87.15	158.05	124.50	41.43	184.51	49.70	3.1200	68.25	53.42	72.65
8	102.59	89.26	151.99	122.92	45.15	183.71	45.11	79.340	66.34	44.49	64.57
9	101.67	92.71	156.47	121.66	34.94	190.28	47.94	-	64.39	35.00	70.61
10	104.55	96.27	155.41	120.13	37.90	166.77	49.48	105.80	69.24	47.37	62.02
11	102.08	83.09	152.26	125.49	46.38	176.44	49.29	0.4300	69.43	40.22	67.54
12	99.790	93.54	148.42	116.39	31.49	180.23	46.54	86.760	66.08	52.49	72.91

Table 6.16 Average lead time lengths for Retailers.

Period	Retailer 1		Retailer 2				Retailer 3			Retailer 4	
	P-T	P-D	P-T	P-D	C-T	C-D	P-D	C-T	C-D	P-T	C-D
1	63.43	55.01	68.72	43.50	46.98	40.67	45.42	49.07	-	57.39	41.74
2	62.71	54.25	69.53	42.79	46.15	40.75	47.47	49.08	66.50	57.03	43.45
3	64.36	55.22	68.85	44.52	47.26	41.46	43.98	49.46	67.85	57.46	42.53
4	64.19	54.77	68.70	43.36	47.90	40.15	45.81	49.21	67.42	58.42	43.18
5	62.31	54.94	69.45	42.65	48.07	41.55	44.83	48.88	66.10	57.78	42.99
6	60.86	54.96	68.58	42.59	48.03	40.33	46.11	49.23	66.77	59.60	42.04
7	63.07	54.26	71.50	42.89	47.60	40.28	45.63	48.79	66.82	57.90	42.99
8	63.65	54.50	71.62	42.39	47.87	37.69	42.68	48.64	67.11	60.42	40.95
9	64.07	53.89	69.36	42.54	47.42	41.63	44.92	49.10	68.45	58.32	42.11
10	63.15	54.69	69.56	43.07	47.35	39.40	46.78	49.24	67.41	58.10	40.67
11	63.59	55.43	68.44	42.59	46.91	40.67	47.29	49.21	67.12	57.43	42.62
12	64.27	55.59	69.67	43.61	47.75	39.68	45.78	49.05	66.57	56.89	42.17

6.4.3.3 Analysis of Order Met Probability

In this part, statistical analysis is extended by calculating order met probabilities per lead time period which is one of the most significant statistics. From Table 6.17 it is clearly seen that order met probabilities per lead time period are generally high for almost all Plants. The order met probability per lead time period for Plants is at most 1 which means that 100% of incoming orders met during the lead time period. The minimum order met probability per lead time period for Plants is observed at Plant 4 with P-T Model as 0.673 which means that 32.7% of incoming orders lost during the lead time period. From Table 6.18 it is clearly seen that the order met probability per lead time period for Retailers is at least 0.032 (P-D Model for Retailer 2) and at most 1. It can be said that order met probability per lead time period should be improved for some Retailers to increase the customer satisfaction. High order met probabilities during lead time can be achieved by using continuous review policy (especially the C-D Model) for Retailers.

Controlling inventory during the lead time period is a crucial foundation for achieving both strategic and tactical success in inventory management. On the other hand, modeling of inventory control system in a stochastic environment needs too much computational effort to solve and sometimes they are not solvable in a reasonable time. Therefore, we used SO model to provide a significant opportunity to respond effectively to dynamic and stochastic problems. The results of the study show that increasing diversity in customer expectations can easily be satisfied using our proposed model since proposed models generally ensure a high level of responsiveness.

Table 6.17 Average order met probabilities per lead time period for all Plants.

Period	Plant 1				Plant 2			Plant 3		Plant 4	
	P-T	P-D	C-T	C-D	P-D	C-T	C-D	P-T	C-D	P-T	P-D
1	-	0.889	1.000	1.000	-	1.000	1.000	-	-	-	-
2	0.840	0.858	1.000	1.000	1.000	1.000	0.964	1.000	-	1.000	0.960
3	0.685	0.858	1.000	1.000	1.000	1.000	0.974	1.000	1.000	1.000	0.950
4	0.685	0.858	1.000	1.000	1.000	1.000	0.993	1.000	1.000	1.000	1.000
5	0.685	0.858	1.000	1.000	1.000	1.000	1.000	-	1.000	1.000	0.953
6	0.685	0.858	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.953
7	0.685	0.858	1.000	1.000	1.000	1.000	0.990	0.842	1.000	0.885	0.953
8	0.685	0.858	1.000	1.000	1.000	1.000	0.988	0.953	1.000	0.947	0.950
9	0.685	0.858	1.000	1.000	1.000	1.000	0.985	-	1.000	1.000	1.000
10	0.685	0.858	1.000	1.000	1.000	1.000	0.973	0.908	1.000	0.673	0.953
11	0.685	0.858	1.000	1.000	1.000	1.000	0.982	1.000	1.000	1.000	0.953
12	0.685	0.858	1.000	1.000	1.000	1.000	0.999	0.908	1.000	1.000	0.953

Table 6.18 Average order met probabilities per lead time period for all Retailers.

Period	Retailer 1		Retailer 2				Retailer 3			Retailer 4	
	P-T	P-D	P-T	P-D	C-T	C-D	P-D	C-T	C-D	P-T	C-D
1	0.051	1.000	0.900	0.032	0.905	0.999	1.000	0.941	-	0.065	1.000
2	0.145	0.455	0.954	0.207	0.931	0.992	0.328	0.938	1.000	0.259	0.998
3	0.163	0.802	0.987	0.165	0.885	1.000	0.898	0.915	1.000	0.227	1.000
4	0.114	0.802	0.995	0.147	0.964	0.996	0.851	0.932	1.000	0.229	1.000
5	0.106	0.838	0.957	0.128	0.910	1.000	0.909	0.915	1.000	0.209	1.000
6	0.123	0.795	0.980	0.123	0.929	1.000	0.805	0.940	1.000	0.087	1.000
7	0.093	0.877	0.970	0.192	0.938	0.992	0.917	0.905	1.000	0.079	1.000
8	0.124	0.856	0.983	0.143	0.956	1.000	0.917	0.915	1.000	0.079	1.000
9	0.141	0.869	0.911	0.146	0.925	0.996	0.861	0.929	1.000	0.054	1.000
10	0.098	0.741	0.981	0.142	0.927	1.000	0.818	0.911	1.000	0.107	1.000
11	0.128	0.774	0.948	0.200	0.966	0.992	0.826	0.931	1.000	0.179	1.000
12	0.154	0.806	0.947	0.142	0.934	1.000	0.941	0.927	1.000	0.138	0.999

6.5 Conclusion

To integrate the forward network and reverse network, we designed SO models that capture many issues concerning with complex real-world problems simultaneously. Due to its ability to mitigate difficulties, SO has become a remarkable option to establish a reliable network of CLSC under today’s stringent pressures. In this study, optimizing inventory level and determining appropriate CLSC member to be opened is considered to improve the performance of the CLSC network. We used four suppliers, four plants, four retailers, two collection centers, two disassembly centers, two refurbishing centers to give a detailed analysis of CLSC network but this does not limit the model's practical usefulness and could be applicable to different kinds of network problems.

Numerical results show that proposed SO model has a significant potential to handle data uncertainty and provides an important guide to researchers and managers throughout the decision-making process. According to the cost analysis, the TCC of P-T model can be improved approximately 11%, 20%, and 22% with P-D model, C-T model, and C-D model, respectively. In addition, the TCC of P-D model can be improved approximately 10% and 12% with C-T model and C-D model, respectively. The TCC of C-T model can be improved approximately 3% with C-D model.

According to the quantity-based analysis, the total value of PLOQ with P-T model can be improved approximately 40%, 68%, and 76% with P-D model, C-D model, and C-T model, respectively. In addition, the total value of PLOQ with P-D model can be improved approximately 47% and 59% with C-D model and C-T model, respectively. The total value of PLOQ with C-D model can be improved approximately 23% with C-T model.

According to the quantity-based analysis, the total value of TLOQ with P-T model can be improved approximately 48%, 95%, and 99.98% with P-D model, C-T model, and C-D model, respectively. In addition, the total value of TLOQ with P-D model can be improved approximately 90% and 99.96% with C-T model and C-D model, respectively. The total value of TLOQ with C-T model can be improved approximately 99.57% with C-D model.

According to the order-based analysis, the total value of NPLO with P-T model can be improved approximately 23%, 62%, and 66% with P-D model, C-T model, and C-D model, respectively. In addition, the total value of NPLO with P-D model can be improved approximately 50% and 57% with C-T model and C-D model, respectively. The total value of NPLO with C-T model can be improved approximately 12% with C-D model.

According to the order-based analysis, the total value of NTLO in P-T model can be improved approximately 47%, 95%, and 99.57% with P-D model, C-T model, and C-D model, respectively. In addition, the total value of NTLO in P-D model can be improved approximately 90% and 99% with C-T model and C-D model, respectively. The total value of NTLO in C-T model can be improved approximately 92% with C-D model.

During the lead time periods, the minimum amount of average holding unit is observed at Retailer 1 with P-T model (i.e., 53 units) and the maximum value is observed at Retailer 2 with C-D Model (i.e., 2527 units). According to the lead time analysis, The minimum length of the lead time period for Plants is observed at Plant 3 with P-T Model (i.e., 0.43 hours of related review period) and the maximum length of lead time is observed at Plant 2 with C-T Model (i.e., 205.56 hours of related review period).

For Plants maximum order met probability during lead time is 1, and the minimum order met probability per lead time period for Plants is observed at Plant 4 with P-T Model as 0.673. The order met probability per lead time period for Retailers is at least 0.032 (P-D Model for Retailer 2) and at most 1.

In conclusion, the result of this study can convince the majority of researchers and managers to make use of SO model due to the high service level. In addition, proposed SO model can easily be adapted to various problems because it is developed as generic as possible to increase its applicability.

CHAPTER 7

CONCLUSION

This chapter summarizes the main results of the thesis, and highlights the main contributions of the thesis. Furthermore, the potential of future studies is included.

7.1 Summary and Concluding Remarks

The main objective of this study is to develop more flexible and responsive SO for SC problems. This study provides to gain a better understanding of dynamic, complex and uncertain SC environment. In the thesis, GA is used to determine decision variables for related SC problems and, a simulation model is created to evaluate these decision variables. The details of proposed SO are given in Chapter 4.

In Chapter 5, a forward SC problem is handled which consists of suppliers, DCs and customers. Inventory control parameters for each DC and each selected suppliers (e.g., initial inventory, reorder point, and order-up-to level) are determined, and suppliers are selected for each DCs. The simulation model is designed for both periodic inventory control policy and continuous inventory control policy. Inventory replenishment systems are taken into account for both DCs and suppliers. Demands, processing times, order processing times, and transportation times are drawn from some specific probability distributions. In addition, several cost parameters are determined by using probability distributions such as average holding cost, lost sales cost, processing cost, order processing cost, and transportation cost.

Two objective functions are used to optimize decision variables, namely the TSCC and the difference between the overordering cost and the underordering cost. The GA and simulation model is run separately for each objective function. Hence, how the system performance metrics affected by both objective functions are analyzed, separately.

According to the computational results, lost sale cost with continuous review policy and TSCC as objective function is less (46%) than other models. It is observed that the model gave better results with the difference between the overordering cost and the underordering cost within periodic review models (33% better than periodic review model with TSCC as the objective function). Moreover, order met probabilities are higher for nearly all SC members with continuous review policies. Similarly, totally met order quantities are higher for continuous review policies.

A CLSC problem is considered in Chapter 6. The problem includes a forward chain, which consists of suppliers, plants, retailers, and customers, and a reverse chain, which consists of collection centers, disassembly centers, refurbishing centers and disposal centers. SO is used to determine which plant/retailer should be opened. And, initial inventory, reorder point, and order up to quantity is determined for both plants and retailers. Additionally, plants' component inventory levels are optimized. Whenever the component inventory level decreases to this level, suppliers send components to the plants. CLSC network produces a single type end-product which consist of three type of components. Customer demands, return rates, processing times, order processing times, transfer times are generated from some specific probability distributions. Also, cost parameters such as fixed opening cost for plants/retailers, lost sales cost, holding cost, purchasing cost from suppliers/collection centers/refurbishing centers, and transportation cost are drawn from probability distributions.

Similar to the forward SC problem, two objective functions are used to optimize decision variables, namely the TCC and the difference between the overordering cost and the underordering cost.

According to the computational results, there is a significant difference between total cost and difference cost for both continuous review and periodic review policies. Minimum total cost is obtained by continuous review policy with difference cost. For C-D model, largest share is the purchasing cost from suppliers. Lost sales cost is the largest share (29%) for P-T model. For C-D model, total purchasing cost from suppliers is the largest share (29.87%).

Lead time-based analysis has a significant importance to give a different point of view about the system behavior. The minimum average holding unit during lead time periods (53 units) is observed at Retailer 1 with P-T model, and the maximum value is observed at Retailer 2 with C-D model.

The minimum length of lead time period for plants is observed at Plant 3 with P-T model (i.e., 0.43 hours of related review period) and the maximum length of lead time is observed at Plant 2 with C-T Model (i.e., 205.56 hours of related review period). And, the minimum length of lead time period for Retailers is observed at Retailer 2 with C-D model (i.e., 37.69 hours of related review period) and the maximum value is observed at Retailer 2 with C-D Model (i.e., 2527 units). According to the analysis of order met probabilities, almost all Plants have high order met probabilities. Least order met probability is observed at Retailer 2 for P-D model (i.e., 0.032).

7.2 Contributions of the Thesis

This study is added to a practical knowledge of SO based inventory management and compared review models to make companies closer towards achieving business excellence.

Firstly, as the current literature provides several solution methodologies in order to solve such FSCPs and CLSCPs with no or only a few parameters stochastic. In this thesis, problems are evaluated in a stochastic and dynamic environment (discrete-event simulation) while decision variables are determined by using GA. Moreover, modelling process is expedited by using several envisaged objects for SC members. This provides to create a simulation model for such a complex and dynamic environment in a more easy way.

Secondly, to understand better the scope of review models and opportunities associated with inventory management, we give a detailed analysis of review models. The analysis composed of cost-based analysis, probability-based analysis, and order-based analysis for all SC members for both forward SC and CLSC problems. This provides to understand how the whole system and its members behave under different conditions.

Finally, the study provides comprehensive analysis on the important decision of whether minimizing total SC/CLSC cost over periods or minimizing difference between overordering cost and underordering cost for each inventory review policy.

To the best of our knowledge, this study aims to determine how many and which supplier should be chosen or plants/retailers should be opened, and how the optimal parameters of periodic/continuous review system are determined in stochastic and dynamic SC/CLSC problems for the first time. Proposed SO model provides a remarkable contribution to manage, set, and meet expectation about today's FSCPs/CLSCPs.

7.3 Future Research Directions

Although SO models have the ability to extract dynamics of the system considered, this study has some limitations. Some future studies can be given as follows:

- Poisson distribution is only used with a rate parameter of 50. Proposed SO models should be compared with different demand rates to determine how they affect the whole SC.
- The review period is fixed in periodic (s, S) models. At this point, GA can be used to optimize review period which may affect the performances of SO models.
- The other good direction for future research would be to consider other metaheuristics such as harmony search and particle swarm optimization to compare the performance of the proposed models.

The study shall also be of great value to researchers to extend their research avenues into this exciting area.

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APPENDIX A. Transfer Times (days) for CLSCP

Table A1. Transfer times between plants and retailers

	Retailer 1	Retailer 2	Retailer 3	Retailer 4
Plants 1	Uniform(2,3)	Uniform(1.33,2)	Uniform(1.8,2)	Uniform(1.25,2)
Plants 2	Uniform(2,2.5)	Uniform(1.66,2)	Uniform(1.5,2)	Uniform(2.25,3)
Plants 3	Uniform(3,3.5)	Uniform(2.5,3)	Uniform(2.3,3)	Uniform(2.5,3)
Plants 4	Uniform(2,2.25)	Uniform(2.8,3.25)	Uniform(1.8,2)	Uniform(2,2.5)

Table A2. Transfer times between plants and collection centers

	Collection center 1	Collection center 2	Refurbishing center 1	Refurbishing center 2
Plants 1	Uniform(3.75,4)	Uniform(4.25,5)	Uniform(2,3)	Uniform(3.15,4)
Plants 2	Uniform(3,3.75)	Uniform(2.5,3)	Uniform(2.5,3)	Uniform(2.8,3)
Plants 3	Uniform(3.15,4)	Uniform(2.8,3)	Uniform(1.8,2)	Uniform(2.25,3)
Plants 4	Uniform(3.8,4)	Uniform(3.5,4)	Uniform(3,4)	Uniform(2.15,2.75)

Table A3. Transfer times between customers and collection centers

	Collection center 1	Collection center 2
Customer1	Uniform(0.75,1)	Uniform(1.75,2)
Customer2	Uniform(1.25,2)	Uniform(1.5,2)
Customer3	Uniform(1.75,2)	Uniform(1,1.25)
Customer4	Uniform(1.5,2)	Uniform(1.5,2)
Customer5	Uniform(2.25,3)	Uniform(1.75,2)

Table A4. Transfer times between suppliers and plants

	Plant 1	Plant 2	Plant 3	Plant 4
Supplier 1	Uniform(1.75,2)	Uniform(2.15,3)	Uniform(1.5,2)	Uniform(2.5,3)
Supplier 2	Uniform(1.75,2)	Uniform(2.5,3)	Uniform(3,3.75)	Uniform(3.15,4)
Supplier 3	Uniform(2.25,3)	Uniform(1.25,2)	Uniform(1.5,2)	Uniform(2.5,3)
Supplier 4	Uniform(3.15,4)	Uniform(3,4)	Uniform(3.5,4)	Uniform(3.5,4)

Table A5. Transfer times between disassembly centers and collection centers

	Collection center 1	Collection center 2	Disposal	Refurbishing center 1	Refurbishing center 2
Disassembly center 1	Uniform(1.5,2)	Uniform(1.15,2)	Uniform(0.5,1)	Uniform(2.15,3)	Uniform(2.5,3)
Disassembly center 2	Uniform(1.75,2)	Uniform(1.5,2)	Uniform(1,1.75)	Uniform(1.75,2.5)	Uniform(2,3)

APPENDIX B Additional Statistics for CLSCP

Table B1. Collection cost of C1 and C2 in proposed models.

Period	P-T		P-D		C-T		C-D	
	C1	C2	C1	C2	C1	C2	C1	C2
1	3989.14	3842.60	3911.62	3979.25	3899.39	4005.71	3994.23	3867.26
2	4054.90	4135.75	4170.04	3934.87	4027.65	4138.11	4124.14	4037.10
3	4035.12	4035.78	4147.51	4026.77	4033.37	4060.28	4154.28	3991.10
4	4110.23	3996.76	4046.05	4054.92	4103.96	3968.82	3942.61	4088.99
5	3986.54	4206.05	4026.87	4089.79	4030.44	4184.55	4133.91	4021.96
6	4095.31	4008.96	4034.60	4087.84	4040.74	4115.30	4113.73	4033.07
7	4126.23	3959.95	4003.40	4166.90	4081.78	4059.64	4056.32	4181.44
8	4105.01	4053.04	4048.63	4055.81	4148.76	4060.83	4037.27	4119.44
9	3962.89	4214.10	4147.32	4049.88	4144.84	3990.60	4137.01	3938.03
10	4004.11	4130.69	4059.14	4067.50	4069.02	4072.48	4064.42	4028.76
11	4127.64	4045.83	4155.74	3986.39	4099.36	4042.06	4136.11	4004.05
12	4112.59	4004.19	4050.00	4127.30	4082.06	4079.76	3991.14	4132.73
Total	48709.70	48633.68	48800.92	48627.21	48761.37	48778.14	48885.16	48443.93

Table B2. Disassembly cost of D1 and D2 in proposed models.

Period	P-T		P-D		C-T		C-D	
	D1	D2	D1	D2	D1	D2	D1	D2
1	2352.58	2204.81	2273.19	2255.23	2263.04	2255.05	2230.72	2305.55
2	2485.19	2551.90	2523.34	2507.30	2521.29	2495.05	2478.81	2571.04
3	2510.65	2497.60	2528.62	2493.66	2464.27	2552.68	2506.97	2498.19
4	2429.59	2591.96	2515.91	2485.05	2441.25	2545.98	2470.22	2576.30
5	2477.51	2581.72	2539.67	2494.68	2501.01	2541.00	2534.71	2494.92
6	2480.97	2511.76	2541.22	2501.83	2510.56	2548.73	2453.68	2558.89
7	2520.59	2514.89	2530.24	2483.53	2489.49	2545.79	2401.31	2655.66
8	2463.86	2555.84	2560.85	2492.11	2536.71	2479.00	2505.70	2508.02
9	2549.66	2463.61	2530.89	2491.05	2578.08	2426.46	2585.20	2431.43
10	2510.76	2501.11	2446.34	2561.59	2490.10	2553.24	2486.45	2554.21
11	2521.94	2545.57	2437.45	2613.08	2497.52	2545.50	2488.81	2512.23
12	2609.37	2406.64	2532.27	2509.47	2562.26	2451.89	2538.82	2487.09
Total	29912.68	29927.42	29959.99	29888.59	29855.57	29940.36	29681.41	30153.52

Table B3. Refurbishing cost of R1 and R2 in proposed models.

Period	P-T		P-D		C-T		C-D	
	R1	R2	R1	R2	R1	R2	R1	R2
1	2126.92	1967.01	2042.77	2049.14	2044.29	2035.46	2019.47	2078.11
2	2510.26	2539.48	2537.73	2472.93	2537.66	2489.36	2465.71	2579.79
3	2474.47	2537.09	2516.51	2494.95	2447.52	2541.06	2535.91	2494.58
4	2433.02	2589.38	2517.23	2507.57	2466.27	2545.16	2451.52	2583.30
5	2470.77	2575.30	2533.69	2521.77	2473.57	2570.78	2517.35	2498.97
6	2512.48	2498.86	2552.78	2480.21	2506.89	2504.40	2483.76	2534.12
7	2502.39	2531.56	2529.00	2491.71	2492.07	2540.29	2407.45	2667.09
8	2456.44	2563.38	2569.06	2453.29	2506.66	2514.87	2495.15	2555.45
9	2567.96	2455.99	2515.27	2524.12	2592.31	2416.98	2581.10	2424.96
10	2498.83	2515.27	2478.03	2529.60	2520.81	2516.24	2474.76	2547.87
11	2537.91	2506.47	2408.74	2610.56	2504.21	2554.85	2531.73	2481.19
12	2583.08	2408.23	2517.73	2539.00	2528.30	2473.33	2509.76	2511.04
Total	29674.53	29688.03	29718.57	29674.83	29620.56	29702.78	29473.67	29956.46

Table B4. Analysis of order processing cost for C1 and C2 in proposed models.

Period	P-T		P-D		C-T		C-D	
	C1	C2	C1	C2	C1	C2	C1	C2
1	5575.64	5353.87	5399.48	5440.73	5425.53	5501.12	5523.35	5417.44
2	5557.45	5663.08	5796.65	5500.43	5530.94	5749.25	5705.47	5515.44
3	5582.96	5671.45	5742.71	5554.51	5598.32	5603.27	5675.65	5530.63
4	5755.73	5511.27	5612.46	5630.76	5696.03	5517.60	5415.34	5744.99
5	5505.56	5773.46	5650.85	5672.45	5603.07	5690.53	5697.89	5483.09
6	5648.38	5548.77	5620.55	5664.80	5525.08	5742.74	5653.21	5593.77
7	5747.93	5438.08	5516.06	5752.44	5584.73	5638.23	5551.86	5702.49
8	5689.37	5631.60	5607.31	5673.62	5691.58	5611.54	5559.03	5624.88
9	5433.14	5827.49	5739.94	5530.90	5765.27	5540.25	5745.88	5441.13
10	5511.74	5707.67	5612.45	5627.03	5590.71	5613.85	5657.24	5557.15
11	5626.15	5629.49	5684.81	5537.97	5615.94	5608.63	5783.17	5504.93
12	5694.80	5580.99	5610.50	5671.03	5647.06	5616.92	5557.58	5688.93
Total	67328.86	67337.21	67593.76	67256.66	67274.25	67433.92	67525.67	66804.87

Table B5. Analysis of order processing cost for D1 and D2 in proposed models.

Period	P-T		P-D		C-T		C-D	
	D1	D2	D1	D2	D1	D2	D1	D2
1	5285.92	4903.97	5099.53	5034.91	5140.19	5086.59	4976.67	5104.24
2	5513.49	5771.38	5606.12	5672.83	5675.01	5535.69	5538.50	5739.42
3	5587.32	5668.61	5663.04	5533.70	5562.19	5688.33	5609.58	5548.79
4	5473.63	5786.85	5636.11	5620.25	5460.49	5765.95	5548.98	5720.91
5	5527.68	5811.62	5657.19	5549.02	5507.44	5673.66	5648.48	5497.10
6	5546.16	5593.53	5721.66	5581.22	5594.28	5715.23	5488.57	5686.37
7	5620.20	5628.66	5649.29	5542.54	5511.37	5712.15	5381.83	5946.89
8	5488.75	5751.98	5687.38	5618.86	5708.63	5557.52	5629.42	5576.73
9	5749.12	5531.85	5572.80	5578.18	5770.20	5465.12	5850.51	5470.33
10	5644.24	5583.91	5525.72	5757.93	5589.02	5707.96	5587.84	5693.93
11	5638.96	5701.68	5374.35	5873.36	5594.00	5709.06	5553.80	5716.15
12	5764.23	5404.55	5698.59	5538.39	5790.65	5466.23	5705.59	5531.41
Total	66839.69	67138.58	66891.77	66901.20	66903.49	67083.48	66519.78	67232.28

Table B6. Analysis of order processing cost for R1 and R2 in proposed models.

Period	P-T		P-D		C-T		C-D	
	R1	R2	R1	R2	R1	R2	R1	R2
1	4754.35	4432.38	4560.19	4597.40	4586.80	4554.06	4576.15	4640.01
2	5573.91	5634.35	5683.25	5577.65	5756.89	5567.85	5492.73	5735.41
3	5498.50	5699.24	5669.83	5591.64	5438.42	5632.41	5613.97	5552.94
4	5443.88	5816.44	5616.93	5581.88	5509.76	5708.76	5479.68	5773.86
5	5527.83	5738.86	5678.53	5613.62	5513.06	5738.72	5631.38	5589.24
6	5627.78	5610.66	5718.14	5575.58	5573.61	5610.47	5579.93	5640.44
7	5604.92	5651.41	5656.66	5548.83	5550.18	5743.57	5311.43	5960.61
8	5496.50	5728.98	5762.00	5496.28	5637.36	5628.78	5594.04	5750.33
9	5773.10	5472.56	5602.47	5657.79	5820.11	5406.20	5807.86	5452.51
10	5585.08	5641.47	5595.88	5693.54	5681.62	5666.55	5539.55	5700.23
11	5639.69	5619.66	5325.98	5896.38	5554.10	5772.45	5705.07	5564.38
12	5772.95	5417.54	5670.25	5619.93	5661.76	5514.67	5611.12	5596.22
Total	66298.49	66463.55	66540.10	66450.53	66283.68	66544.48	65942.90	66956.18

Table B7. Analysis of processing cost for C1 and C2 in proposed models.

Period	P-T		P-D		C-T		C-D	
	C1	C2	C1	C2	C1	C2	C1	C2
1	94.85	91.59	91.62	93.93	91.94	94.23	94.54	91.85
2	95.65	98.18	99.17	93.91	95.32	98.61	98.31	94.68
3	95.98	96.72	98.54	94.79	96.33	96.02	98.84	95.16
4	98.33	94.70	95.30	97.02	97.11	94.66	95.46	98.09
5	94.17	99.14	96.03	96.51	94.63	98.67	98.92	94.26
6	98.23	95.52	96.30	96.58	94.96	98.40	96.68	96.19
7	98.42	95.79	95.18	98.65	97.10	97.36	95.50	98.13
8	97.18	95.89	96.17	97.02	96.44	95.89	95.53	97.39
9	93.71	99.75	98.35	95.85	98.89	94.54	99.44	93.02
10	95.14	97.19	96.01	95.75	95.03	96.84	97.13	95.97
11	97.41	95.16	97.96	94.94	97.75	96.07	98.41	94.07
12	98.13	95.22	95.92	97.44	96.29	97.64	95.92	96.48
Total	1157.18	1154.86	1156.54	1152.40	1151.78	1158.93	1164.67	1145.29

Table B8. Analysis of processing cost for D1 and D2 in proposed models.

Period	P-T		P-D		C-T		C-D	
	D1	D2	D1	D2	D1	D2	D1	D2
1	167.48	156.56	162.64	160.47	162.09	161.40	158.86	164.76
2	176.98	182.63	179.63	178.96	181.19	179.17	177.04	183.83
3	179.49	178.16	180.99	177.42	174.78	182.99	179.37	179.52
4	174.27	184.59	179.94	178.17	174.29	182.81	176.39	183.98
5	176.78	183.48	181.09	177.14	178.09	180.55	181.34	177.46
6	177.12	179.04	180.95	178.83	179.14	181.12	175.17	182.68
7	181.25	179.81	181.14	177.22	177.29	180.56	172.33	189.91
8	176.87	182.06	182.91	176.97	181.95	177.22	179.07	177.68
9	182.10	176.16	180.94	178.18	184.00	173.11	184.35	173.82
10	178.90	179.06	174.39	182.93	178.46	182.62	177.17	181.45
11	179.49	181.83	173.60	186.67	178.78	180.87	177.06	179.37
12	185.14	172.80	180.37	179.08	182.91	175.12	181.18	177.95
Total	2135.87	2136.18	2138.60	2132.03	2132.99	2137.54	2119.32	2152.41

Table B9. Analysis of processing cost for R1 and R2 in proposed models.

Period	P-T		P-D		C-T		C-D	
	R1	R2	R1	R2	R1	R2	R1	R2
1	152.68	140.71	145.92	146.19	146.03	145.29	145.01	149.69
2	179.64	181.16	181.73	177.66	181.12	178.93	176.14	184.31
3	176.46	181.55	179.87	177.98	175.82	181.50	179.51	177.80
4	174.12	183.63	179.72	178.72	176.03	182.12	175.07	184.19
5	176.54	183.91	180.43	180.67	176.69	183.14	180.07	177.42
6	179.13	178.44	181.56	177.77	180.01	179.04	178.04	180.71
7	179.17	181.13	181.32	177.55	178.63	181.91	171.55	189.73
8	175.96	182.84	183.60	174.73	179.76	179.30	178.67	182.67
9	183.70	174.58	179.45	179.34	185.40	173.01	183.81	173.10
10	179.39	179.79	177.35	180.76	179.71	179.77	176.65	182.13
11	181.51	179.57	172.62	187.22	178.13	182.22	180.62	177.92
12	184.61	171.62	181.08	180.65	180.37	176.35	179.62	179.78
Total	2122.92	2118.94	2124.64	2119.25	2117.70	2122.59	2104.74	2139.45

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Enrollment	Department	University	Year
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Thesis

MSc, *Dynamic Flexible Job Shop Scheduling with Simulation Optimization by using Genetic Algorithm*. 2012. Gaziantep University Fen Bilimleri Enstitüsü. (Supervisor: Assist.Prof.Dr. Faruk Geyik)

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Scholarships

Tübitak Bideb 2211-C National PhD Scholarship Program

Foreign Languages

English (YDS (2014) 85/100)

Courses Taken

MSc

IE 513	Sequencing and Scheduling
IE 501	Optimization Techniques I
IE 570	Technology Assessment
IE 549	Fuzzy Systems and Control
IE 566	Scheduling in Service Systems
IE 563	Productivity Analysis
IE 520	System Simulation

PhD

IE 511	Computer Application to Industrial Engineering Problems
IE 547	Logistics and Supply Chain Management
IE 519	Forecasting
IE 525	Integer Programming
IE 546	Neural Networks in Engineering
IE 526	Topics in Multiple Objective Decision Making
IE 536	Advanced Object Oriented Analysis and Programming
EB 522	Öğretimde Planlama ve Değerlendirme
EB 521	Gelişim ve Öğrenme