PLANNING OF DISASSEMBLY, REFURBISHING, AND REMANUFACTURING OPERATIONS IN A GENERIC CLOSED LOOP SUPPLY CHAIN UNDER UNCERTAIN DEMAND AND RETURNS

by

Fatih Bağcı

A Thesis Submitted to the
Graduate School of Engineering
in Partial Fulfillment of the Requirements for
the Degree of

Master of Science

in

Industrial Engineering

Koç University

July, 2011

Koç University

Graduate School of Sciences and Engineering

This is to certify that I have examined this copy of a master's thesis by

Fatih Bağcı

and have found that it is complete and satisfactory in all respects,

and that any and all revisions required by the final

examining committee have been made.

Committee Members:

Assoc. Prof. Metin Türkay (co-Advisor)

Assist. Prof. Onur Kaya (co-Advisor)

Assist. Prof. Sibel Salman

Assist. Prof. Yalçın Akçay

Assist. Prof. Fadime Yüksektepe

Date:

To Gülşen and Hüseyin Bağcı

ABSTRACT

There is growing interest over closed loop supply chain management according to the cost, the legislation issues and environmental considerations. In this thesis, we are interested in disassembly, remanufacturing and refurbishing operations of closed loop supply chains for products with modularity properties. We develop a generic mathematical model for commercial retail products such as computers, cell phones etc. We use stochastic optimization and robust optimization approaches to assist in making more accurate decisions under uncertain environment conditions.

First we present the mathematical model in detail and then we use two different approaches which are Robust Optimization and Stochastic Optimization for the generic model. The generic disassembly and refurbishing model has two stages to give decisions. In the first stage we determine the number of product disassembly and part refurbishing sites which are given strategically. In the second stage, we determine the operational decisions such as the quantity of disassembled products, refurbished parts etc. We give first stage decisions with Stochastic Optimization and Robust Optimization Approaches. Stochastic Optimization minimizes the expected cost while giving the first stage decisions for the combined problem. Robust Optimization Approach which minimizes the deviation between optimum cost and robust cost for each scenario while giving the first stage decisions for the combined problem.

The generic model has complexity because it is a large scale mixed integer problem. In addition, it has two different uncertain factors which are the distribution of demand and returns. Thus to give strategic decisions like opening disassembly and refurbishing sites , we should be aware of the expected costs and what we lose under different situations if we give the first stage decisions at the beginning of the planning horizon.

In the numerical results section, we solve different scenarios in a combined prob-

lem and give strategic decisions at the beginning of the time horizon using Stochastic Optimization and Robust Optimization and compare the results of these two different approaches. The numerical results part show us which approach is appropriate under different conditions.The variability of demand and returns affect the first stage decisions directly. We conclude that variability of returns has more effects over strategic decisions rather than variability of demand.

The second important result that we obtain is if the costs and capacities of opening disassembly and refurbishing sites are high (inflexible environment), Stochastic Optimization Approach gives better solutions and if the costs and capacities of opening disassembly and refurbishing sites are low(flexible environment), Robust Optimization Approach gives better solutions. Finally, we conclude that determining the length of planning horizon has a critical importance in giving strategic decisions.

ÖZETÇE

Günümüzde yasal mevzuatlar ve maliyet sorunları dolayısıyla kapalı döngülü tedarik zinciri sistemleri üzerine gittikçe artan bir ilgi belirmektedir. Bu tezde parça modülerliğine sahip ürünlerin kapalı döngülü tedarik zincirindeki yeniden üretim, demontaj ve yenileme işlemleri ile ilgili matematiksel bir model geliştirilmiştir. Bu matematiksel model belirgin olmayan koşullarda geçerli sonuçlar verecek yöntemler kullanılarak çözülmüştür.

Kapalı döngü tedarik zinciri yönetimi ve bu tezde kullandığımız robust optimizasyon ve stokasftik optimizasyon yöntemleri ile ilgili makaleleri gözden geçirdikten sonra tezin ikinci aşamasında geliştirdiğimiz modeli ve bu modelin robust optimizasyon ve stokasftik optimizasyon yöntemleri ile nasıl çözüleceği anlatılmıştır.Geliştirdiğimiz model iki aşamalıdır. İlk aşamada ürün demontaj ve parça yenileme sahalarının sayısı gibi stratejik kararları belirlerken ikinci aşamada bu sahalardaki operasyonel kararlar verilmektedir. İlk aşama kararını verirken farklı senaryoların toplam maliyetini optimize eden stokasftik optimizasyon yöntemi veya senaryoların teker teker çözülerek bulunan en iyi sonucu ile toplu olarak çözülen sonuçları arasındaki farkı optimize eden robust optimizasyon yöntemi kullanılmaktadır.

Geliştirdiğimiz model büyük ölçekli bir karışık tam sayı programlama modelidir. Senaryolar arasındaki değişik dağılımlı talep ve geri dönüşler de modelin yapısını karmaşıklaştırmaktadır. Numerik sonuçlar bölümü bize geliştirdiğimiz modelin hangi şartlar altında hangi yöntemler kullanılarak çözülmesi gerektiğini göstermektedir.

Çalışmanın sonucu demontaj ve yenileme sahasının büyük maliyet ve kapasiteli olduğu durumlarda stokasftik optimizasyon yönteminin daha iyi tam tersi durumda da robust optimizasyon yönteminin daha iyi sonuçlar verdiğini göstermektedir. Buna ek olarak senaryolar arasındaki talep ve geri dönüş dağılımlarındaki farklılıkların ilk

aşama kararlarında kritik öneme sahip olduğu ancak geri dönüşlerin talepten daha önemli olduğu belirlenmiştir. Son olarak da stratejik kararlar verirken planlama zaman aralığının çok kısa veya çok uzun belirlenmemesi gerektiği belirlenmiştir.

ACKNOWLEDGMENTS

I would like to thank Onur Kaya and Metin Türkay , my advisors, for their endless patience, great supports and friendly attitudes during the completion of this thesis.

Special thanks to my dearest friends Gökçen and Uğur. I am happy to say I gained knowledge as well as valuable friendships from the journey of graduate life.

My little sister Eda, special friends Can, Gülçün, Ulvi, Okan, Serhat, homemates Selimcan, Hüseyin, Akcaabat Tayfa Yılmaz and Kayhan; thank you all for being a part of my life.

You all have been more than a family to me.

Love you all...

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

NOMENCLATURE

CLSCM Closed Loop Supply Chain Management

dip difference in percent

GSCM Green SUpply Chain Management

Pa Part

Pr Product

RL Revere Logistics

ROA The Robust Optimization Approach

SOA The Stochastic Optimization Approach

Chapter 1

INTRODUCTION

In the past, companies thought that they were not responsible for products after being sold since nobody regulated the recovery operations and the companies were not aware of the value of the used products. However, in the modern era, people are more sensitive to sustainability and environmental consciousness . Many people might prefer recycled or remanufactured products. Besides environmental concerns, Jayaraman et al. (2) imply that to increase profitability and survive within the competitors companies must coordinate their activities due to the enviromontel considerations. For instance, the cost of returned products are %2 of total sales of Hewlett-Packard (3).In addition, municipal corporations and governments encourage these operations to decrease the incineration activities and landfill areas. Thus, the universities and companies want to answer society's needs and while they are increasing sustainability, they want to minimize their cost and perhaps increase profitability. Their interest over the closed loop supply chain rises day after day. Nevertheless , to explain the closed loop supply chain, we should understand what the traditional supply chain is.

In this thesis, we develop a generic closed loop supply chain mathematical optimization model. We are interested in disassembly, refurbishing and remanufacturing operations of the products with modularity properties. After used products return to the system, the model decides the quantity of disposed and disassembled products and refurbished parts. Since the returns and demand are uncertain, opening disassembly and refurbishing sites are strategic decisions. Thus we use Stochastic Optimization and Robust Optimization Approaches to handle uncertainty. We analyze the results of these two approaches and determine which approach gives more accurate results under different conditions.

Beamon (4) defines the traditional supply chain that different business echelons such as vendors,manufacturers, distributors control their processes together. The forward flow of raw materials, half products and final products and the backward flow of information are managed efficiently. Practitioners try to decide inventory levels, production quantities, the locations and number of echelons under certain or uncertain demand. However, the closed loop supply chain involves the traditional supply chain activities. For instance, Kumar and Malegeant (5) define the Closed Loop Supply chain as re-design of traditional supply chain. As well as the forward flow of the raw materials and products, the backward flow of used and remanuafactured products are considered.

Dekker et al. (6) give the detailed closed loop supply chain definition: *"The process of planning,implementing and controlling backward flows of raw materials, in process inventory, packaging and finished goods, from a manufacturing, distribution or use point, to a point of recovery or point of proper disposal"*.

When we compare the definition of closed loop supply chain and tradiotonal supply chain, the planning of the closed loop supply chain management is harder than the traditional supply chain management. Difficulty of the closed loop supply chain management comes from not only the increased number of echelons or processes but also the complexity of the dynamics. Thus, Sarkis et al. (7) tries to explain how reverse supply chain operations are difficult to handle. Supply chain systems are originally designed for forward channels, reverse distribution costs are higher and returns may not be transported or handled as easy as first hand products.

Tibben-Lembke and Rogers (8) summarize the differences between traditional supply chain and the closed loop supply chain in a very proper way. The most important closed loop supply chain characteristics which increase complexity of the supply chain are listed as :

- Two types of uncertain variables which are returns and demand.

- Two types of transportation modes which are distribution and collection.
- The quality and packagings are mostly not standardized.
- The pricing of the returns and demand are uncertain.

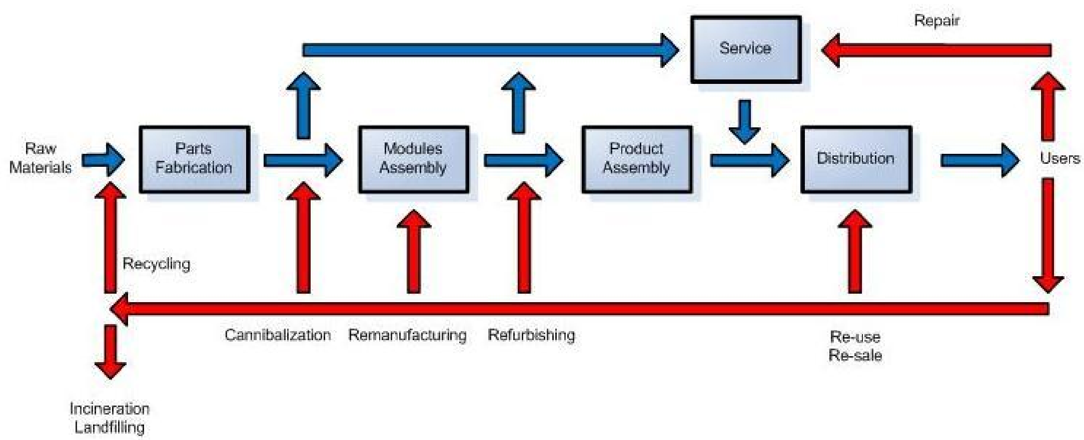


Figure 1.1: The Closed Loop Supply Chain (adopted by Thierry et al. (1))

The most well-known chart for the closed loop supply chain activities is shown by Thierry et al. (1). Blue arrows imply the forward flows of the closed supply chain activities and red ones imply the backward flows. In this thesis, we will focus on the backward flows of the closed loop supply chain activities. The definitions of the main closed loop supply chain activities should be made before we explain the structure of Figure 1.1. We define the activities by order of complexity of activity's output:

- **Reuse** The returns come to the distributors or retailers and they are sold as the second-hand products.
- **Repair:** The damaged returns are harnessed by service facilities and they are sold as the second-hand products.

- **Refurbishing:** The returns are technologically improved and sold as second hand products.

- **Remanufacturing:** The returns are divided into the parts or modules and they are used to produce a new product.

- **Cannibalization:** Only few parts of the returns are used for new products because of insufficient quality of the returns and remaninig parts are sent to the disposal.

- **Recycling:** The parts of the returns are converted into the raw materials such as aluminum, plastics etc.

- **Land-filling:** The returns are sent to the waste disposing areas and they are buried under the soil.

- **Incineration:** The returns are burned under the municipal restricted areas.

As we can see in Figure 1.1, there are different types of actions in a closed loop supply chain. If the quality of the product is sufficient, it can be reused and sold. This is the most preferable for companies because the cost is minimum.If customers want, the broken products may be repaired at the customer location or companies can take the broken product and sell as second hand products after refurbishing. To use the valuable parts, returned products may be disassembled and some of them may be used in the remanufacturing operations after refurbishing operations and some of them may be recycled or land-filled. Lund (9) expresses that the used products or parts can be used as first hand products or parts after refurbishing operations.

The challenge of the closed loop supply chain activities are driven by uncertain demand from forward flows of supply chain and uncertain returns of backward flows of supply chain. Guide et al. (10) mentions that companies don't have much information related with the quality, quantity and timing of the returned products. To handle the uncertainty of demand and returned products, we can use different approaches such as Stochastic Optimization(**SOA**) or Robust Optimization(**ROA**).

In **SOA**, briefly we integrate different scenarios into the large scale mixed integer optimization problem and solve all scenarios for same strategic decisions. In **ROA**, we try to minimize the deviation between optimum costs and expected cost while giving the same strategic decisions for all scenarios.

In this thesis, chapter 2 reviews the closed loop supply chain management literature in detail and then evaluate the **SOA** and **ROA** practices. Chapter 3 builds a generic disassembly and remanufacturing model which can be used in the problems which have product modularity such as personal computers, cellphones, automobiles etc. and present how **SOA** and **ROA** are implemented the generic model. Section 4 shows the experimental design of the problem and show the results of deterministic, stochastic and robust optimization approaches. Finally, section 5 concludes our thesis.

Chapter 2

LITERATURE REVIEW

Since there are numerous types of research topics in closed loop supply chain systems, we review the most important articles related to closed loop supply chain management and we examine the most related articles with our topic in detail. Closed loop supply chain operations are studied in different names in literature. We use green manufacturing, closed loop supply chain management and reverse logistics key words in our literature review and use related articles with our topic.

2.1 Reviews

Firstly, we analyze three important literature review articles and explain their classification method for literature. Fleischmann et al. (11) , one of the pioneers in reverse logistics, mainly discuss the literature over three sections. These sections are distribution planning, inventory control and production planning. Distribution planning section analyzes the content of the collection and transportation of the used materials articles and these articles are explained in details. Also the actors in distribution planning, the difference between forward and reverse logistics and modeling and solution approaches are inquired. In inventory control section, authors separate literature into two parts. Deterministic inventory management models which use Economic Order Quantity (EOQ) models and stochastic inventory management models. Stochastic models generally use periodic and continuous review solution approaches in this review. Finally, production planning section review the articles which use Material Resource Planning (MRP) models and shop flor controlling models.

In recent years, the number of articles related with closed loop supply chain management rapidly increased. Thus researchers need more complex reviews. Pokharel and Mutha (12) divide the reverse logistics review into four sections: Inputs and collection, structure, processes and outputs. Reverse logistics processes and structure are the most important section for our research. Processes section is divided into five parts: disassembly, coordination, supply chain, inventory and repair and after-sales service. Structure section is divided into four parts : general, inspection and consolidation, integrating manufacturing and remanufacturing and product modularity. In our thesis, we use product modularity, disassembly, supply chain and inventory. Thus, this literature review gives a helpful insight for our research.

Srivastava (13) gives us the most detailed review and it is more consistent to our literature review structure. Srivastava (13) uses the term of green supply chain management for its review. Firstly, articles are divided into three sections: importance, design and operations. Then, operations section is divided into three subsections: remanufacturing, reverse logistics and network design and waste management. We did research for remanufacturing and reverse logistics and network design in our thesis.

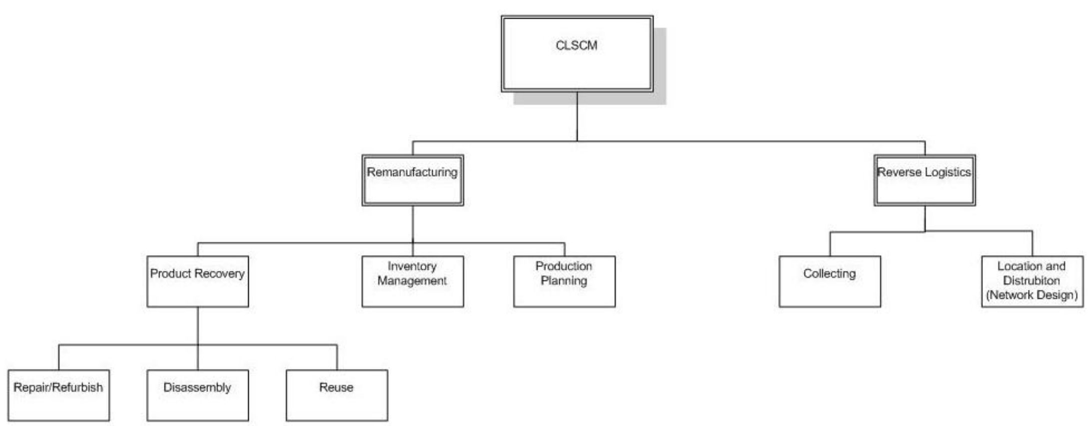


Figure 2.1: Literature Review Scheme

The reason we used the literature review scheme in figure 2.1 is our mathematical model which is explained our model in the next chapter . Mainly, we use refurbishing and disassembly facilities for processing. Thus, we review for product recovery. We hold inventory with holding costs and we determine the production quantities. Then, we review for inventory management and production planning. Although we don't use reverse logistics, this part is very important to us. The first reason of this is that closed loop supply chain management can't be understand without logistic operations. Collecting and distributing is very important in this topic. Second reason is that the methods which we use to handle uncertainty in our models. We use robust and stochastic optimization methods and these methods are generally used in reverse logistics operations.

2.2 Reverse Logistics, Network Design

Jayaraman et al. (14) and Fleischmann et al. (15) model closed loop supply chains as reverse logistics model and try to find the locations of facilities. Jayaraman et al. (14) define the remanufacturing as transporting the used products and converting them into products which have new conditions. They developed a closed remanufacturing model which takes the used products from collection zones and distribute them to the demand zones after remanufacturing. They try to find the location of facilities which store the used products, convert them to the remanufactured products and store them. As a result, they concluded that in reverse production system the reverse flow(returns) has crucial importance as well as the demand. Fleischmann et al. (15) add a new echelon to the network design as well as the remanufacturing sites. This new echelon is disassembly center. They solve the problem for two different cases: Copier remanufacturing and paper recycling. In these cases, the forward flow's effect over total cost is more than reverse flow. However, the impact of return flows will increase with the decreasing number of potential facility locations. Jayaraman et al. (14) and Fleischmann et al. (15) detect that increasing the return rate decrease the total cost for facility location models.

Jayaraman et al. (2) use the capacitated facility location model to design reverse logistics operations. They assume that customers bring the used products to the retailer points. They find the location and the number of collection and refurbishing sites and the transshipment quantities to these sites.In this article, the reverse and forward flows are not integrated and authors model the system only for reverse logistics operations. Jayaraman et al. (2) explain that the capacitated facility location model is NP-Hard and they use a heuristic which is "heuristics concentration" to find the near optimal solutions.

Demirel and Gokcen (16) mention that there are two classes of reverse logistics models: independent models and integrated models. The models which consider only reverse channels are independent models and the models which consider forward and reverse channels are integrated models. Demirel and Gokcen (16) propose a mixed integer mathematical model for network optimization in integrated reverse logistics. The model finds the optimal locations of disassembly,collection and distribution centers while determining the transportation and production quantities. In the model, transportation and production quantity variables are continuous but opening facility variables are binary. The fractions of disassembly, recovery and disposal are determined for products and the authors find the quantity of purchasing parts form external suppliers to satisfy demand. In the experimental design, three different rate of returns (low, medium and high) are analyzed for several number of products, manufacturers, collection centers etc. It is concluded that in integrated reverse logistics model when rate of returns are increasing, the cost is decreasing in most experiments. Thus, Demirel and Gokcen (16) emphasize that customers should be encouraged to return the used products.

Barros et al. (17) study over a two-level network design for a recycling sand case study. The aim of this study was increasing the recycling construction wastes due to the government regulations. Before reusing sand, quality should be controlled. Thus storing and cleaning facilities are necessary and they should plan the number, type and location of these facilities and distribute the cleaned sand. They assume that planning horizon is one year and demand and supply of sand is known and they create different scenarios to solve the deterministic problem. This two-level network is modeled as capacitated multi-level location problem with capacity constraints. Because these types of problems are NP-hard, they use different solution techniques which are linear relaxation of the constraints due to the data sets for lower bounds of constraints and upper bound linear relaxation for objective function.After solving the different scenarios, they conclude that opening depots are generally more profitable than shipping the sand over long distances and regional depots use their capacity efficiently and cleaning facilities are opened at the demand sites or the places which are near the sea because of transportation costs.

2.3 Production Planning

Jayaraman (18) uses a deterministic linear programming model for production planning in closed loop supply chains. Product recovery and reuse are the main operations in this model. Jayaraman (18) mentions six options in its remanufacturing system: selling products as secondhand products(if it has a sufficient quality level), replacement of components of the products(cleaning and repairing), refurbishing the product(selling the product as a new product), remanufacturing the whole product, taking some component of the product and recycling the product. The objective of the model is minimizing the cost while using these six options. Thus objective function consists of the holding cost, disposing cost, remanufacturing cost and purchasing costs. Products are disassembled to modules and so there are inventory balance restrictions. There are different quality levels for product types and each has different processing times for remanufacturing, disassembly, disposal and testing. This model can be used for operational level decisions and Jayaraman (18) use this model in cellular telephone using at a company for two types of products,two types of modules, two types of periods and six types of quality levels. In addition to this model, the recovery design problem is discussed in the final part of the article.

Franke et al. (19) study generic model for remanufacturing of cellular phones. They mention that consumer goods are started to remanufacture besides long living goods. Cellular phone is one of them because new technology cellular phones are increasing and old phones are not being used. Thus, companies want to reassemble and use some components or update the phones if it is profitable. The aim of this article is doing production and capacity planning. Mixed integer mathematical model is used to analyze the processes. The company takes the phones and after identification of the type, it is being tested. According to its condition, some are being disassembled and some are directly sent to the recycling. Disassembled components and new components are being combined and remafacturing is completed. The difference of the model from (18) that there is no disposal operation, the model is based on integer programming and there is no time period for facility.

According to Krikke et al.(20), closed loop supply chain management operations literature separate the product design and logistics operations. Krikke et al. (20) solve a real life problem using MIP modeling technique and sensitivity analysis are made considering different product designs, different network design options and environmental legislations. Authors believe that reverse supply chain operations should decrease environmental impacts in addition to decrease costs. Thus, the complexity of the problem will increase because lowering supply chain costs may increase the environmental effects. In the problem, refrigerator remanufacturing operations are analyzed. The model consists almost all of the remanufacturing operations: warehousing, repairing, disassembling, rebuilding etc. The objective of the model is minimizing cost, energy use and waste (each has different weight) subject to logical,demand and supply constraints. This method is defined as multi criteria optimization method with conflicted objectives. This model is one of the most complex remanufacturing model in the related literature. Authors obtain the solutions for centralized and decentralized networks for facilities. They conclude that centralized case minimize supply chain costs but increase waste.In addition to network design, different product types are analyzed over effects of cost, energy and waste minimization. Finally they investigate the effect of rate of returns over the cost and energy. When rate of return becomes more than 0.5, cost decreases dramatically and after that the movement is stable in the refrigerator case.

Kim et al. (21) create a generic model for remanufacturing operations for products which have different types of countable parts. They denote that many companies don't want to establish a remanufacturing facility because of high operation and facility costs and small return on investments. They propose two mathematical models for tactical (investment) and operational (production) level decisions. In the first model they decide the capacity of each site and in the second model they determine the production and remanufacturing quantities. Collected products come to the system and disassembled into the parts. Some collected products are sent to the external supplier to disassemble products. Finally parts which come from external supplier, subcontractor and the company sent to the manufacturer. They do planning for only remanufacturing operations so this system is not integrated.Each product type has a bill of materials thus each product may have different type and quantity of products. After the refurbishment, they sell these parts as new parts to the manufacturer. Both model want to maximize cost saving because they assume that they have to collect products and disassemble them. When they increase the total available investment, the cost saving increases but unlike other models we mention in this thesis , increasing return rate causes a decrease in cost saving because remanufacturing is expensive in the system.

Kim et al. (22) uses the second model which is shown in (21) to make sensitivity analysis over collection,refurbishing and disassembly site's capacity. When we increase these sites' capacity, cost saving will increase and then remain same after specific values. Thus the manufacturing company wants to find these specific values for sites. They recommend this model in the technlogic products markets such as mobile phones, copiers, computers etc.

2.4 Inventory Management

Richter and Sombrutzki (23) use Wagner/Whitin method to analyze the return and reuse of the products. They look at the production planning and inventory control problems from the used products' side. Authors emphasize that the Wagner/Whitin model plans process of ordering, manufacturing and holding the product over time periods. Authors use this model to create three different models. In the purely reverse model, used products are hold in the storage and remanufactured due to the demand at each period. In the second model, used and remanufactured products are hold in the storage. In the third model, they integrate manufacturing and remanufacturing operations and remanufactured and manufactured products are used as new products. These three models are solved for given demand and return values in a finite horizon. The most important assumption in the method is that the cost of returned products are low and they can satisfy all the demand of remanufactured products.

Sbihi and Eglese(24) introduce basic inventory management model formulation in remanufacturing problems. Inventory management problems can be formulated using mathematical programming or dynamic lot sizing models. The dynamic lot sizing problem is started by Wagner (25) and the solution method is based on dynamic programming. Sbihi and Eglese (24) show a mathematical programming formulation for remanufacturing operations. The company holds returns inventory and serviacable inventory and try to satisfy serviceable goods demand by using manufacturing and remanufacturing operations. They differentiate the model by using joint and separate set up costs for manufacturing and remanufacturing operations. They don't use disposing options in the model and they assume that serivcable inventory holding cost is greater than returns.

Like (24), Teunter et al. (26) use the joint and separate set-up costs for manufacturing and remanufacturing operations. Both articles use same mathematical model but Teunter et al. (26) use three well-known heuristics: Silver Meal, Least Unit Cost and Part Period Balancing to solve the dynamic programming problem. These heuristics consider zero-inventory property and ignore future costs for ordering. They modify these methods due to the returned products. They solved many problems to predict the effect of demand and return variabilities and quantities and most importantly they conclude that decreasing return increases the cost and a better prediction of demand decreases the cost.

2.5 Stochastic Optimization

The deterministic network location model(17) which is explained in section 2.2 is studied for stochastic optimization approach in the article Listes and Rommert (27). They try to find a solution which is proper for different scenarios. After solving the deterministic sand case problem with an effective heuristic, authors want to solve the problem with stochastic data because they believe that demand of sand and quality of the sand are uncertain for different scenarios. Like the deterministic problem, they want to find the locations of storage depots and cleaning facilities but objective function is maximizing net revenues instead of minimizing cost in this article. The returned sand may come to the system as clean, half-clean and polluted and there are two types of demand for clean and half-clean sand. Hence, polluted sand is sent to the treatment facility. In the problem, there are ten type of projects and each project has different clean and half-clean sand demand and the location of each projects is different. Then authors aggregate these projects and create 7 different scenarios. First, they solve two stage stochastic optimization problem for low and high supply case for uncertain demand and after that they solve three stage stochastic optimization problem for uncertain demand and supply. In the result section of the article, two stage **SOA** gives approximately 5% less revenue than optimum solution. In addition, high supply case gives more revenue rather low supply case. It is noteworthy that low supply and high supply two stage approaches and three satege approach give very different decisions. The reason of that is the uncertain demand locations. Finally they analyze the worst case and the expected costs are approximately 15% less than optimum which are not very low.

Chouinard et al. (28) also propose a stochastic optimization model to reduce the impacts of randomness in demand, supply and processing. They want to locate warehouses and disposal centers and distribute the recovered products. Thus they use a type of network location model and mixed integer linear programming modeling technique. Because the problem size is very large, they aggregate the products into families and use bill of materials for these product families. In addition to product types, each product comes to the system with a different condition. These condition types are new, good,damaged,unusable and unknown. Damaged products are disassembled and parts from these products are refurbished or cleaned before using. Chouinard et al. (28) mention that demand and supply are normally distributed for product types but the condition of the products are distributed according to the Weibull or Gamma distribution. In the mathematical model, they want to minimize fixed costs and expected variable costs with **SOA** and satisfy the demand of remanufactured and new products. The model is applied to the wheelchairs remanufacturing case and the company decreased the total costs almost 10% in three years. To obtain more appropriate solutions, authors use Sample Avarage Approximation(SAA) technique while solving the two stage stochastic optimization problem. They find lower and upper bound for objective function and try to find the reasonable scenario number for the spesific type of the problem.

Listes (29) explains the stochastic optimization problems in network design such that the location decisions are given in the first stage and then we give product flow decisions in the second stage. He uses **SOA** to handle uncertainty in demand for remanufactured products and supply for used products and creates 12 scenarios for 3 different demand rates and 4 different supply rates. In the article, computational efficiency and impact of uncertainty are analyzed. Due to the problem size, author uses a branch and cutting algorithm which is named decomposition method for stochastic optimization problems. When problem size increases, computational time increases dramatically because of integrality of location decisions. Moreover increasing demand rate increases profit. In addition, remanufacturing operations are profitable in the system and increasing return rate also increases the profit. Expected profit in **SOA** is almost 30% than optimal profit under perfect information. This percentage is very high and implies that the first stage decisions which are opening plants and test centers affect the expected profit strongly and the first stage decisions for each scenario are not similar.

Multi-period multi-echelon network design for integrated logistics problem is modeled by El-Sayed et al. (30). Their closed loop supply chain consists of suppliers, facilities, distributors, disassemblies and disposal sites. They use stochastic programming approach to analyze uncertainties in the demand for new products. The article is diffentiated from the articles in the literature because the authors don't determine different ratios for each scenario. They solve the stochastic mixed integer problem for different demand means and return rates. Like other models in the literature, the increase in the return rate and demand mean increases the total expected profit for integrated reverse and forward logistics. But unlike the articles in the literature, the flows are integer and this increases the problem's solution time and complication.

2.6 Robust Optimization

Robust optimization is another modeling technique to handle uncertain data for optimization problems like stochastic optimization. In stochastic optimization approach the objective function is maximizing expected profit or minimizing expected cost but in robust optimization there are different types of objective functions such as minimizing minimum deviation in different scenarios or minimizing the cost with penalty functions.

Kouvelis and Yu (31) define the measure of robust deviation as: *"The performance measure(appropriate for the single scenario decision) is applied for evaluating the decision across all scenarios, and then the worst case performance is recorded as the robustness indicator of the decision."*

Mulvey and Ruszczynski (32) and Mulvey and Vanderbei (33) propose three different approaches for robust optimization in logistics problems. In the first approach, the authors add penalty costs to objective function for supply and demand equality constraints and decrease the constraint numbers. In addition, they add a new nonlinear cost function to minimize the scenario cost deviation. In the second approach, the penalty and nonlinear cost functions are used in constraints for calculation and they are added to objective function. In the third approach, they increase the number of variables to calculate the deviations due to the sign of the differences in the inequalities.

Yu and Li (34) mention the importance of the uncertainty for logistics problems are mentioned. The authors propose a new robust optimization method for generic logistics management problem and compare the results and computational times with the second approach which are found by (32) and (33) and introduced in the article (34). They use the linearization theorem for absolute values in the objective function and decrease the constraint and variable numbers in comparison to other approaches. In the proposed model, solution time decreases 30% although they can find the optimal solution. Logistic problems are large scale and when we add scenerios to the logistics problems, the problem size increases dramatically. Moreover, decreasing the computational time is very important.

Realff et al. (35) use deterministic reverse logistics model for carpet recycling. In this article, carpet recycling is modeled as a reverse logistics system and the model tries to give decisions for the number of collecting and processing sites while maximizing revenue from recycled carpet products. Realff et al. (36) convert the deterministic model to the robust optimization model. In the robust approach, authors want to respond the future needs and they want to decide strategically on the locations of open sites before operational decisions. In this approach, they try to find feasible first stage decisions for different scenarios and maximize the difference between each scenario's optimum solution and robust solution.Thus, they determine maximum deviation across all scenarios. In this model, authors use 9 scenarios. They determine these decisions due to the 3 levels of collection volume and 3 levels of end product prices. We see that the difference between optimum solution and robust solution for each scenario is approximately 10%. They conclude that expensive system design and uncertain environment force people to solve the problems using stochastic-based approaches such as robust optimization approach.

Wei et al. (37) is one of the most recent studies in the robust optimization literature. They propose a periodic review inventory control model with uncertain demand and returns and then they convert the inventory control problem to the mathematical programming model and use robust optimization approach. (37) is deviated from the articles which we review above in the structure of constraints. In this model, authors change the constraints for each scenario and calculate the probability of violation of constraints and they conclude if upper and lower bounds are known, robust optimization model can be used to decrease the effect of uncertain returns and demand.

Prajapati (38) uses a production planning model. However, the importance of this study for us is that robust optimization approach, stochastic optimization approach and expected value approach are compared in this study. It seems that stochastic optimization approach gives more accurate results than the other two approaches and total cost is very close to the optimum cost under perfect information.

Chapter 3

PROBLEM STATEMENT AND MODEL

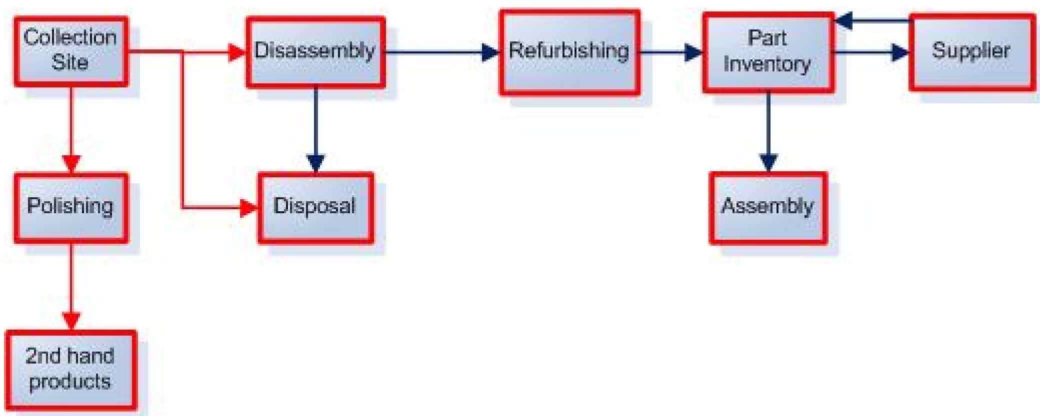


Figure 3.1: The Schematic Representation of the Model

There exists different types of remanufacturing processes in closed loop supply chain systems. In our study, we model collection, disassembly , polishing and refurbishing operations while we minimize operating, purchasing and holding costs. We see the schematic representation of disassembly and refurbishing operations of the basic computer remanufacturing case in 3.1. The red arrows denote products and the blue arrows denote parts. In addition, arrows are used to represent the direction of products and parts. Collected products come into the system. Since collected products have different damage conditons, they are segmented into different types. Then these products are held in the collection site and there is holding cost to store these products for each period. Some of the collected products are sent to the second hand products site due to the second hand products' demand. These products are polished before they are sold as the second hand products. Since each product type has different damage and part combination, each product type may earn different profit to the company. Some of collected products are sent to the disposal site. These products are seen as waste. These products are sent to the landfill sites and landfilling a part or product has a cost to the company. The other products which are not sent to the disposal or sold as the second hand products are sent to the disassembly site. As we mention above, each product type has different types of working parts and there are operating costs to disassemble products into these parts. Some of these parts are sent to the disposal site and some of them are sent to the refurbishing site. These parts are refurbished in the refurbishing site and they can be used as new parts after refurbishing operation. There are capacity restrictions for refurbishing and disassembly sites. Deciding the capacity of these sites are tactical level decisions for the company. After refurbishing, parts are hold in refurbishing site or part inventory site and they are used to satisfy assembly site's part demand. The company can also use asupplier to satisfy the assembly sites' demand but there is cost to order at each time period.As a result, assembly site can supply its demand from refurbishing site or a supplier. In addition, if parts exceed the company's needs , they can be sold to the supplier or other customers and there is no fixed cost to sell these parts. Selling these parts give a profit to the company.

There are some assumptions in this reverse supply chain system. Each product has different types of parts but we assume that these parts can be used as new parts after refurbishing. We should satisfy the assembly site's demand either by remanufacturing or buying from suppliers. Selling price of each type of part should be smaller than the purchasing price of this part. Thus, the system sells these parts only when it doesn't need to satisfy the demand.

In the mathematical model, we try to minimize the cost minus revenue. Our cost value consists of remanufacturing operations which are disassembling,refurbishing and holding costs and site opening costs. Revenue value consists of the revenue from the second hand sold products and sold parts to the supplier. While minimizing the cost minus revenue, we determine the site opening decisions and the quantity of the second hand sold, disassembled and disposed products at each period. After disassembling operations, we determine the quantity of diassambled, refurbished, sold and purchased parts at each time period.

3.1 Deterministic Model

Sets:

Set of parts I; index $i \in I$

Set of products P; index $p \in P$

Set of periods T; index $t \in T$

Parameters

RFC: the time capacity of refurbishing site at each period

DSC: the time capacity of disassembly site at each period

PrC_{pt}: the quantity of collected product p at time t

D_{it}: the demand for part i at time t

PaV_i: the volume for one unit part i

$PrIC_p$: the capacity of collection site for each product p

$PaIC$: the volume capacity of part inventory site at each period

DS_{pt}: the demand of second hand product p at time t

BM_{pi}: the quantity of part i from product p

$PrDC_p$: the disposal cost for product p

$PaDC_i$: the disposal cost for part i

PrU_p: the upper bound of disposal rate for product p

PaU_i: the upper bound of disposal rate for part i

PrI_p: the unit inventory holding cost for product p at collection site

PaI_i: the unit inventory holding cost for part i at the part inventory

$PaIRF_i$: the unit inventory holding cost for part i at refurbishing site

$PrIS_p$: the unit inventory holding cost for product p at 2nd hand site

OD_p: the unit operating cost for product p at the disassembly site

ORF_i: the unit operating cost for part i at the refurbishing site

OPO_P: the unit operating cost for product p at the polishing site

OC: the order cost from supplier

PuC_i: the purchasing cost for part i

$PaSe_i$: the selling price of part i

$PrSe_p$: the selling price of second hand product p

PrT_p: the time needed for disassembling one unit of product p

PaT_i: the time needed for refurbishing one unit of part i

$Dsec$: the opening cost of disassembly site

$Rfec$: the opening cost of refurbishing site

Decision variables:

IPR_{pt}: the inventory level for product p at time t at collection site

ISH_{pt}: the inventory level for product p at time t at 2nd hand products site

IPA_{it}: the inventory level for part i at time t at part inventory site

IRF_{it}: the inventory level for part i at time t at refurbishing site

$PrDA_{pt}$: the quantity of disassembled product p at time t

$PrDS_{pt}$: the quantity of product p sent to the disposal site at time t

$PrPO_{pt}$: the quantity of polished product p at time t

$PrSH_{pt}$: the quantity of 2nd hand product p sold at time t

$PaDS_{it}$: the quantity of part i sent to the disposal site at time t

$PaDA_{it}$: the quantity of part i sent to the refurbishing site at time t

$PaRF_{it}$: the quantity of refurbished part i at time t

$PaSUP_{it}$: the quantity of sold part i to the supplier at time t

PaB_{it}: the quantity of purchased part i at time t from supplier

$Ordr_t$: the binary variable for ordering fron supplier at time t

Dse: the number of disassembly site

Rfe: the number of refurbishing site

Objective Function:

Min $z =$

$$\sum_p \sum_t PrI_p * IPR_{pt} \tag{3.1.1}$$

$$+ \sum_p \sum_t PrIS_p * ISH_{pt} \tag{3.1.2}$$

$$+ \sum_p \sum_t PrPO_{pt} * OPO_p \tag{3.1.3}$$

$$+ \sum_p \sum_t PrDA_{pt} * OD_p \tag{3.1.4}$$

$$+ \sum_p \sum_t PrDS_{pt} * PrDC_p \tag{3.1.5}$$

$$+ \sum_i \sum_t PaRF_{it} * ORF_i \tag{3.1.6}$$

$$+ \sum_i \sum_t PaI_i * IPA_{it} \tag{3.1.7}$$

$$+ \sum_i \sum_t PaIRF_i * IRF_{it} \tag{3.1.8}$$

$$+ \sum_i \sum_t PaDS_{it} * PaDC_i \tag{3.1.9}$$

$$+ \sum_i \sum_t PaB_{it} * PuC_i \tag{3.1.10}$$

$$+ \sum_t Ordr_t * OC \tag{3.1.11}$$

$$+(Dse) * Dsec \tag{3.1.12}$$

$$+(Rfe) * Rfec \tag{3.1.13}$$

$$- \sum_i \sum_t PaSUP_{it} * PaSe_i \tag{3.1.14}$$

$$- \sum_p \sum_t PrSH_{pt} * PrSe_p \tag{3.1.15}$$

s.t.

$$PrC_{pt} + IPR_{p(t-1)} = IPR_{pt} + PrDA_{pt} + PrDS_{pt} + PrPO_{pt} \qquad \forall p, t \tag{3.1.16}$$

$$\sum_p BM_{pi} * PrDA_{pt} = PaDS_{it} + PaDA_{it} \qquad \forall i, t \tag{3.1.17}$$

$$\sum_t PrDS_{pt} \leq PrU_p * \sum_t PrC_{pt} \qquad \forall p \tag{3.1.18}$$

$$\sum_t PaDS_{it} \leq PaU_i * \sum_t (PaDS_{it} + PaDA_{it}) \qquad \forall i \tag{3.1.19}$$

$$PrDS_{pt} + PrPO_{pt} + PrDA_{pt} \leq PrIC_p \qquad \forall p, t \tag{3.1.20}$$

$$\sum_p PrT_p * PrDA_{pt} \leq Dse * DSC \qquad \forall t \tag{3.1.21}$$

$$\sum_i PaT_i * PaRF_{it} \leq Rfe * RFC \qquad \forall t \tag{3.1.22}$$

$$IRF_{i(t-1)} + PaDA_{it} = IRF_{it} + PaRF_{it} \qquad \forall i, t \tag{3.1.23}$$

$$ISH_{p(t-1)} + PrPO_{pt} = ISH_{pt} + PrSH_{pt} \qquad \forall p, t \tag{3.1.24}$$

$$IPA_{i(t-1)} + PaRF_{it} + PaB_{it} = D_{it} + PaSUP_{it} + IPA_{it} \qquad \forall i, t \tag{3.1.25}$$

$$\sum_i PrV_i * IPA_{it} \leq PaIC \qquad \forall t \tag{3.1.26}$$

$$PaB_{it} \leq D_{it} * Ordr_t \qquad \forall i, t \tag{3.1.27}$$

$$PrSH_{pt} \leq DS_{pt} \qquad \forall p, t \tag{3.1.28}$$

$$PaSUP_{it} \leq D_{it} \qquad \forall i, t \tag{3.1.29}$$

$$Dse \geq 1 \tag{3.1.30}$$

$$Rfe \geq 1 \tag{3.1.31}$$

$$IPR_{pt}, ISH_{pt}, PrDA_{pt}, PrDS_{pt}, Dse, Rfe \in \mathbb{Z}^+ \qquad \forall p, t \tag{3.1.32}$$

$$IPA_{it}, IRF_{it}, PaDS_{it}, PaSUP_{it} \in \mathbb{Z}^+ \qquad \forall i, t \tag{3.1.33}$$

$$PrPO_{pt}, PrSH_{pt} \geq 0 \qquad \forall p, t \tag{3.1.34}$$

$$PaRF_{it}, PaB_{it}, PaDA_{it} \geq 0 \qquad \forall i, t \tag{3.1.35}$$

$$Ordr_t \in 0, 1 \forall t \tag{3.1.36}$$

The objective of our model is minimizing total cost minus revenue. (3.1.1) and equation (3.1.2) give holding cost for collection site and for second hand products site,respectively. (3.1.3) and (3.1.4) are operating costs for polishing second hand products and disassembling products to the parts, respectively. (3.1.5) indicates the total costs to dispose products. Operating cost for refurbishing site is shown in equation (3.1.6). Holding cost for part inventory and for refurbishing sites are calculated in (3.1.7) and (3.1.8), respectively. Disposal cost and purchasing costs are shown in (3.1.9) and (3.1.10). In (3.1.11) total ordering cost from supplier can be seen. (3.1.12) and (3.1.13) are opening costs for disassembly and refurbishing sites. Finally, (3.1.14) and (3.1.15) are revenues from selling parts to the supplier and selling second hand products, respectively. Thus we subtract revenues from the total cost.

There are some restrictions in this disassembly and refurbishing operations. Constraints (3.1.16) shows the inventory balance equation at collection site for each product and time period. At time period $t = 0$, a certain level of inventory for all of the products or parts at all inventory sites is included in the model. Thus for inventory balance equations , at time $t = 0$ these values are used as parameters.(3.1.17) gives the disassembly site equalities. The quantity of each part which is sent to the refurbishing and disposal site will be equal to the sum of parts which are disassembled from all types of products at each period. (3.1.18) and (3.1.19) are disposal restrictions. The sum of wasted products and parts for all time periods can not exceed the particular proportions of the sum of the collected products for each product type and the sum of collected parts for each part type, respectively. (3.1.20) is used to restrict collection site's capacity at each time period for each product type. The total products which are sent to the second hand products site, disposal site and disassembly site should be smaller than collection site's capacity restriction for each product. Disassembling one unit product and refurbishing one unit part need time and refurbishing and disassembly sites have time capacities. (3.1.21) and (3.1.22) provide the expansion of disassembly and refurbishing sites due to the each site's time capacity and determine the decisions on how many man or machines are used. (3.1.23), (3.1.24) and (3.1.25) are inventory balance equalities for refurbishing site, second hand site and part inventory site, respectively. The company holds parts or products at these sites. For instance, (3.1.25) shows that incoming and outgoing parts are equal for each part at each time period. In addition, part inventory site has a volume capacity. In (3.1.26), total used volume for parts can not exceed the total capacity at each time period.

(3.1.27) restricts the company's part purchasing quantity for each part type at each period. If the company gives an order for a type of parts, the quantity of the order can not exceed the demand of the part at that period because we assume that the remanufacturing facility should use the supplier only when it can not supply the demand with remanufacturing operations at that period and we don't want to use the part inventory site as an outsourced part warehouse. (3.1.28) shows that each type of second hand product are sold due to the demand of that type of second hand product at each time period. The company might sell each type of parts. (3.1.29) restricts the amount of sold parts to the supplier at each time period. (3.1.30) and (3.1.31) show that there is at least one refurbishing and disassembly site and the company might expand these sites. (3.1.32), (3.1.33), (3.1.34), (3.1.35) and (3.1.36) show the type of variables. Although all variables except ordering decisions are integer, we can relax some of these integrality constraints. Because of equalities in our constraints, some variables are forced to be integer at the . Thus, even if we say that some variables may not be integer, they will be integer resulting solution. These variables are shown in (3.1.34) and (3.1.35).(3.1.36) shows that ordering decisions are given by binary variables.

3.2 Two-stage Stochastic Optimizaton Approach

In optimization problems, decisions can be given in different stages due to the importance, cost or time restriction of these decisions. In our remanufacturing problem we can divide our mathematical programming model into the two stage for long term and short term decisions. In stochastic programming approach, we use these two stages as strategic and operational levels. Strategic level is used as first stage decisions and operational level is used as second stage decisions. We are using the two-stage stochastic programming approach to handle uncertainty in demand and supply quantities. Strategic level decisions should be made before the system starts. Thus, first stage decisions should be given before we know the real demand and supply. After we realize the demand and supply , second stage decisions will be given due to the optimization results.

Opening the capacity of disassembly and refurbishing sites are our first stage level decisions in our optimization problem. The number of disassembly sites Dse and the number of refurbishing sites Rfe are our first stage integer decision variables. We determine different scenarios to handle uncertainty in demands and returns for parts and products, respectively. We connote S as the set of demand-supply scenarios and s as the specific scenario.

In order to handle uncertainty of demand and supply, we use the deterministic model above inside the following stochastic optimization model. First stage variables Dse and Rfe are shown as y and other variables are shown as x in two-stage stochastic programming approach. Thus, variables y are used as first stage variables and variables x are used as second stage variables. Two-stage stochastic programming model is shown as:

$$Min \quad fy + E_s\left[Q\left(y,s\right)\right] \tag{3.2.1}$$

s.t.

$$y \in Z^+ \tag{3.2.2}$$

where

$$Q(y,s) = min(cx) \tag{3.2.3}$$

s.t.

$$W_1 x = b(s) \tag{3.2.4}$$

$$W_2 x = d(s) \tag{3.2.5}$$

$$W_3 x \leq Ty \tag{3.2.6}$$

$$x \in Z^+ \tag{3.2.7}$$

(3.2.1) is the objective function of first stage in two-stage stochastic optimization approach. First stage y variables are determined in this stage and expectation of

$Q(y, s)$ over s plus fy gives the total cost of the optimization problem. We see that y variables are fixed in the first stage and second stage decisions x are given later according to the observed scenario. (3.2.3) shows the second stage objective functions. $Q(y, s)$ is the minimum objective value for a particular scenario s. Parameters $b(s)$ and $d(s)$ are used for supply and demand quantities for particular scenario s, respectively. W is used as resource matrices. (3.2.4) and (3.2.5) are used to satisfy demand and supply restrictions. Each constraint depends on scenario s. (3.2.6) is used to show scenario independent constraints. This two-stage stochastic optimization method creates different set of variables for each particular scenario s. We can show them as x_s. This approach is originated by Dantzig (39). In this approach, we assign probabilities for each scenario and we find a solution for each scenario((40),(41)). The optimal solution for particular scenario s is not optimal for general of the problem. Consequently, using these different variables for each scenario. The problem can be shown as :

$$Min \quad fy + E_s\left[cx_s\right] \tag{3.2.8}$$

s.t.

$$W_1 x_s = b(s) \qquad \forall s \in S \tag{3.2.9}$$

$$W_2 x_s = d(s) \qquad \forall s \in S \tag{3.2.10}$$

$$W_3 x_s \leq Ty \qquad \forall s \in S \tag{3.2.11}$$

$$y \in Z^+ \tag{3.2.12}$$

$$x_s \in Z^+ \qquad \forall s \in S \tag{3.2.13}$$

With Stochastic Optimization Approach, the problem's size increases due to the scenario numbers and it becomes large scale integer optimization problem.

When we apply the Stochastic Optimization Approach into the our generic model, each stochastic optimization equation is covered by our constraints. (3.1.16) covers the (3.2.4) since returns are our main supply . (3.1.25) covers the (3.2.4) and (3.2.5) together since part demand is satisfied according to remanufacturing and suppliers. (3.1.20) and (3.1.21) cover the (3.2.6) together since these constraints depend on the first stage decisions. Other constraints that we don't mention here are operational constraints. They are indirectly related to supply, demand and first stage decisions.

3.3 Robust Optimization Approach

Minimizing the risk may be more preferable than minimizing expected cost in certain situations and models. If we can not minimize the variability or prevent uncertain conditions, we should use a different technique to handle uncertainty.Risk and variability is very related to variance of demand or supply in supply chain operations. However in closed loop supply chain operations, both demand and returns are uncertain. Thus, risk occurs according to variance of demand and returns in our model. Robust Optimization Approach is a reliable method to solve problems like our generic remanufacturing problem since we have different demand and return distributions for each scenario.

Although Stochastic Optimization Approach minimizes the expected cost over scenarios, robust optimization aims to decrease variability of scenario costs from each scenario's optimum cost. Robust optimization model wants to find a solution that is close to each scenario's optimal solution. It minimizes the difference between optimum cost and robust cost for each scenario. Robust Optimization Approach is very important since its solution is less risky than Stochastic Optimization Approach. It minimizes the results that we don't want to encounter.

Robust optimization model can be stated as:

$$Min \quad \delta \tag{3.3.1}$$

s.t.

$$\delta \geq R_s - Q_s^* \qquad \forall s \in S \tag{3.3.2}$$

$$W_1 x_s = b(s) \qquad \forall s \in S \tag{3.3.3}$$

$$W_2 x_s = d(s) \qquad \forall s \in S \tag{3.3.4}$$

$$W_3 x_s \leq Ty \qquad \forall s \in S \tag{3.3.5}$$

$$y \in Z^+ \tag{3.3.6}$$

$$x_s \in Z^+ \qquad \forall s \in S \tag{3.3.7}$$

where

Q_s^*: Net cost of optimal solution for scenario s

R_s: Net cost of robust solution for scenario s

As we mention in stochastic programming approach, our aim in robust optimization approach is determining the long term decisions first and then determining the short term decisions to minimize total cost. We connote S as the set of demand-supply scenarios and s as the specific scenario like in stochastic programming approach. These scenarios are deterministic values which represent the possible demand and supply data. We don't assign any probabilities in robust programming model because we don't take an expectation. Firstly all scenarios are solved separately and optimal cost value is found for each particular scenario. As we see above, Q_s^* is the optimal cost value for scenario s. R_s is the robust solution cost for each scenario s. (3.3.1) and (3.3.2), we see that difference between optimum cost and robust cost will be smaller than δ. When we minimize δ, difference between robust and optimum cost will be minimized for all scenarios. (3.3.3),(3.3.4), (3.3.5), (3.3.6), and (3.3.7) are same as stochastic programming constraints. Thus, y variables are used for tactical level decision variables and they are given before time periods start. After that, x decision variables are determined as operational level decisions. This robust optimization approach is developed by Kouvelis and Yu (31). As we mention above, the basic idea is minimizing deviation between scenarios while optimizing objective value of integer programming.

When we apply the Robust Optimization Approach into the our generic model, each robust optimization equation is covered by our constraints. (3.1.16) covers the (3.3.3) since returns are our main supply . (3.1.25) covers the (3.3.3) and (3.3.4) together since part demand is satisfied according to remanufacturing and suppliers. (3.1.20) and (3.1.21) cover the (3.3.5) together since these constraints depend on the first stage decisions. Other constraints that we don't mention here are operational constraints. They are indirectly related to supply, demand and first stage decisions.

Chapter 4

COMPUTATIONAL RESULTS

In this chapter , we solve a sample problem and make sensitivity analysis. We used a GAMS 23.3.3 and Cplex 12.1.0 for solving proposed models on a PC with Intel Xeon 3.0 GHz and 4 GB of Ram. First, we explain the sample problem.

4.1 Input Parameters for the Sample Problem

We have 3 types of product and 5 types of parts and solve the problem for 20 time periods. We assume that inventory holding costs and operation costs are dependent to purchasing prices of parts and selling prices of products. Purchasing prices (PuC) are \$200, \$150, \$50, \$100 and \$150 for parts 1,2,3,4 and 5, respectively. We hold parts in the refurbishing sites and part inventory site. After refurbishing, quality of the part will increase so holding cost for part inventory site is higher than holding cost for the refurbishing sites. The holding costs for each part part at each time period will be 15% of the part's purchasing cost in the refurbishing sites and 25% of the part's purchasing cost in part inventory site. Thus holding costs for refurbishing sites ($\%PaIRF$) are \$30, \$22.5, \$7.5, \$15, \$22.5 and holding costs for part inventory sites (PAI) are \$50, \$37.5, \$12.5, \$25, \$37.5 for parts 1,2,3,4 and 5, respectively. The refurbishing cost for a part (ORF) is 40% of purchasing cost of that part and selling price of a part 50% of purchasing cost of that part. The volume for one unit part i (PaV), the disposal cost for part i (PaDC), the upper bound of disposal rate for part i (PaU), the necessary time for refurbishing one unit of part i (PaT), and initial inventories for part inventory site($xIPA$) and refurbishing sites ($xIRF$) for each part i are shown in table 4.1.

As we mentioned above, holding costs and operating costs for products depend

Table 4.1: Data Set for Part Types

	PaV	PaDC	PaU	PaI	PaIRF	ORF	PuC	PaSe	PaT	xIPA	xIRF
Pa1	1	2	0.2	50	30	80	200	100	1	0	0
Pa2	1	1.5	0.2	37.5	22.5	60	150	75	1	0	0
Pa3	1	0.5	0.2	12.5	7.5	20	50	25	1	0	0
Pa4	1	1	0.2	25	15	40	100	50	1	0	0
Pa5	1	1.5	0.2	37.5	22.5	60	150	75	1	0	0

on selling prices of second hand products ($PrSe$). Although we have three different types of products, selling prices of these three types of products are equal to each other in the sample problem. $PrSe$ is equal to $200 for all product types. The unit operating cost for product p at the disassembly site (OD) and polishing site (OPO) are 10% of selling prices of that product. The unit inventory holding cost for product p is 20% of the product's selling price. In addition to this, the capacity of collection site ($PrIC$), the disposal cost ($PrDC$), the upper bound of disposal rate (PrU), the necessary time to disassemble one unit of product (PT), initial inventories at collection site($xIPR$) and initial inventory at second hand products site($xISH$) are shown in table 4.2.

Table 4.2: Data Set for Product Types

	PrIC	PrDC	PrU	PrI	PrIS	OD	OPO	PrSe	PrT	xIPR	xISH
Pr1	1,000	2	0.3	40	40	20	20	200	2	0	0
Pr2	1,000	2	0.3	40	40	20	20	200	2	0	0
Pr3	1,000	2	0.3	40	40	20	20	200	2	0	0

The quantity of part i from product $p(BM)$ for each pair is shown in table 4.3. For example type 1 product has parts of type 1, 2, and 3.

In addition to parameters for different types of products or parts, we have 6 different scalars. The volume capacity of part inventory site at each period ($PaIC$), the ordering cost from supplier (OC), the time capacity of refurbishing site at each period(RFC), the time capacity of disassembly site (DSC), the opening cost of dis-

Table 4.3: The Quantity of Part i from Product p

	$BM_{p,i}$				
	Pa1	**Pa2**	**Pa3**	**Pa4**	**Pa5**
Pr1	1	1	0	1	0
Pr2	1	0	1	0	1
Pr3	0	1	1	1	0

assembly site ($Dsec$) and the opening cost of refurbishing site ($Rfec$). These scalars are shown in table 4.4.

Table 4.4: Scalars

PaIC	**OC**	**RFC**	**DSC**	**Dsec**	**Rfec**
400	10,000	100	100	100,000	20,000

We solve the sample problem for 9 scenarios. First, we decide the levels of demand and return because we have stochastic demand and return. There are three levels for demand and return for the sample problem: Low, Medium and High. These levels give the mean of the distribution. We assume that our demand (D) and return (PrC) come to the system according to normal distribution with mean and standard deviation values depending on the level in the scenario. Each type of products and parts are independent from each other. For example, in scenario 1 demand has low level of normal distribution, $\mathcal{N}(50, 30^2)$. Thus, in scenario 1 each type of part demand at each period come to the system due to the normal distribution and its mean is 50 and variance is 30^2. Like demand, return come to the system with normal distribution, $\mathcal{N}(30, 18^2)$ in scenario 1. So, each type of product at each period come to the system according to the normal distribution and its mean is 30 and variance is 18^2. We assume there is no negative demand and return. Thus, we accept negative demand or return as no demand or return come to the system. In addition to part demand and product return, second hand product demand is stochastic but the distribution is not same for different scenarios. Second hand products (DS) come to the system with $\mathcal{N}(20, 12^2)$. The scenarios for the sample problem are shown in table 4.5.

Table 4.5: Distributions of Scenarios

		Return		
		Low $\mathcal{N}(30, 18^2)$	Medium $\mathcal{N}(120, 72^2)$	High $\mathcal{N}(250, 150^2)$
Demand	Low $\mathcal{N}(50, 30^2)$	Scenario 1	Scenario 4	Scenario 7
	Medium $\mathcal{N}(200, 120^2)$	Scenario 2	Scenario 5	Scenario 8
	High $\mathcal{N}(450, 270^2)$	Scenario 3	Scenario 6	Scenario 9

4.2 Results for the Sample Problem

As we mention, the sample problem has 9 scenarios and each scenario has its own deterministic optimum solution. We analyze the first stage decisions for the optimum solution under different approaches which we explained in chapter 3. In table 4.6, we see the optimal first stage decisions for each scenario. If we analyze table 4.6 with the demand and return distributions, we see that the company doesn't open more than 1 disassembly site(Dse) and it opens 2 refurbishing site(Rfe) when return levels are low (We assume that the company has to open at least 1 refurbishing and 1 disassembly site in the mathematical model). Thus, first three scenarios have the same optimum first stage decisions. When return levels are medium or high, optimum first stage decisions give different results. We see that different scenarios might need different first stage decisions.

When we solve these scenarios with the approaches explained in chapter 3 for the sample problem, each approach gives different solutions for this sample problem. We give equal probabilities to determine decisions in **SOA** and to calculate expected costs for **SOA** and **ROA**. In table 4.51, we see the first stage decisions for these different two approaches.As we see **SOA** and **ROA** have not identical first stage decisions with optimum decisions.

Table 4.6: Optimum First Stage Decisions for Each Scenario

Scenario	Optimum Rfe	Optimum Dse
1	2	1
2	2	1
3	2	1
4	4	3
5	7	5
6	8	5
7	5	5
8	12	9
9	20	13

Table 4.7: First Stage Decisions for ROA and SOA

	Rfe	Dse
SOA	9	6
ROA	10	7

In table 4.8, we can see the optimum costs for each scenario. For instance, the cost of optimal solution for scenario 1 is 592,612. If we give the first stage decisions due to the **SOA**, the cost for scenario 1 is 1,154,657. The cost for scenario 1 in the **ROA** is 1,274,657. In addition to scenario costs, expected costs for optimum solutions and other approaches can be seen in table 4.8. In the sample problem, the expected solution for three approaches are close. Nevermore, the expected cost for **SOA** is smaller because we want to minimize the expected cost with this approach. In table 4.9, the percentage differences are shown between optimum solution and our three approaches. For instance, the percentage difference for **SOA** and optimum cost for scenario 1 will be calculated as:

$$difference = \frac{(\mathbf{SOA} cost for scenario 1) - (optimum cost for scenario 1)}{\mathbf{SOA} cost for scenario 1} \tag{4.2.1}$$

For instance the optimum cost is %48.68 less than **SOA** cost and %53.50 less than **ROA** cost . But the most important values are expected cost percentages since we want to minimize the expected cost in **SOA**. The expected optimum cost is %11.47 less than **SOA** cost and %11.97 less than **ROA** cost. Although first stage decisions are similar, expeceted costs are very close in terms of percentage. If only expected costs are important for the company, there is no difference to choose one of these two approaches for these two stages.

Table 4.8: Costs for Each Scenario and Expected Costs

Scenario	optimum cost	**SOA** cost	**ROA** cost
1	592,612	1,154,657	1,274,657
2	2,727,798	3,332,050	3,452,050
3	6,150,498	6,752,290	6,872,290
4	574,640	900,548	1,019,854
5	2,329,224	2,382,808	2,466,746
6	5,872,264	5,882,430	5,946,658
7	2,424,865	2,567,398	2,666,283
8	2,289,123	2,722,146	2,472,669
9	6,003,770	7,024,522	6,732,861
Expected Cost	3,218,310	3,635,427	3,656,007

Table 4.9: Differences from Optimum in Percents for **SOA** and **ROA**

Scenario	Difference in percent **SOA**	Difference in percent **ROA**
1	0.4868	0.5351
2	0.1813	0.2098
3	0.0891	0.1050
4	0.3619	0.4365
5	0.0225	0.0558
6	0.0017	0.0125
7	0.0555	0.0905
8	0.1591	0.0742
9	0.1453	0.1083
Average	0.1147	0.1197

In addition to minimizing expected cost, we want to minimize the maximum difference between optimum cost and our solution to decrease the risks and variance among different scenarios and use **ROA** for this purpose. In the table 4.10, we see the cost differences between optimum solutions and our approaches. For example, if we give decision due to the **SOA**, the cost difference will be \$562,046. If we use **ROA**, the difference from optimum cost for scenario 1 is \$682,046. We imply that the purpose of **ROA** is minimizing the cost difference in all scenarios. Thus , in table 4.10, the most important values are maximum cost differences. It is clear that maximum difference for **ROA** is smaller than other approaches. The maximum difference from optimum is approximately less than \$300,000 from **SOA** .

Table 4.10: Cost Differences between Optimum Solutions and **SOA** and **ROA**

Scenario	Difference SOA	Difference ROA
1	562,046	682,046
2	604,253	724,253
3	601,792	721,792
4	325,909	445,215
5	53,584	137,522
6	10,166	74,394
7	142,533	241,418
8	433,024	183,547
9	1,020,752	729,091
Average	417,117	437,697
Maximum	1,020,752	729,091

To sum up, to give first stage decisions for the sample problem. The company wants to use **ROA** because the expected costs for all of the approaches are similar but the maximum difference from optimum in **ROA** is very small rather than **SOA**.

4.3 Sensitivity Analysis for the Sample Problem over Opening Costs and Capacities

In this section, we aim to analyze the effect of opening costs and capacities over first stage decisions and costs. As we show in table 4.4, in the sample problem opening cost for new refurbishing site is $20,000$ and opening cost for new disassembly site is $100,000$ and capacities are 100. We solve the sample problem due to the these scalars. In table 4.11, we see three options for RFC, DSC, $Rfec$ and $Dsec$. We don't change the remaining data set. Thus option 1 actually shows the results of the sample problem. We multiply the opening costs and capacities with 2 for option 2 and we multiply the opening costs with 3 for option 3. We analyze the effect of flexibility over first stage decisions.

Table 4.11: Costs for Three Options

	RFC	DSC	Rfec	Dsec
Option 1	100	100	20,000	100,000
Option 2	200	200	40,000	200,000
Option 3	300	300	60,000	300,000

As we expect, the first stage decisions for option 2 and option 3 is smaller that option 1 in table 4.12. When we decrease flexibility of the system, we push the system to the suppliers and the company want to take more parts from them.

Table 4.12: First Stage Decisions for Three Options

	Option 1		**Option 2**		**Option 3**	
	Rfe	Dse	Rfe	Dse	Rfe	Dse
SOA	9	6	4	3	3	2
ROA	10	7	5	4	4	3

In table 4.13, we can see the expected and optimum cost values for three options. Optimum costs and **ROA** costs are increasing when we decrease flexibility but **SoA** doesn't give us any path. If we use the equation 4.2.1 to calculate the difference in percent for two approaches, we obtain the results which are shown in table 4.14. The difference decreases by %9,25 for **SOA** and increases by %12,57 for **ROA** in option 3. We can say that expected cost differences in percentages have a tendency to decrease for **SOA** and have a tendency to increase for **ROA**.

In table 4.15, maximum and average cost differences from optimum are shown for 3 options. These cost values are decreasing in **SOA** and increasing in **ROA**. For instance, the maximum difference decreases from $1,020,752$ to 995,930 and increases from $729,091$ to $777,708$ when we use option 3 instead of option 1 for the sample problem.

Table 4.13: Expected Costs for Three Options

	Option 1	**Option 2**	**Option 3**
Optimum Cost	3,218,310	3,270,186	3,299,075
SOA cost	3,635,427	3,637,339	3,635,427
ROA cost	3,656,007	3,706,016	3,773,336

Table 4.14: Cost Differences in Percent for Three Options

	Option 1	**Option 2**	**Option 3**
dip SOA	0.1147	0.1009	0.0925
dip ROA	0.1197	0.1176	0.1257

Table 4.15: Maximum and Average Cost Differences for Three Options

	Option 1		**Option 2**		**Option 3**	
	Average	Maximum	Average	Maximum	Average	Maximum
difference SOA	417,117	1,020,752	367,153	1,086,274	336,352	995,930
difference ROA	437,697	729,091	435,830	743,488	474,260	777,708

As a result this sensitivity analysis shows that when we decrease the flexibility, **SOA** gains more advantage rather than **ROA** because the difference in percent for expected values and maximum cost differences in all scenarios have a tendency to decrease in the sample problem.

4.4 *Sensitiviy Analysis over the Product Holding Cost Rate for the Sample Problem in the SOA*

As we discuss in section 4.1, the holding cost rate for three products are equal to the %20 of the each product for one time period. In this section, we analyze the first stage decisions and costs when we change the holding cost rate for products at the collection site. Table 4.16 shows that when we increase the holding cost, the number of refurbishing and disassembly sites increase until the product holding cost is below 20%. However, as the holding cost rate becomes more than 20% the decisions are not affected.This can be explained by the quantity of demand and returns. If system can satisfy demand with the returns, there is no need to open more sites.

Table 4.16: First Stage Decisions over the Product Holding Cost Rate for the Sample Problem

PrI	Rfe	Dse	PrI	Rfe	Dse	PrI	Rfe	Dse
0	3	2	0.35	9	6	0.70	9	6
0.05	5	3	0.40	9	6	0.75	9	6
0.10	6	4	0.45	9	6	0.80	9	6
0.15	7	5	0.50	9	6	0.85	9	6
0.20	9	6	0.55	9	6	0.90	9	6
0.25	9	6	0.60	9	6	0.95	9	6
0.30	9	6	0.65	9	6	1.00	9	6

In the Figure 4.1, We see the cost behaviour when we change the product holding cost rate. It seems that after %30, the cost of the system does not increase very much. Thus, we can say that the system doesn't have very much inventory after satisfying the part demand,second hand demand and sends the products to the disposal site.

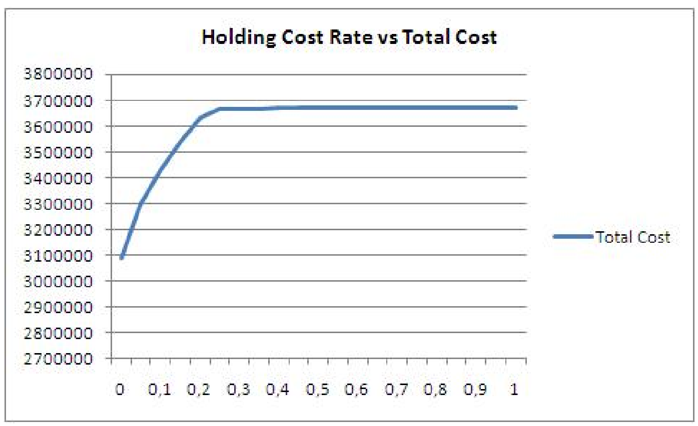


Figure 4.1: Total Expected Cost over the Holding Cost Rate for the Sample Problem

4.5 *Sensitiviy Analysis over Upper Bound of Product Disposal Rate for the Sample Problem*

(3.1.18) shows that the total quantity of products sent to the disposal site can not exceed the total quantity of returns for each product type. This constraint prevents the system from sending the products to the disposal site and the total holding cost of collection site may increase due to these constraints. In this section, we analyze the effect of changing the upper bound of disposal rate PrU over total cost and first stage decisions. In the sample problem(section 4.2), PrU is equal to 30%.However , Table 4.17 shows that this level is very tight for the system. But the behaviour of the first stage decisions is complicated. When we decrease the upper bound, the system opens more disassembly sites and send the products to the disposal after disassembling them into the parts. When we increase the upper bound, the products are sent to the disposal directly.

Table 4.17: First Stage Decisions over Upper Bound of Product Disposal Rate for the Sample Problem

PrU	Rfe	Dse	PrU	Rfe	Dse	PrU	Rfe	Dse
0	12	9	0,35	7	5	0,70	3	2
0,05	12	9	0,40	7	5	0,75	3	2
0,10	11	8	0,45	6	4	0,80	3	2
0,15	10	7	0,50	6	4	0,85	3	2
0,20	10	7	0,55	6	4	0,90	3	2
0,25	9	6	0,60	5	3	0,95	3	2
0,30	9	6	0,65	5	3	1	3	2

In Figure 4.2, the cost will decrease when we increase the upper level bacause of the realaxion of the tight constraint.

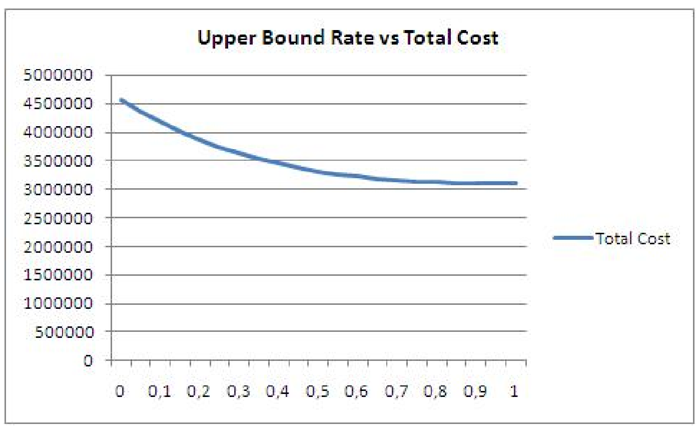


Figure 4.2: Total Expected Cost over Upper Bound of Product Disposal Rate for the Sample Problem

4.6 *Results for the Sample Problem with 10,20 and 50 Time Periods for the Planning Horizon*

The Planning Horizon is fundamental for the **SOA** and **ROA** because the first stage decisions are strategic level decisions. On the other hand, increasing the time periods brings the complexity to the system and increases the computational time. Thus we solve the sample problem for 10, 20 and 50 time periods and compare the results. We can see the results of the 20 time periods in section 4.2. The iteration count is decreasing dramatically when we decrease the time periods to 10 (table 4.18). However iteration count is not our only criteria to determine the planning horizon.

Table 4.18: Iteration Counts for the sample problem with 10 and 20 time periods

	Iteration Count(10 Time Periods)	Iteration Count(20 Time Periods)
SOA	10,678	477,334
ROA	25,293	288,536

Table 4.19: Optimum First Stage Decisions for Each Scenario with 10 Time Periods

Scenario	Optimum Rfe	Optimum Dse
1	2	1
2	1	1
3	1	1
4	3	2
5	6	4
6	6	4
7	4	3
8	9	6
9	12	8

In Table 4.20, we see that the first stage decisions for **SOA** and **ROA** are different from each other. But the total cost of **ROA** and **SOA** is very close to the optimum cost value as we see in table 4.21 and 4.22. In addition to the cost, maximum differences are very close to each other for **SOA** and **ROA** in table 4.23. Thus, solving the problems with 20 time periods give better results to compare **SOA** and **ROA** .

Table 4.20: First Stage Decisions for ROA and SOA with 10 Time Periods

	Rfe	Dse
SOA	3	2
ROA	4	3

Table 4.21: Costs for Each Scenario and Expected Costs with 10 Time Periods

Scenario	optimum cost	**SOA** cost	**ROA** cost
1	313,236	395,214	515,214
2	1,408,098	1,524,680	1,644,680
3	3,302,346	3,417,470	3,537,430
4	449,371	449,371	466,178
5	1,409,941	1,436,410	1,412,674
6	2,970,699	3,011,381	2,983,542
7	884,518	888,926	884,518
8	1,667,487	1,852,989	1,797,821
9	3,266,908	3,535,302	3,475,715
Expected Cost	1,861,400	1,954,638	1,977,530

When time periods are 50, iteration counts increase dramatically but first stage decisions don't change for **SOA** and **ROA** (Tables 4.24 and 4.25). When we increase the time periods very much, the cost effect of the first stage decisions over the planning horizon is decreasing. For instance, difference in percent decrease from %11.4 to %7.5 for **SOA** (Tables 4.9 and 4.26). A planning horizon with 20 time periods give small iteration couts for our problem and it seems that first stage decisions reach steady state.

Table 4.22: Differences from Optimum in Percents for **SOA** and **ROA** with 10 Time Periods

Scenario	Difference in percent **SOA**	Difference in percent **ROA**
1	0.2074	0.3920
2	0.0765	0.1438
3	0.0337	0.0665
4	0.0000	0.0361
5	0.0184	0.0019
6	0.0135	0.0043
7	0.0050	0.0000
8	0.1001	0.0725
9	0.0759	0.0601
Average	0.0508	0.0625

Table 4.23: Cost Differences between Optimum Solutions and **SOA** and **ROA** for 10 Time Periods

Scenario	Difference SOA	Difference ROA
1	81,979	201,979
2	116,582	236,582
3	115,125	235,085
4	0	16,807
5	26,470	2,733
6	40,683	12,843
7	4,408	0
8	185,502	130,334
9	268,394	208,807
Average	93,238	116,130
Maximum	268,394	236,582

Table 4.24: Iteration Counts for the sample problem with 20 and 50 time periods

	Iteration Count(20 Time Periods)	Iteration Count(50 Time Periods)
SOA	477,334	30,004,432
ROA	288,536	22,199,951

Table 4.25: First Stage Decisions for ROA and SOA with 50 Time Periods

	Rfe	Dse
SOA	9	6
ROA	10	7

Table 4.26: Expected Costs for the Sample Problem with 50 Time Periods

	optimum cost	**SOA** cost	**ROA** cost
Expected	6,878,449	7,438,885	7,469,457
dip		0.0753	0.0791

4.7 Results for the Sample Problem with the Continuous First Stage Decisions

To understand how first stage decisions affect the complexity of the problem and results, we relax integer first stage variables and compare the results with the sample problem in section 4.2. It seems that when we relax first stage variables, the costs will not decrease dramatically (table 4.8 and 4.27). For instance, optimum total cost decreases to $3,212,215$ from $3,218,310$. If we compare the iteration counts, we can see the results in the table 4.29. Using integer first stage variables is more accurate, since refurbishing and disassembly operations are done by machines or workers and using binary variables for these decisions does not increase computation time very much.

Table 4.27: First Stage Decisions for ROA and SOA with the Continuous First Stage Decisions

	Rfe	Dse
SOA	8.83	5.42
ROA	10.09	6.96

Table 4.28: Costs for Each Scenario and Expected Costs with the Continuous First Stage Decisions

Scenario	optimum cost	**SOA** cost	**ROA** cost
1	583,173	1,073,250	1,272,450
2	2,719,865	3,250,650	3,449,850
3	6,141,358	6,670,890	6,870,090
4	572,119	819,632	1,017,678
5	2,323,514	2,343,898	2,463,909
6	5,862,383	5,868,055	5,943,903
7	2,419,351	2,500,035	2,664,897
8	2,285,703	2,904,273	2,479,544
9	6,002,475	7,243,845	6,732,568
Expected Cost	3,212,215	3,630,503	3,654,988

Table 4.29: Iteration Counts for the sample problem with Integer and Relaxed First stage

	Iteration Count(Continuous First stage)	Iteration Count(Integer First Stage)
SOA	306,495	477,334
ROA	219,487	288,536

4.8 Results for the Sample Problem with the Increased Opening Costs

In this section, we try to analyze disassembly and refurbishing sites' opening costs. As we see in the input parameters in table 4.4, opening disassembly and refurbishing costs are 100,000 and 20,000, respectively. We set $Dsec$ to 300,000 and $Rfec$ to 60,000 and compare the results with the sample problem.

When we increase the opening costs, first stage decisions for **ROA** and **SOA** close up. Opening a new site will increase expected cost for **SOA** and increase maximum difference for **ROA** and the model tries to open few sites. As a result, first stage decisions are the same in this section(4.30).

Table 4.30: First Stage Decisions for ROA and SOA with the the Increased Opening Costs

	Rfe	Dse
SOA	3	2
ROA	3	2

When we increase the opening costs, the total expected costs and optimum cost increases(4.31). For instance the optimum cost in the sample problem is 3,218,310 increases to 3,839,219. On the other hand, percentage difference decreases from 0.1147 to 0.0604. Opening a new site is expensive and the model chooses to buy the parts from suppliers and accepts the holding costs for the collection site. Thus we can easily say that high opening costs prevent the system's sustainability.

Table 4.31: Costs for Each Scenario and Expected Costs with the Increased Opening Costs

Scenario	optimum cost	**SOA** cost	**ROA** cost
1	512,612	798,217	798,217
2	2,616,648	2,980,105	2,980,105
3	6,038,694	6,395,035	6,395,035
4	903,344	903,344	903,344
5	2,862,302	2,867,541	2,867,541
6	6,482,590	6,505,826	6,505,826
7	3,068,619	3,114,496	3,114,496
8	3,895,302	4,423,496	4,423,496
9	8,172,861	8,785,500	8,785,500
Expected Cost	3,839,219	4,085,951	4,085,951

Table 4.32: Differences from Optimum in Percents for **SOA** and **ROA** with Increased Opening Costs

	Difference in percent	Difference in percent
Scenario	**SOA**	**ROA**
1	0.3578	0.3578
2	0.1220	0.1220
3	0.557	0.0557
4	0.0000	0.0000
5	0.0018	0.0018
6	0.0036	0.0036
7	0.0147	0.0147
8	0.1194	0.1194
9	0.0697	0.0697
Average	0.0604	0.0604

Table 4.33: Cost Differences between Optimum Solutions and **SOA** and **ROA** with Increased Opening Costs

Scenario	Difference SOA	Difference ROA
1	285,605	285,605
2	363,458	363,458
3	356,341	356,341
4	0	0
5	5,239	5,239
6	23,236	23,236
7	45877	45,877
8	528,194	528,194
9	612,639	612,639
Average	246,732	246,732
Maximum	612,639	612,639

4.9 *Sensitivity Analysis for the Five Different Sample Problems over Opening Costs and Capacities*

To determine the effect of flexibility for refurbishing and disassembly sites more efficiently, we create 5 different sample data sets for demand and return. In Table 4.11, we can see that option 2 is less flexible than option 1 and option 3 is less flexible than option 2 since the capacity and cost increase at the same rate in option 2 and option 3. Each sample has scenarios as in the table 4.5. In the appendix A, we can see the cost values and first stage decisions for all of the samples with three options and we draw charts for these cost values and differences to analyze the effect of the opening costs and capacities.

Although samples have same demand and return distributions, first stage decisions may change between samples at each option. This is the main idea that we solve the problem more than 1 sample . Although each sample has same distribution, the exact demand and return values are different according to variability. Thus, each sample may have different first stage decisions under exactly same conditions. For instance , *Dse* for sample 1, option 3 and **ROA** is 4 but *Dse* for sample 2, option 3 and **ROA** is 3.

Table 4.34: First Stage Decisions for Three Options and five Different Samples in **SOA** and **ROA**

		Option1		Option2		Option3	
		Dse	Rfe	Dse	Rfe	Dse	Rfe
Sample1	SOA	9	6	4	3	3	2
	ROA	10	7	5	4	4	3
Sample2	SOA	9	6	4	3	3	2
	ROA	10	7	5	4	3	3
Sample3	SOA	9	6	4	3	3	2
	ROA	8	6	5	3	3	2
Sample4	SOA	9	6	4	3	3	2
	ROA	8	7	4	4	3	3
Sample5	SOA	9	6	4	3	3	2
	ROA	9	6	5	3	3	2

The first stage decisions for different samples in table 4.34 show the differences between two approaches. In option 2 and 3, when flexibility is low , **ROA** and **SOA** give more consistent first stage decisions rather than option 1. But the gap between *dip* values of **ROA** and **SOA** is increasing if decisions are not exactly same in option 2 and 3. The gap values between **ROA** and **SOA** *dip* for different samples and each option are shown in Table 4.35. For instance, for sample 1 and option 1 **ROA** cost is 11.97% bigger than optimum cost and **ROA** cost is 11.47% bigger than optimum cost. Thus, first value of the Table 4.35 is 0.005. If first stage decisions are not exactly same, the gap for option 3 is always larger than the gap for option 2 and option 1. Nevertheless we can not say we always prefer **SOA** in option 3 because we also use the maximum differences and expected cost values in our analysis.

Table 4.35: Gap Values for Three Options and five Different Samples between **ROA** and **SOA** *dip* values

	Sample1	**Sample2**	**Sample3**	**Sample4**	**Sample5**
Option 1	0.0050	0.0039	0.0010	0.0103	0.0000
Option 2	0.0167	0.0121	0.0030	0.0270	0.0034
Option 3	0.0331	0.0383	0.0000	0.0403	0.0000

Expected costs are not always increasing when we decrease flexibility in **SOA** and **ROA**. For instance, in table A.2 the cost of option 2 is $3,637,339$ and decreases to $3,521,726$ in option 3. Like expected costs, we can not say maximum cost differences has a path when we change the flexibility as we see in figures A.3 and A.1. However we want to decide which approach we will use to determine first stage decisions.Thus we should look at maximum differences and expected cost differences for each option at the same time. To analyze the effect of maximum differences over expected costs, we calculate a parameter for each data sample and for each option. If we want to illustrate with an example, this parameter for option 1 is calculated as:

$ESOA$: Expected Cost for **SOA**

$EROA$: Expected Cost for **ROA**

$maxSOA$: The maximum difference for **SOA**

$maxROA$: The maximum difference for **ROA**

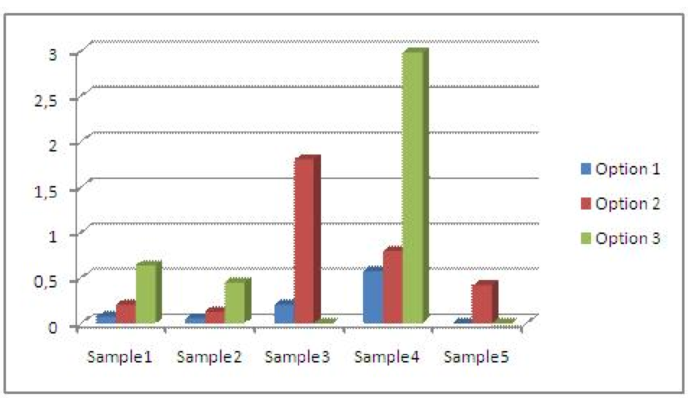
$$\Phi = \frac{EROA - ESOA}{maxSOA - maxROA} \tag{4.9.1}$$

When the parameter Φ is high , we should decide according to **SOA** and when the parameter Φ is low, we should decide first stage decisions according to **ROA**. We see the parameter Φ values for each option and sample data. Figure 4.3 and table 4.36 show that **SOA** is more advantageous in option 3 and option 2 rather than option 1 if first stage decisions are not similar for **SOA** and **ROA**. In a conclusion, when flexibility is small(option 3), we should use **SOA** and when flexibility is high(option 1), we should use **ROA** because maximum difference from optimum costs among all scenarios will be high.

Table 4.36: Φ values for Different Samples and each Option

	Sample1	**Sample2**	**Sample3**	**Sample4**	**Sample5**
Option 1	0.0705	0.0517	0.1984	0.5739	0
Option 2	0.2003	0.1258	1.8018	0.7931	0.4195
Option 3	0.6319	0.4461	0	2.9768	0

Figure 4.3: Φ values for Different Samples and each Option



In Table 4.37 for **SOA** and table 4.38 for **ROA**, the average five sample costs and difference in percent values for three options are shown. Like we explain above, averages of samples give similar results. Option 3 has smaller costs but difference in percent value is higher rather than option 2.

Table 4.37: Average Optimum and **SOA** Costs for Five Samples

	Optimum Cost	SOA Cost	Difference in Percent
Average_of_5Samples_Option1	3,003,334	3,395,000	11.54%
Average_of_5Samples_Option2	2,929,188	3,279,030	10.67%
Average_of_5Samples_Option3	2,844,478	3,155,783	9.86%

In the appendix A, all cost and difference in percent values are shown in detail and graphically.

Table 4.38: Average Optimum and **ROA** Costs for Five Samples

	Optimum Cost	ROA Cost	Difference in Percent
Average_of_5Samples_Option1	3,003,334	3,411,174	11.96%
Average_of_5Samples_Option2	2,929,188	3,328,814	12.01%
Average_of_5Samples_Option3	2,844,478	3,246,209	12.38%

In the next section, we want to see the effects of variability in demand and return over first stage decisions and *dip* values. Our model is created to satisfy demand while minimizing cost. The most compelling issue in the model is the stochasticity of demand and return because we have different scenarios and each scenario has different demand and return distributions. We will determine the cost values and first stage decision variables if each scenario in the problem has same mean and standard deviation for demand or return. We create two cases for only variable return and only variable demand.

4.10 Case 1: The Sample Problem for Variable Return

Table 4.39: Distributions of Scenarios in Case 1

		Return		
		Low $\mathcal{N}(30, 18^2)$	Medium $\mathcal{N}(120, 72^2)$	High $\mathcal{N}(250, 150^2)$
Demand	Medium $\mathcal{N}(200, 120^2)$	Scenario 1	Scenario 4	Scenario 7
	Medium $\mathcal{N}(200, 120^2)$	Scenario 2	Scenario 5	Scenario 8
	Medium $\mathcal{N}(200, 120^2)$	Scenario 3	Scenario 6	Scenario 9

In the variable return case, we have 9 scenarios and each has same distribution $\mathcal{N}(200, 120^2)$ for demand. Return distributions are similar as the sample problem which is analyzed in section 4.2. First stage decisions in table 4.40 and cost differences in percent 4.42 are similar with the values for five different samples which are shown in section 4.9. For instance, the first stage decisions for **SOA** and **ROA** are different in option 1, 2 and 3 and the cost difference in percent for **SOA** in option 1 is 0,1428. In addition, we can see the expected costs in table 4.41 and the maximum and average cost differences in table 4.43.

Table 4.40: First Stage Decisions for Three Options in Case 1

	Option 1		**Option 2**		**Option 3**	
	Rfe	Dse	Rfe	Dse	Rfe	Dse
SOA	11	8	5	4	4	3
ROA	9	7	4	4	3	3

Table 4.41: Expected Costs for Three Options in Case 1

	Option 1	**Option 2**	**Option 3**
Optimum Cost	2,517,433	2,555,761	2,608,721
SOA cost	2,936,778	2,940,272	2,967,455
ROA cost	2,947,028	3,026,024	3,037,102

Table 4.42: Cost Differences in Percent for Three Options in Case 1

	Option 1	**Option 2**	**Option 3**
dip SOA	0.1428	0.1308	0.1209
dip ROA	0.1458	0.1554	0.1410

Table 4.43: Maximum and Average Cost Differences for Three Options in Case 1

	Option 1		**Option 2**		**Option 3**	
	Average	Maximum	Average	Maximum	Average	Maximum
difference SOA	419,345	862,615	384,511	752,578	358,734	779,348
difference ROA	429,595	722,615	470,264	712,578	428,382	719,348

4.11 Case 2: The Sample Problem for Variable Demand

Table 4.44: Distributions of Scenarios in Case 2

		Return		
		Medium $\mathcal{N}(120, 72^2)$	Medium $\mathcal{N}(120, 72^2)$	Medium $\mathcal{N}(120, 72^2)$
Demand	Low $\mathcal{N}(50, 30^2)$	Scenario 1	Scenario 4	Scenario 7
	Medium $\mathcal{N}(200, 120^2)$	Scenario 2	Scenario 5	Scenario 8
	High $\mathcal{N}(450, 270^2)$	Scenario 3	Scenario 6	Scenario 9

In the variable demand case, we have 9 scenarios and each has same distribution $\mathcal{N}(120, 72^2)$ for return. Demand distributions are similar as the sample problem which is analyzed in section 4.2. In this case, first stage decisions in 4.45, expected costs in 4.46, the maximum and average cost differences in 4.48 are very close for **SOA** and **ROA** and the cost differences from optimum is very small. For instance, *dip* value for option 1 in **SOA** is % 2,35 in table 4.47.

Table 4.45: First Stage Decisions for Three Options in Case 2

	Option 1		**Option 2**		**Option 3**	
	Rfe	Dse	Rfe	Dse	Rfe	Dse
SOA	6	4	3	2	3	2
ROA	6	4	3	2	2	2

Table 4.46: Expected Costs for Three Options in Case 2

	Option 1	**Option 2**	**Option 3**
Optimum Cost	2,769,680	2,800,496	2,798,359
SOA cost	2,836,370	2,836,370	2,898,866
ROA cost	2,836,370	2,836,370	2,985,885

Table 4.47: Cost Differences in Percent for Three Options Case 2

	Option 1	**Option 2**	**Option 3**
dip SOA	0.0235	0.0126	0.0347
dip ROA	0.0235	0.0126	0.0628

Table 4.48: Maximum and Average Cost Differences for Three Options in Case 2

	Option 1		**Option 2**		**Option 3**	
	Average	Maximum	Average	Maximum	Average	Maximum
difference SOA	66,690	129,049	35,874	115,367	100,507	315,719
difference ROA	66,690	129,049	35,874	115,367	187,525	255,730

The results of Case 1 and Case 2 show that our first stage variables are determined due to the return quantity and variability. When we decrease the variability of return, the system starts to give same first stage decisions for **SOA** and **ROA** and most importantly, the *dip* values close to 0. If we know the exact distribution of the return, we can solve the problem easily and give more consistent decisions.

4.12 Case 3: The Sample Problem for Stable Return and Stable Demand

Sections 4.10 and 4.11 show the effect of variability in demand and return. In this section, we assume that each scenario has same distribution and with $\mathcal{N}(120, 72^2)$ for returns and with $\mathcal{N}(200, 120^2)$ for demand. The aim of this section is to analyze the benefit of **SOA** and **ROA** under more stable conditions. In table 4.49, we see that each scenario has same distribution.

The first stage optimum results are similar for each scenario in table 4.50 and **SOA** and **ROA** gives exactly same first stage decisions. In addition, expected costs for **SOA** and **ROA** are very close to the expected optimum cost. This result shows that under stable return and demand distributions or if know the exact distributions, making an effort to solve the problem with different approaches is not meaningful.

Table 4.49: Distributions of Scenarios in Case 3

		Return		
		Low $\mathcal{N}(120, 72^2)$	Medium $\mathcal{N}(120, 72^2)$	High $\mathcal{N}(120, 72^2)$
Demand	Low $\mathcal{N}(200, 120^2)$	Scenario 1	Scenario 4	Scenario 7
	Medium $\mathcal{N}(200, 120^2)$	Scenario 2	Scenario 5	Scenario 8
	High $\mathcal{N}(200, 120^2)$	Scenario 3	Scenario 6	Scenario 9

Table 4.50: Optimum First Stage Decisions for Each Scenario in Case 3

Scenario	Optimum Rfe	Optimum Dse
1	8	5
2	6	4
3	8	5
4	8	5
5	8	5
6	8	5
7	9	6
8	8	5
9	8	5

Table 4.51: First Stage Decisions for ROA and SOA in Case 3

	Rfe	Dse
SOA	8	5
ROA	8	5

Table 4.52: Costs for Each Scenario and Expected Costs in Case 3

Scenario	optimum cost	**SOA** cost	**ROA** cost
1	2,581,015	2,581,015	2,581,015
2	2,440,803	2,450,796	2,450,796
3	2,143,232	2,143,232	2,143,232
4	2,559,372	2,559,372	2,559,372
5	2,281,640	2,281,640	2,281,640
6	2,527,717	2,527,717	2,527,717
7	2,390,044	2,408,372	2,408,372
8	2,110,774	2,110,774	2,110,774
9	2,306,131	2,306,131	2,306,131
Expected Cost	2,371,192	2,374,339	2,374,339

4.13 *Case 4: The Sample Problem for Variable Return and Variable Demand with 4 scenarios*

In this section, we decrease the problem size and the scenario number is 4 instead of 9. Although we decrease the scenario number, the variability of the problem increases. The reason of the increasing variability is that the medium level distributions of return and demand does not exist in this case as we see in table 4.53.

Table 4.53: Distributions of Scenarios in Case 4

		Return	
		Low $\mathcal{N}(30, 18^2)$	High $\mathcal{N}(250, 150^2)$
Demand	Low $\mathcal{N}(50, 30^2)$	Scenario 1	Scenario 3
	High $\mathcal{N}(450, 270^2)$	Scenario 2	Scenario 4

Table 4.54: Optimum First Stage Decisions for Each Scenario in Case 4

Scenario	Optimum Rfe	Optimum Dse
1	2	1
2	1	1
3	5	4
4	18	12

When we increase the variability, optimum first stage decisions recede from each other (Table 4.54). Increasing the varibality produce two different results. First one is the probability of different first stage decisions for **SOA** and **ROA** increases. Secondly, the expected costs for **SOA** and **ROA** are very different than expected optimum cost (Tables 4.55 and 4.56). Difference in percent for **SOA** is %11.4 in section 4.2 but it reaches %16.2 in this case. The reason of this dramatic uptrend is the difference of optimum cost and **SOA** and **ROA** costs for each scenario. These results orientate us if the distribution of scenarios are unstable, giving the first stage decisions according to the **SOA** and **ROA** approaches is more reasonable rather than giving the decisions according to just one scenario.

Table 4.55: First Stage Decisions for ROA and SOA in Case 4

	Rfe	Dse
SOA	10	7
ROA	11	7

Table 4.56: Costs for Each Scenario, Expected Costs and difference in Percents in Case 4

Scenario	optimum cost	**SOA** cost	**ROA** cost
1	491,629	1,200,668	1,220,668
2	5,329,585	6,064,085	6,084,085
3	1,869,755	2,123,080	2,143,057
4	5,130,531	5,919,282	5,908,621
Expected Cost	3205375	3826778	3839108
dip		16.2%	16.5%

Chapter 5

CONCLUSIONS

In this thesis, we developed a large scale mixed integer mathematical optimization model to solve the remanufacturing, refurbishing and disassembly operations for the products which have product modularity in a closed loop supply chain management system. There are two stages in our model. First one is giving the opening decisions for product disassembly sites and part refurbishing sites, named as first stage decisions. Second stage is operational decisions such as the quantity of the disassembled products, refurbished parts, sold products as second hand etc. These two stages are separated as operational and strategic stages.

After developing the sample problem and solving the model with deterministic approach for different scenarios, we determined that the changes in demand and return affects the first stage decisions dramatically. The model decides opening disassembly and refurbishing sites due to the change in part demand and product returns.

To analyze the results of demand and returns variability, we integrate our mathematical model into two different approaches. First one is Stochastic Optimization which minimizes the expected cost while giving the same first stage decisions for all scenarios. Second one is Robust Optimization Approach which minimizes the deviation between optimum cost and robust cost for each scenario while giving the same first stage decisions for all scenarios. We compare these tow approaches with deterministic optimum solutions in this thesis.

We solved the sample problem with deterministic, stochastic and robust approaches and conclude that the expected costs for **SOA** and **ROA** are close but the cost differences for each scenario are not close and **ROA** gives more accurate solutions for the sample problem. After that, we analyze the sample problem under less flexible conditions which has more expensive and more capacitated disassembly and refurbishing sites.Under less flexible conditions, **SOA** gives more valuable results. We run the model for 5 different sample problems and the results show that giving the first stage decisions due to the **SOA** is more advantageous when we increase opening diassambly and refurbishing site costs and capacities.

In this thesis, we analyze two different sensitivity analysis to see the change in first stage decisions and expected costs for the sample problem. Increasing the holding rate for products, increase the firs stage decisions and expected cost until the specific point. Unlike holding rates for products, the increasing upper bound for disassembly sites decrease the first stage decisions and total expected cost until the specific point.

In this thesis, to analyze the planning horizon's effect over first stage decisions, we experiment three different planning time horizons . The results of short horizon indicate that the model opens few disassembly and refurbishing sites because holding the products at holding sites for short horizon gives less cost. We can't use short horizon through strategic first stage decisions. However, it is noteworthy that Medium and High horizon solutions give same first stage decisions but long time horizon has two disadvantages. Firstly, run time increases dramatically and secondly the first stage costs' effect over total expected costs decrease.

Finally, we analyze four different cases to see first stage decisions, deterministic costs, stochastic costs and robust costs under different variability conditions for demand returns. Each case use same parameters like the sample problem.However, the difference comes from the distribution of demand and returns and the number of scenarios. We can make inferences through these cases. Firstly, the variability of scenarios' distribution change the first stage decisions and expected costs. But the effect of return is more distinctive rather than demand. In addition, to use **SOA** and **ROA** we should have scenarios which have different demand and return distributions. Finally, decreasing the scenario number and diverge the distributions of scenarios increase variability and different approaches are useful under these conditions.

Consequently, to solve large scale remanufaturing and disassembly problems which have product modularity and to give strategic decisions, **SOA** and **ROA** can be very helpful and can give valuable insights to the decision makers if they can determine the scenarios and the distributions of uncertain factors.

BIBLIOGRAPHY

[1] M. Thierry, M. Solomon, J. V. Nunen, and L. V. Wassenhove, "Strategic issues in product recovery management," *California Management Review*, vol. 37, no. 2, pp. 114–135, 1995.

[2] V. Jayaraman, R. A. Patterson, and E. Rolland, "The design of reverse distribution networks: Models and solution procedures," *European Journal of Operational Research*, vol. 150, no. 1, pp. 128 – 149, 2003. O.R. Applied to Health Services.

[3] V. R. R. Guide and L. N. V. Wassenhove, "Or forum—the evolution of closed-loop supply chain research," *Oper. Res.*, vol. 57, pp. 10–18, January 2009.

[4] B. M. Beamon, "Supply chain design and analysis:models and methods," *International Journal of Production Economics*, vol. 55, pp. 281–294, 1998.

[5] S. Kumar and P. Malegeant, "Strategic alliance in a closed-loop supply chain, a case of manufacturer and eco-non-profit organization," *Technovation*, vol. 26, pp. 1127–1135, 2006.

[6] R. Dekker, M. Fleischmann, K. Inderfurth, and L. N. V. Wassenhove, *Reverse Logistics:quantitative models for closed-loop supply chains*. Springer Series in Operations Research, Springer , Berlin, 2004.

[7] J. Sarkis, N. Darnall, G. Nehman, and J. Priest, "Remanufacturing," *Electronics and the Environment, 1995*, pp. 229 – 234, 1995.

[8] R. S. Tibben-Lembke and D. S. Rogers, "Differences between forward and reverse logistics in a retail environment," *Supply Chain Management*, vol. 7, no. 5, pp. 271 – 282, 2002.

[9] R. Lund, "Remanufacturing," *Technology Review*, vol. 87, no. 2, pp. 18 – 23, 1984.

[10] V. D. R. Guide, T. P. Harrison, and L. N. V. Wassenhove, "The challenge of closed-loop supply chains," *Interfaces*, vol. 33, no. 6, pp. pp. 3–6, 2003.

[11] M. Fleischmann, J. M. Bloemhof-Ruwaard, R. Dekker, E. v. D. Laan, J. A. V. Nunen, and L. N. V. Wassenhove, "Quantitative models for reverse logistics: A review," *European Journal of Operational Research*, vol. 103, no. 1, pp. 1 – 17, 1997.

[12] S. Pokharel and A. Mutha, "Perspectives in reverse logistics: A review," *Resources, Conservation and Recycling*, vol. 53, no. 4, pp. 175 – 182, 2009.

[13] S. K. Srivastava, "Green supply-chain management: A state-of-the-art literature review," *International Journal of Management Reviews*, vol. 9, no. 1, pp. 53 – 80, 2007.

[14] V. Jayaraman, V. D. R. Guide, and R. Srivastava, "A closed-loop logistics model for remanufacturing," *The Journal of the Operational Research Society*, vol. 50, pp. 497–508, 1999.

[15] M. Fleischmann, P. Beullens, J. M. Bloemhof-Ruwaard, and L. N. Wassenhove, "The impact of product recovery on logistics network design," *Production and Operations Management*, vol. 10, pp. 156–173, 2001.

[16] N. O. Demirel and H. Gokcen, "A mixed integer programming model for remanufacturing in reverse logistics environment," *The International Journal of Advanced Manufacturing Technology*, vol. 39, no. 11-12, pp. 1197 – 1206, 2008.

[17] A. I. Barros, R. Dekker, and V. Scholten, "A two-level network for recycling sand: A case study," *European Journal of Operational Research*, vol. 110, no. 2, pp. 199 – 214, 1998. EURO Best Applied Paper Competition.

[18] V. Jayaraman, "Production planning for closed-loop supply chains with product recovery and reuse: an analytical approach," *International Journal of Production Research*, vol. 44, no. 5, pp. 981 – 998, 2006.

[19] C. Franke, B. Basfere, M. Ciupek, and S. Seliger, "Remanufacturing of mobile phones–capacity, program and facility adaptation planning," *Omega*, vol. 34, no. 6, pp. 562 – 570, 2006. Reverse production systems - Reverse production systems.

[20] H. Krikke, J. Bloemhof-Ruwaard, and L. N. V. Wassenhove, "Concurrent product and closed-loop supply chain design with an application to refrigerators," *International Journal of Production Research*, vol. 41, no. 16, pp. 3689–3719, 2003.

[21] K. Kim, B. Jeong, and S. Jeong, "Optimization model for remanufacturing system at strategic and operational level," in *Lecture Notes in Computer Science*, pp. 566–576, Springer Berlin / Heidelberg, 2005.

[22] K. Kim, I. Song, J. Kim, and B. Jeong, "Supply planning model for remanufacturing system in reverse logistics environment," *Computers and Industrial Engineering*, vol. 51, no. 2, pp. 279 – 287, 2006. Special Issue: Logistics and Supply Chain Management, Selected Papers from The 33rd. ICC and IE.

[23] K. Richter and M. Sombrutzki, "Remanufacturing planning for the reverse wagner/whitin models," *European Journal of Operational Research*, vol. 121, no. 2, pp. 304 – 315, 2000.

[24] A. Sbihi and R. W. Eglese, "Combinatorial optimization and green logistics," *4OR: A Quarterly Journal of Operations Research*, vol. 5, no. 2, pp. 99 – 116, 2007.

[25] H. M. Wagner, "Dynamic version of the economic lot size problem," *Management science*, vol. 5, p. 89, 1958.

[26] R. H. Teunter, Z. P. Bayindir, and W. V. D. Heuvel, "Dynamic lot sizing with product returns and remanufacturing," *International Journal of Production Research*, vol. 44, pp. 4377 – 4400, 2006.

[27] O. Listes and R. Dekker, "A stochastic approach to a case study for product recovery network design," *European Journal of Operational Research*, vol. 160, pp. 268 – 287, 2005.

[28] M. Chouinard, S. D'Amours, and D. At-Kadi, "A stochastic programming approach for designing supply loops," *International Journal of Production Economics*, vol. 113, no. 2, pp. 657 – 677, 2008.

[29] O. Listes, "A generic stochastic model for supply-and-return network design," *Computers and Operations Research*, vol. 34, no. 2, pp. 417 – 442, 2007. Reverse Logistics.

[30] M. El-Sayed, N. Afia, and A. El-Kharbotly, "A stochastic model for forward-reverse logistics network design under risk," *Computers and Industrial Engineering*, vol. In Press, Corrected Proof, pp. –, 2008.

[31] P. Kouvelis and G. Yu, *Robust Discrete Optimization and Its Applications.* Kluwer, Boston, MA, 1997.

[32] J. M. Mulvey and A. Ruszczynski, "A new scenario decomposition method for large-scale stochastic optimization.," *Operations Research*, vol. 43, no. 3, p. 477, 1995.

[33] S. M. Mulvey and R. J. Vanderbei, "Robust optimization of large-scale systems.," *Operations Research*, vol. 43, no. 2, p. 264, 1995.

[34] C. Yu and H. Li, "A robust optimization model for stochastic logistic problems," *International Journal of Production Economics*, vol. 64, no. 1-3, pp. 385 – 397, 2000.

[35] M. J. Realff, J. C. Ammons, and D. Newton, "Carpet recycling: Determining the reverse production system design," *Polymer-Plastics Technology and Engineering*, vol. 38, pp. 547 – 567, 1999.

[36] M. Realff, J. Ammons, and D. Newton, "Robust reverse production system design for carpet recycling," *IIE Transactions*, vol. 36, no. 8, pp. 767 – 776, 2004.

[37] C. Wei, Y. Li, and X. Cai, "Robust optimal policies of production and inventory with uncertain returns and demand," *International Journal of Production Economics*, vol. In Press, Corrected Proof, pp. –, 2009.

[38] M. Prajapati, "A stochastic production planning model under uncertain demand," Master's thesis, Wright State University, 2008.

[39] G. B. Dantzig, "Linear programming under uncertainty," *Management Science*, vol. 1, pp. 197–206, 1955.

[40] J. Birge and F. Louveaux, *Introduction to Stochastic Programming.* Springer Series in Operations Research, Springer Verlag, New York, 1997.

[41] P. Kall and S. W. Wallace, *Stochastic Programming.* John Wiley and Sons, Chichester, UK, 1994.

Appendix A

NUMERICAL RESULTS FOR THE FIVE DIFFERENT SAMPLE PROBLEMS OVER OPENING COSTS AND CAPACITIES OPTIONS

Table A.1: Optimum Costs for Three Options and Five Different Samples

	Sample 1	Sample 2	Sample 3	Sample 4	Sample 5
Option 1	3,098,310	2,923,456	3,037,560	2,981,875	2,975,471
Option 2	3,030,186	2,844,237	2,956,102	2,906,748	2,908,669
Option 3	2,939,075	2,762,546	2,885,515	2,820,286	2,814,968

Table A.2: Expected Costs for Three Options and Five Different Samples in **SOA**

	Sample1	Sample2	Sample3	Sample4	Sample5
Option 1	3,635,427	3,451,139	3,521,716	3,490,979	3,475,740
Option 2	3,637,339	3,460,762	3,637,339	3,493,736	3,477,621
Option 3	3,635,427	3,455,055	3,521,726	3,490,968	3,475,740

Table A.3: Maximum Cost Differences for Three Options and five Different Samples between **SOA** and the Optimum Costs

	Sample1	Sample2	Sample3	Sample4	Sample5
Option 1	1,020,752	1,038,701	610,248	798,229	613,932
Option 2	1,086,274	1,131,537	584,940	850,129	581,678
Option 3	995,930	1,061,601	523,511	774,017	596,792

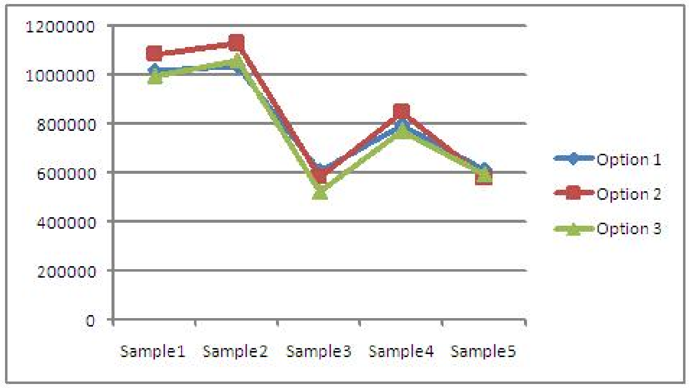


Figure A.1: Maximum Cost Differences for Three Options and Five Samples between **SOA** and the Optimum Costs

Table A.4: Cost Differences in percent for Three Options and five Different Samples between **SOA** and the Optimum Costs

	Sample1	Sample2	Sample3	Sample4	Sample5
Option 1	0.1147	0.1181	0.1034	0.1115	0.1094
Option 2	0.1009	0.1088	0.0935	0.0993	0.0946
Option 3	0.0925	0.0962	0.0784	0.0890	0.0865

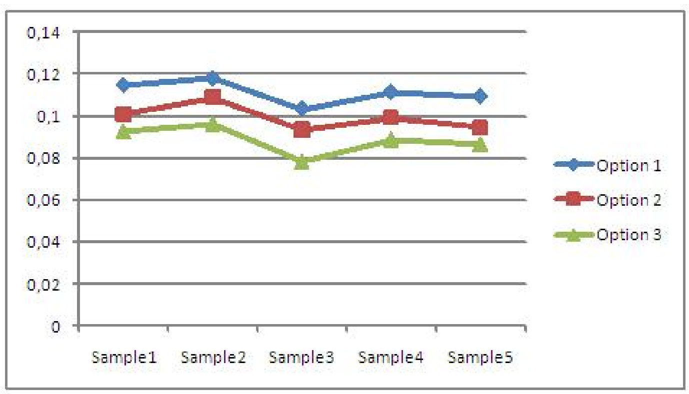


Figure A.2: Differences in Percents for Three Options and Five Samples between **SOA** and the Optimum Costs

Table A.5: Expected Costs for Three Options and five Different Samples in **ROA**

	Sample1	Sample2	Sample3	Sample4	Sample5
Option 1	3,656,007	3,466,504	3,525,685	3,531,932	3,475,740
Option 2	3,706,016	3,508,283	3,706,016	3,601,567	3,490,676
Option 3	3,773,336	3,607,597	3,521,726	3,652,648	3,475,740

Table A.6: Maximum Cost Differences for Three Options and five Different Samples between **ROA** and the Optimum Costs

	Sample1	**Sample2**	**Sample3**	**Sample4**	**Sample5**
Option 1	729,091	742,013	590,248	726,880	613,932
Option 2	743,488	753,908	546,825	714,170	550,562
Option 3	777,708	719,685	523,511	719,704	596,792

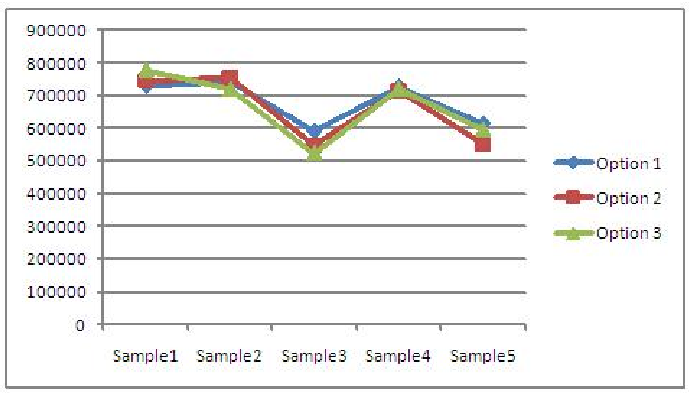


Figure A.3: Maximum Cost Differences for Three Options and Five Samples between **ROA**and the Optimum Costs

Table A.7: Cost Differences in percent for Three Options and Five Different Samples between **ROA** and the Optimum Costs

	Sample1	**Sample2**	**Sample3**	**Sample4**	**Sample5**
Option 1	0.1197	0.1220	0.1044	0.1218	0.1094
Option 2	0.1176	0.1209	0.0965	0.1263	0.0980
Option 3	0.1256	0.1345	0.0784	0.1293	0.0865

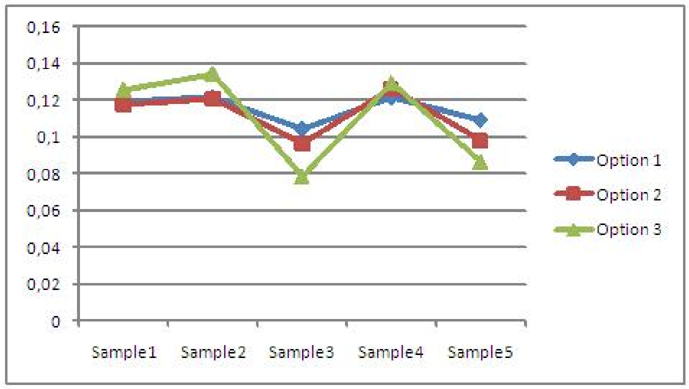


Figure A.4: Differences in percents for Three Options and Five Samples between **ROA** and the Optimum Costs

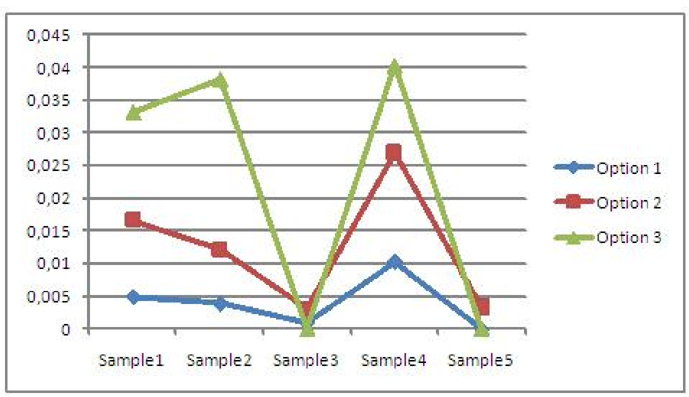


Figure A.5: Gap Values Between SOA and ROA *dip* for Five Different Samples and each Option

VITA

Fatih Bağcı was born in Gaziantep, on May 13, 1985. He graduated from Gaziantep Science High School in Gaziantep in 2003. He received his B.Sc. major degree in Industrial Engineering from Koç University, Istanbul, in 2008. In September 2008, he joined the Industrial Engineering Department of Koç University, Istanbul, as a research and teaching assistant.