MODELLING AND ANALYSIS OF SUSTAINABLE SUPPLY CHAINS

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DOCTOR OF PHILOSOPHY DISSERTATION

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This thesis titled "Modelling and Analysis of Sustainable Supply Chains" has been prepared and submitted by Mehmet ALEGOZ in partial fulfillment of the requirements in "Eskişehir Technical University Directive on Graduate Education and Examination" for the Degree of Doctor of Philosophy (PhD) in Industrial Engineering Department has been examined and approved on 08/11/2019.

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ABSTRACT

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Nowadays many companies started to collect and remanufacture used products to obtain economic and environmental benefits and comply with regulations. Product recovery is not always beneficial to all supply chain actors and appropriate policies are needed to be developed to increase its benefit. This thesis focuses on mainly two research questions. First, in which cases product recovery may be a beneficial option for a specific supply chain actor or for the entire supply chain? Second, how can we develop appropriate policies to maximize the profit of a specific supply chain actor or the profit of the entire supply chain? We investigate these questions in three phases of the thesis. In the first phase, we focus on a collection center which needs to decide on the acquisition fee and dispatching time in order to collect the right amount of used products and maximize its profit. In the second phase, we focus on different remanufacturing systems and investigate in which cases product recovery may be a beneficial option for a specific supply chain actor, i.e. for the manufacturer, remanufacturer or retailer. To this end, we develop policies for them to maximize their own profits. Finally, in the third phase, we focus on the entire supply chain and try to determine in which cases product recovery may be a beneficial option for the entire supply chain. Each phase of the study is supported by comprehensive numerical experiments and sensitivity analyses, which bring significant managerial insights regarding a supply chain actor or the entire supply chain.

Keywords: Sustainability, Supply chain management, Product recovery

ÖZET

SÜRDÜRÜLEBİLİR TEDARİK ZİNCİRLERİNİN MODELLENMESİ VE ANALİZİ

Mehmet ALEGÖZ

Endüstri Mühendisliği Anabilim Dalı
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Danışman: Prof. Dr. Onur KAYA
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Günümüzde, birçok firma ekonomik ve çevresel fayda sağlamak amacıyla kullanılmış ürünleri toplamaya ve geri dönüşüm sürecine almaya başlamıştır. Buna karşılık, geri dönüşüm tüm tedarik zinciri aktörleri için her zaman faydalı değildir ve geri dönüşümün faydasını artırmak için uygun politikaların geliştirilmesi gerekir. Bu tez temelde iki araştırma sorusuna odaklanmaktadır. Birincisi, yeniden üretim hangi durumlarda bir tedarik zinciri aktörü veya tüm tedarik zinciri açısından yararlı bir seçenek olabilir? İkincisi ise, bir tedarik zinciri aktörünün veya tüm tedarik zincirinin kazancını enbüyüklemek için uygun politikalar nasıl geliştirilebilir? Bu sorular tezin üç aşamasında irdelenmiştir. İlk aşamada kazancını enbüyüklemeye çalışan ve bu amaçla en uygun toplama fiyatı ve sevkiyat zamanını belirlemesi gereken bir toplama merkezine odaklanılmıştır. İkinci aşamada ise hangi durumlarda geri dönüşümün üretici, yeniden üretici veya perakendeci gibi bir tedarik zinciri aktörü için faydalı olacağı araştırılmış ve bu amaçla tedarik zinciri aktörlerinin kendi kazançlarını enbüyükleyecek politikalar geliştirilmiştir. Son olarak, üçüncü aşamada tüm tedarik zincirine odaklanılmış ve hangi durumlarda geri dönüşümün tüm tedarik zinciri için yararlı olacağı araştırılmıştır. Çalışmanın her bir fazı kapsamlı sayısal deneyler ve duyarlılık analizleri ile desteklenmiş, bu deneyler ve duyarlılık analizleri tüm tedarik zincirine ya da herhangi bir tedarik zinciri aktörüne dair önemli yönetimsel çıkarımları beraberinde getirmiştir.

Anahtar Kelimeler: Sürdürülebilirlik, Tedarik zinciri yönetimi, Ürün geri dönüşümü

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Mehmet ALEGOZ

11/10/2019

STATEMENT OF COMPLIANCE WITH ETHICAL PRINCIPLES AND RULES

I hereby truthfully declare that this thesis is an original work prepared by me; that I have behaved in accordance with the scientific ethical principles and rules throughout the stages of preparation, data collection, analysis and presentation of my work; that I have cited the sources of all the data and information that could be obtained within the scope of this study, and included these sources in the references section; and that this study has been scanned for plagiarism with "scientific plagiarism detection program" used by Eskişehir Technical University, and that "it does not have any plagiarism" whatsoever. I also declare that, if a case contrary to my declaration is detected in my work at any time, I hereby express my consent to all the ethical and legal consequences that are involved.

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1. INTRODUCTION

A forward supply chain (FSC) is a network including suppliers, manufacturing plants, warehouses and distribution channels created to acquire raw materials, convert these raw materials to finished products and finally distribute these products to customers (Santoso et al., 2005). The concept of "closing loops" refers to the integration of forward and reverse supply chains; this concept is considered as one of the options to increase the sustainability (Banasik et al. 2017). In a closed-loop supply chain (CLSC), forward flows are responsible for demand satisfaction for new products, while reverse flows are responsible for collection and recovery of returned products (Haddadsisakht and Ryan, 2018).

Initially, the growing attention on closed-loop supply chain issues originated with public awareness. Then governmental legislation forced producers to take care of their end-of-life (EOL) products (Govindan et al. 2015). Recently, product and material recovery has received growing attention throughout the world, with its three main motivators that include governmental legislations, economic value to be recovered and environmental concerns (Suyabatmaz et al. 2014).

As an industry, product recovery has been thriving in many developed and industrialized countries such as United States of America, United Kingdom and Japan. For example, in the United Kingdom, the output value of remanufacturing exceeds $7 billion annually and it provides approximately 50,000 jobs in that country (Cao et al., 2020). Firms such as Caterpillar, GE, IBM, HP, Ford, Sony and others, have established cost-effective remanufacturing systems either by themselves or via outsourcing to a third party (Saha et al., 2016).

In this thesis, our research focuses on mainly two research questions. First, in which cases may product recovery bring economic or environmental benefit to the entire supply chain or to a specific supply chain actor, i.e. to the manufacturer? Second, how can we develop appropriate policies for supply chain actors to increase their economic or environmental benefits from product recovery; i.e. how can we maximize the profit of a collection center or a remanufacturer?

In order to investigate these questions, in Chapter 3, we focus on collection, disassembly, warehousing and dispatching processes of a collection center that acquires used products from end users and sells them to remanufacturing facilities. Collection centers are one of the most important actors in product recovery systems and they play a significant role in sustainable development. As stated in the literature (e.g. Bakal and Akcali, 2006; Karakayali et al., 2007; Zheng et al. 2017), the amount of collected products depends on the acquisition fee offered to the end users as an incentive to return their products. Thus, the collection center first needs to decide on the acquisition fee in order to collect the right amount of used products from the end users. Since the core product is composed of many different components, the collection center then disassembles the collected products in order to extract the reusable components. Each component has a different value and some of the components might be more likely to be reusable than the others. After the disassembly and quality control of the components, reusable components are stored until their dispatching time to the remanufacturer. The collection center needs to decide when to dispatch the reusable components. If the components are dispatched too frequently, there will be a high dispatching and transportation cost and if they wait too long at the collection center warehouse, there will be a high holding cost. Since there are many components with different values and different characteristics, determination of the optimal dispatching decision of these components in a coordinated manner can become very complex. In this context, in Chapter 3, we develop exact and heuristic solution approaches for the dispatching and acquisition fee decisions of collection centers.

In Chapter 4, we focus on pricing and sustainability level decisions in pure manufacturing and hybrid manufacturing-remanufacturing systems and compare the systemwide performances and the performances of supply chain actors under different settings in terms of economic and environmental performance measures. We consider the case in which manufactured and remanufactured products are sold in the same market and they are not perfect substitutes of each other. Thus if, only manufactured products are available in the market, demand for manufactured products depends only on the selling price of manufactured products, whereas if both manufactured and remanufactured products are available for customers, due to the competition between them demand for one is affected by its own price as well as other type of product's price.

Nowadays, many countries prepare to bring an emission regulation within a few years, whereas there are already some regulations in some countries forcing the companies to control their emission level (State and Trends of Carbon Pricing, 2019). In Chapter 4 of this thesis, we consider one of the well-known and widely used emission regulation, the carbon tax policy under which companies pay a certain fee, that is called carbon tax, for each unit of their carbon emission. Based on this policy, we assume that a carbon tax is paid for the emissions resulting from the manufacturing and remanufacturing processes, whereas making sustainability investments and increasing the sustainability level decreases these emissions and consequently paid carbon tax. Since the unit emission cannot be removed completely, we assume that the sustainability level can be increased only up to a certain limit.

In this context, we focus on a supply chain including a manufacturer, a remanufacturer, a retailer and customers and we consider four settings. Under Setting 1, no remanufacturing is made and the manufacturer sells only the manufactured products to the retailer and the retailer sells these products to customers, whereas under Setting 2, Setting 3 and Setting 4, some of the used products are collected and remanufactured by the manufacturer, retailer and a third-party remanufacturer respectively.

Considering the above-mentioned settings, in Chapter 4, we particularly investigate the following research questions.

[1] How are the manufacturer, the retailer and the customers affected when the manufacturer the retailer or a third-party remanufacturer decides to collect and remanufacture the used products; i.e. how the wholesale prices and selling prices are changed, whose profit is increased and whose profit is decreased?

[2] In which setting, are the lowest selling prices achieved?

[3] In which setting, is the highest sustainability level achieved?

[4] In which setting, are the economic and environmental performance measures closest to the centralized case?

In order to investigate these questions, we propose stylized models under centralized control, in which a central authority makes all the decisions regarding the system, and decentralized control, in which the actors make their own decisions, of each setting. We investigate the above-mentioned research questions by comparing the wholesale prices, selling prices, profits and sustainability levels achieved under different settings. We discuss which setting is better for the manufacturer, retailer, customers and environment and under which setting highest collection and remanufacturing quantity can be achieved. We also make a comprehensive sensitivity analysis on parameters to see the effect of a specific parameter on the decisions.

Finally, in Chapter 5, we focus on the financial and environmental effects of closing the loop in supply chains by comparing the forward and closed-loop supply chain network designs and investigate the question in which cases closing the loop may be a beneficial option for the entire system. Network design problem includes the decisions regarding the number, location and capacity of each facility, the assignment of each market region to one or more supply locations, and supplier selection for sub-assemblies, components and materials. (Meixell and Gargeya, 2005). The strategic configuration of the supply chain is a key factor influencing efficient tactical operations, and thus has a long-lasting impact on the company (Santoso et al., 2005).

More specifically, in Chapter 5, we focus on the investigation of the following research questions.

[1] What are the financial and environmental effects of closing the loop in supply chains, i.e. how much cost and emission difference can be observed by closing the loop in supply chains

[2] In which cases, closing the loop in supply chains may be a beneficial option for cost reduction?

[3] What are the effects of a change in return rate and returned product quality?

[4] What are the effects of carbon cap, carbon cap-and-trade and carbon tax policies on the cost and emission difference between FSC and CLSC?

In first three questions, we assume that the company is in an area where there is no emission regulation, i.e. there is no emission limit and emission-related cost. In order to investigate the first question, we propose a set of supply chain network design models for both forward and closed-loop supply chains and compare the model results with each other under optimal decisions. Second and third questions are investigated by sensitivity analysis. Finally, for the last question, we assume that the company is in an area where there is an emission regulation and we modify our models for carbon cap, carbon cap-and-trade and carbon tax policies.

During the lifetime of a supply chain, various parameters are exposed to dramatic changes. Considering these parameters as deterministic is highly unrealistic and it could result in irrecoverable costs and inefficiencies (Hasani et al. 2012). Hence, our network design models in Chapter 5 simultaneously consider demand, return rate and returned product quality uncertainties.

Capacity expansion availability provides a good proxy to how big each facility should be and an opportunity to reduce overall supply chain costs by providing flexibility to address the trade-offs between fixed and variable costs (Üster and Hwang, 2016). In this context, we assume that the capacities of manufacturing plants, distribution centers, collection centers, repair centers and disassembly centers can be expanded up to a limit.

Similar to Chapter 4, while creating the network design models in Chapter 5, we consider emissions resulting from the operations and shipments. Since there may be different emission policies in different countries, focusing only on a single emission policy may make the model useless in some cases. Hence, in Chapter 5, we focus on three well known and widely-used emission policies, carbon cap, carbon cap-and-trade and carbon-tax, together with the case of no emission regulation.

2. LITERATURE REVIEW

We divide the review into three groups as collection process and shipment consolidation (related to Chapter 3), remanufacturing and competition (related to Chapter 4) and supply chain network design (related to Chapter 5).

Interested readers may refer to Guide and Van Wassenhove (2009), Souza (2013), Govindan et al. (2015), Eskandarpour et al. (2015), Diallo et al. (2017) and Govindan et al. (2017) for comprehensive reviews about the latest developments in various aspects of product recovery and supply chains. Please also refer to Bouchery et al. (2016) for detailed discussions about various aspects of sustainable supply chains.

2.1. Collection Process and Shipment Consolidation

In this subsection, we provide the literature related to collection process and shipment consolidation. A stream of research focuses on different aspects of collection process to gain insights regarding the collection system. Reimer et al. (2006) examine the issue of determining configurations for trucks that are involved in the collection of recyclables. Hong and Yeh (2012), Hong et al. (2013), Chuang et al. (2014) and Shi et al. (2015) focus on the collection channel alternatives and compare various alternatives such as retailer collection, third party collection and manufacturer collection in different problem settings. Tagaras and Zikopoulos (2008) and Gu and Tagaras (2014) focus on the sorting issue and study various sorting alternatives such as no sorting, sorting at manufacturer, sorting at collection center. Zikopoulos and Tagaras (2015) examine simultaneously the issues of multiple collection sites, uncertain quality and inaccurate classification of returns in reverse supply chains. Paredes-Belmar et al. (2017) propose a new approach to solve the problem of hazardous waste collection in a transportation network. Paydar et al. (2017) propose a mixed-integer linear programming model for a closed-loop supply chain of used engine oil with the objectives of maximizing profit and minimizing the risk of the collection.

Another stream of research considers collection systems in a coordinated or uncoordinated manner. For instance, Hong et al. (2015) propose Stackelberg game models for coordinated advertising, pricing and collection decisions. Mobasher et al. (2015) focus on coordinated collection and appointment scheduling operations at the blood donation sites by considering processing time requirement of donated blood units for platelet production. Zheng et al. (2017) focus on a reverse supply chain consisting of a collector and a remanufacturer. They propose models to cope with pricing, collecting and contract design decisions. Habibi et al. (2017a) propose an optimization model to optimize the collection-disassembly problem in a coordinated manner. Then, Habibi et al. (2017b) focus on the same problem and propose a two-phase iterative heuristic to address large size instances efficiently. Hong et al. (2017) focus on quantity, collection and technology licensing decisions. They investigate two licensing patterns, namely fixed fee versus royalty. Han et al. (2017) focus on collection channel and production decisions under various remanufacturing disruption cases. Liu et al. (2017) examine the influence of competition intensity on pricing, collection effort and reverse channel choice decisions.

There are also various studies in literature considering dispatching and shipment consolidation in forward supply chains under random demand. Bookbinder and Higginson (2002) evaluate the performance of several shipment consolidation practices in forward supply chains. Cetinkaya and Lee (2000) develop a model for this problem to compute the optimal replenishment quantity and dispatch frequency. Axsater (2001) provides a simple procedure to solve the exact model in Cetinkaya and Lee (2000). Chen et. al. (2005), Cetinkaya et. al. (2006) and Cetinkaya et. al. (2008) extend the analysis of this system under different settings considering time-based, quantity-based and hybrid shipment policies. Mutlu and Cetinkaya (2010) consider common carriage, rather than a private fleet of vehicles in the analysis of the model of Cetinkaya and Lee (2000). Cetinkaya and Bookbinder (2003) and Mutlu et. al. (2010) determine the optimal solutions for time-based, quantity-based and hybrid policies with private or common carriage opportunities and compare the performances of the three policies analytically.

Zaarour et al. (2013) analyze a similar system to the one analyzed in Chapter 3 and they state that their study is one of the first to develop a mathematical model that can determine the optimal collection period at an initial collection point before transshipping the returned products to a centralized return center. However, different from our study, they assume deterministic returns and they only analyze a time-based policy in order to determine the shipment periods for a single product. They also assume that all collected products are reusable and checking the reusability of returned items is out of scope of their paper.

Our study in Chapter 3 differs from the studies in the literature in various aspects. Firstly, to the best of our knowledge, this is the first study in literature which analyzes the optimal dispatching policy for collection centers that collect end-of-life products composed of multiple reusable components with different characteristics (i.e. different values, different holding costs and different reusability probabilities). Secondly, we analyze quantity-based and time-based dispatching heuristics, which are widely used in practice, and compare their performances with the optimal dispatching decisions. In addition, in this study, acquisition fee decision is integrated with time-based, quantity-based and optimal dispatching policies. We determine the optimal dispatching and acquisition fee decisions in a coordinated manner and also compare static and dynamic pricing models for the acquisition fee decisions. All these policies as well as static and dynamic acquisition fee decisions are studied in a setting including nonlinear transportation costs, random arrival rates and batch sizes, as well as random quality levels of EOL products with different reusability probabilities of components.

2.2. Remanufacturing and Competition

In this subsection we provide the literature related to remanufacturing and competition. A stream of research in the literature focuses on the comparison of different product recovery systems. Savaşkan et al. (2004) compare the performances of different collection channels such as manufacturer collecting, retailer collecting or third-party collecting and find that the agent, who is closer to the customer (i.e., the retailer), is the most effective undertaker of product collection activity. Choi et al. (2013) investigate a CLSC, which consists of a retailer, a collector, and a manufacturer, and compare the performance of CLSC under different channel leaderships. They find that the retailer-led model gives the most effective CLSC. Govindan et al. (2014) consider the two and three-echelon supply chains and report that the introduction of the distributor into the setting affects the profit of the manufacturer such that, under the three-echelon setting, he shares the revenue with two participants, as opposed to sharing it with only one participant in the two-echelon setting. Saha et al. (2016) focus on three different modes of collection such as third party, directly by the manufacturer and from the retailer. They show that the remanufacturing rate is maximized when the used product is procured directly from the manufacturer.

Zheng et al. (2017) investigate the pricing and collecting decisions in CLSC's under different channel power structures. They find that the retailer-led model attains the highest return rate. Feng et al. (2017) examine single traditional recycling channel, single online-recycling channel, and a hybrid recycling channel. Their analysis shows that the hybrid recycling channel always outperforms its single channel counterparts from the recyclable dealer's and system's perspectives. Heydari et al. (2017) consider a reverse supply chain and a closed-loop supply chain to analyze the incentives of government. They find that it is more economical for the government to propose incentives to the manufacturer rather than to the retailer in both reverse and closed-loop supply chains.

Another stream of research focuses on the effects of competition between supply chain actors. Majumder and Groenevelt (2001) consider a supply chain in which an original equipment manufacturer (OEM) competes with a local remanufacturer for the returned items. They find that an increase in the fraction available for remanufacturing increases remanufacturing activity but such an increase does not always increase the OEM's profit. Atasu et al. (2008) propose models that consider various issues in remanufacturing systems such as original equipment manufacturer competition and product life-cycle effects. They show that under competition remanufacturing can become an effective marketing strategy, which allows the manufacturer to defend its market share via price discrimination. Wu et al. (2012) consider a supply chain including an original equipment manufacturer (OEM) and a remanufacturer that competes with each other. The OEM decides on the degree of disassemblability which affects both OEM's manufacturing cost and remanufacturer's remanufacturing cost. They indicate that even if a high degree of disassemblability is profitable, the OEM may adopt low disassemblability due to concerns about competition with the remanufacturer.

Örsdemir et al. (2014) consider an original equipment manufacturer (OEM) who faces competition from an independent remanufacturer. The OEM decides the quality of the new product, which also determines the quality of the competing remanufactured product. They observe that the OEM relies more on quality as a strategic lever when it has a stronger competitive position, and, in contrast, it relies more heavily on limiting quantity of cores when it has a weaker competitive position. Zhang and Ren (2016) focus on a CLSC including an original manufacturer, a third-party remanufacturer and a retailer in which manufactured and remanufactured products are sold in the same market and thus there is a competition between them. After comparing the centralized and decentralized systems, they report that in centralized system the decision maker obtains more used products and consequently a higher profit. He et al. (2019) investigate the impacts of the recovery inconvenience perceived by customers. They find that although the manufacturer and the retailer bilaterally monopolize the forward supply chain, they compete in the reverse supply chain based on the channel inconvenience perceived by customers. Chakraborty et al. (2019) study how a retailer and each of two competing manufacturers can be benefited by collaborative product quality improvement strategies in a supply chain. Their analysis shows that price competition between two products has a positive influence on the quality improvement levels of those products. Further, it has a positive impact on the unit prices, profits of individual members and systemwide profit.

Another stream of research focuses on the comparison of centralized and decentralized systems. Li et al. (2017) focus on a CLSC consisting of a single collector, a single remanufacturer and two retailers. Their analysis shows that with the same potential market demand of remanufactured products and utilization ratio of used products, a centralized model maximizes both the economic and social benefit compared to the other models. Heydari et al. (2019) addresses pricing and greening decisions in supply chain in which the manufacturer produces a good with an arbitrarily green level. Their analysis shows that the centralized setting provides better profit values compared to decentralized setting. Xie et al. (2017) consider the recycling rate fluctuation and study the centralized and decentralized CLSC's consisting of a manufacturer, a retailer and customers. They report that prices under decentralized decisions are higher than those under centralized decisions.

Finally, another stream of research that can be considered as close to our study put the environmental impact into account. Bazan et al. (2015) present two models that consider energy along with the greenhouse gases emissions. They find that energy is the main environmental cost component for both models, and targeting a reduction in energy usage is a priority. Bazan et al. (2017) consider three critical environmental issues (energy, emissions and the number of times to remanufacture a used item and propose models for CLSC. Their analysis shows that considering environmental costs suggested remanufacturing an item for higher number of times. Bai et al. (2018) propose a revenue and investment sharing contract for a supply chain with a supplier and a manufacturer and show that coordination with this contract may lead to an increase in profit and to a reduction of carbon emissions.

Tao et al. (2018) propose a dynamic programming model to investigate the impact of carbon transfer cost and carbon holding cost. Their analysis shows that when the supply chain is coordinated, the chain's profit is more sensitive to carbon transfer cost while inventory level is more sensitive to carbon holding cost. Chen and Akmalul'Ulya (2019) investigate the greening efforts in green CLSC's. They find that the retailer will put in more effort in greening the supply chain if either the market responsiveness to his efforts is greater than that of the manufacturer; or the cost efficiency of the retailer is lower than that of the manufacturer; or both.

In our study in Chapter 4, different from the literature, we focus on the pricing and sustainability level decisions in pure manufacturing and hybrid manufacturing-remanufacturing systems and compare the performances of supply chain actors under different settings with each other. Ferguson and Toktay (2006) can be considered as one of the closest studies to our study. They consider a supply including a manufacturer and in some problem settings a remanufacturer and investigate the financial effects of remanufacturing decision of the manufacturer or the third-party remanufacturer. In their setting, manufactured and remanufactured products are sold in the same market and thus have a competition with each other. Main insight obtained from their study is that a manufacturer may choose to remanufacture or preemptively collect its used products to deter entry, even when the firm would not have chosen to do so under a pure monopoly setting. Our study extends the analysis in Ferguson and Toktay (2006) and has several major differences from that study. First, we focus on a setting which includes the retailer and we investigate whether the findings of them are valid under the settings where the products are sent to customers via the retailers. Secondly, we investigate the effects of entry on the retailer. Thirdly, we investigate an additional case in which instead of the remanufacturer or manufacturer, the retailer itself collects and remanufactures the products. By this way, we compare the effects of entrance of the remanufacturer and retailer and determine which one among the entrance of the remanufacturer and the retailer brings the highest profit reduction to manufacturer. Fourthly, we put the environmental impact into account and add the carbon emissions to our models. We also have a decision variable that does not exist in Ferguson and Toktay (2006), the sustainability level decision of the manufacturer which has an effect on the unit emissions. Finally, we consider the carbon tax policy which is widely used in many countries. We investigate whether the insights of Ferguson and Toktay (2006) are valid under such a policy.

2.3. Supply Chain Network Design

In this subsection, we present the literature related to network design problem which is closely related to our study in Chapter 5. A stream of research focuses on developing network design models either to investigate some specific research questions or to address some specific cases or industries. For example, Fleischmann et al. (2001) propose a CLSC model and show that simultaneous design of forward and reverse network may bring significant cost savings compared to adding a recovery network to an existing forward network. Beamon and Fernandes (2004) propose a mixed-integer linear programming model for CLSC design problem and make a sensitivity analysis to see the effects of parameters. Their analysis shows that different values of demand and return rate may bring different network designs. Salema et al. (2007) mention that most of the proposed models on the CLSC design are case based and thus, they lack generality. To overcome this shortcoming, they propose a generalized model for CLSC network design problem. Özkır and Başlıgil (2012) propose a mixed integer linear programming model that integrates various recovery options such as material recovery, component recovery and product recovery for CLSC network design problem. Amin et al. (2017) propose a CLSC network design model by focusing on global factors such as exchange rates. They show that global factors play an important role and optimal network can be different when global factors are not considered.

Another stream of research focuses on the uncertainty in supply chains. Pishvaee et al. (2011) mention that the concern about significant changes in the business environment (such as customer demands) has spurred an interest in designing robust supply chains and develop a robust optimization model to handle the uncertainty. Ramezani et al. (2013) propose a robust optimization approach for CLSC design and show that the deterministic configuration is infeasible under some demand and return rates while the robust configuration is feasible for all conditions. Jindal and Sangwan (2014) propose a fuzzy mixed integer linear programming model to address the CLSC design problem under various uncertainties related to costs, demand and fraction of parts recovered. Subulan et al. (2015) focus on financial and collection risks in CLSC and integrate different risk measures such as variability index, downside risk and conditional value at risk within the proposed model. Jabbarzadeh et al. (2018) present a stochastic robust optimization model for the design of a CLSC that is vulnerable to random disruptions and they show that significant cost savings can be achieved by planning for disruptions when designing supply chain networks. Fathollahi-Fard et al. (2018) focus on the social aspect of CLSC and propose a stochastic mixed integer programming model which simultaneously considers economic and social objectives under demand uncertainty. Dehghan et al.

(2018) consider the edible oil supply chain under uncertainty. Since their model includes two kinds of uncertain parameters, the scenario- and fuzzy-based parameters, they propose a novel Robust Stochastic-Possibilistic Programming (RSPP) approach to cope with uncertain parameters.

Another stream of research that is closely related to our study considers the environmental aspect of the network design problem. Paksoy et al. (2011) propose a mathematical model for CLSC network design. Their model considers environmental costs such as costs of CO_2 emissions due to transporting material in forward and reverse logistics networks. Das and Posinasetti (2015) integrate environmental concerns in a facility location model for a CLSC and show that environmental sustainability can be improved by trading-off a very small percentage of profit. Garg et al. (2015) consider operational and environmental performance measures in the CLSC and formulate a bi-objective integer nonlinear programming model. In order to solve it they also propose an interactive multi-objective programming approach algorithm. Mohajeri and Fallah (2016) develop a CLSC model under demand and return uncertainties in which carbon emission is expressed in terms of environmental constraints.

Moreover, Talaei et al. (2016) propose a robust optimization approach for CLSC network design by focusing on CO_2 emission throughout the network and show that their robust model is capable of controlling the network uncertainties. Xu et al. (2017) focus on the effects of emission policies and market factors on the design of hybrid and dedicated CLSCs and propose a set of integrated mixed integer linear programming models for CLSC network design problem. According to their numerical experiments, they report the cases in which hybrid or dedicated CLSCs are better in terms of cost or emission. Mohammed et al. (2017) propose an optimization model for design and planning of a multi-period, multi-product CLSC with carbon footprint consideration under demand and return uncertainties.

In addition, Haddadsisakht and Ryan (2018) consider the uncertainty in carbon tax rate together with demand and returned product uncertainties. They formulate a CLSC network design model, which accommodates carbon tax policy by ensuring that the resulting solutions are robust to the uncertain carbon tax rate. Mota et al. (2018) focus on economic, environmental and social objectives in supply chains and propose a multi-objective mixed integer linear programming model, which integrates several interconnected decisions such as facility location and capacity determination, production and remanufacturing planning and technology selection. Rad and Nahavandi (2018) focus on the integrated problem of network design and supplier selection under quantity discount option. They propose an integrated mathematical programming model for closed-loop green supply chain in which suppliers offer quantity discounts in order to motivate buyers to purchase more. Sahebjamnia et al. (2018) develop a multi objective mixed integer linear programming model for designing sustainable tire closed-loop supply chain network. In addition to cost minimization, they also focus on the minimization of environmental impact and maximization of social impact.

Similar to our study in Chapter 5, Gaur et al. (2017) also make an FSC and CLSC comparison. They assume a given supply chain network design and focus on the supply chain configuration problem in order to decide on the alternative options to be selected for different stages of CLSC, the level of inventories and the level of production and sales throughout the entire life-cycles of both new and reconditioned products. However, in our study, we focus on the supply chain network design problem and compare the FSC network with the CLSC network. In addition, we do not only make a cost comparison, but also focus on the environmental aspects of supply chains and compare the FSC and CLSC in terms of total supply chain emission considering uncertainties in the system, while they only focus on cost comparison in a deterministic setting.

Main motivation and contribution of the study in Chapter 5 is investigating and quantifying the financial and environmental effects of closing the loop in supply chains. More specifically, we want to show in which cases closing the loop may be beneficial and in which cases it may not with respect to total supply chain cost and emission. From the theoretical point of view, to best of our knowledge, this study is the first study in the literature that compares the forward and closed-loop supply chain designs considering financial and environmental effects under optimal decisions. From the practical point of view, this study is expected to be a guide to those companies which consider closing the loop in their supply chains and seeking the consequences of it. It should also be noted that since we create generic models, a company can easily adopt our models to their specific case and investigate the impact.

Moreover, in order to create a real-life oriented model and obtain meaningful results, we consider various issues in our models. Firstly, as we numerically show in our computational study, there are instances in which ignoring the uncertainties may bring wrong decisions and consequently higher cost and emission values. Thus, we take various uncertainties into account and make the comparison of FSC and CLSC in an uncertain environment. More specifically we consider demand, return rate and returned product quality uncertainties simultaneously. Secondly, it should be noted that “environment” is an important issue in today’s world and findings obtained by ignoring the environmental aspect may be useless for the companies operating under an emission policy. Thus, in addition to the case of no emission policy, we consider the cases in which there is an emission policy such as carbon tax policy and report the obtained findings.

3. DISPATCHING AND ACQUISITION FEE DECISIONS OF COLLECTION CENTERS

Collection centers play an important role for sustainable development in closed-loop supply chains by managing the collection activities of end-of-life (EOL) products and presenting them back to the economy. In this part of thesis, we focus on a collection center which collects EOL products that are composed of multiple components, disassembles the collected products, checks the quality of their components and sends the reusable parts to a remanufacturer at a certain price. The collection center needs to decide when to dispatch the collected products to the remanufacturer as well as the optimal acquisition fee in order to collect the right amount of EOL products from the end users and maximize its profit. We develop a dynamic programming model to maximize the long-run average profit of the collection center per unit time and analyze the optimal dispatching and acquisition fee decisions. We analyze quantity-based and time-based dispatching heuristics, which are widely used in practice, and compare their performances with the optimal dispatching decisions. We also compare static and dynamic acquisition fee models. We finally present a sensitivity analysis in order to analyze the effects of the parameters in our model.

3.1. Problem Definition and Model

We consider a collection center which collects an EOL product composed of two main components, component 1 and component 2. The products are brought to the collection center by the end users in exchange for an acquisition fee per product, denoted as c_p. We assume random batch arrivals, such that the time between the arrivals of end users are assumed to be exponentially distributed with rate λ and each arriving end user brings a random amount of EOL products. Upon arrival, all products are disassembled and sent to a quality control area. In that area, basic quality control is made with a fixed quality control cost, denoted as c_q, and the company determines the reusability of component 1 and component 2. If they are reusable, the products are sent to the warehouse of the collection center to be stored until the next dispatching time. If not, they are sent to landfill. When the reusable components are dispatched to the remanufacturer, a revenue is obtained based on the amount of components shipped to the remanufacturer, where r_1 denotes the revenue per unit of component 1 and r_2 denotes the revenue per unit of component 2. We assume that the demand for reusable components is unlimited such that all the reusable components can be sold to the remanufacturer. The system is illustrated in Figure 3.1.

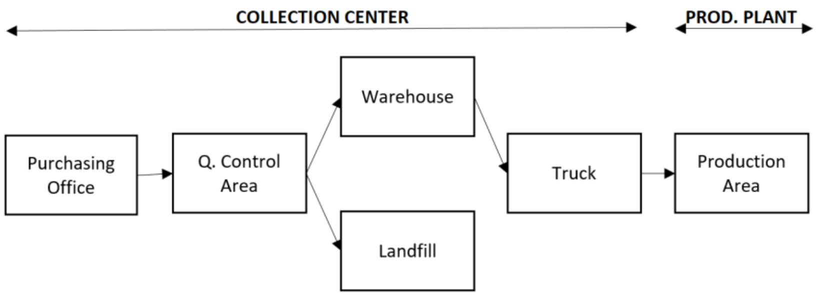


Figure 3.1. *The collection center*

Moreover, we present the notation used for parameters and decisions variables in our models in Table 3.1.

Table 3.1. *Notation used for parameters and decision variables*

S_n	Time of n^{th} arrival
X_n	Interarrival times (time between S_{n-1} and S_n)
Y_n	Batch size of n^{th} arrival
λ	Arrival rate of EOL products
q_k	Probability that the batch size of an arrival will be k
p_1	Probability of having a reusable component 1 from an EOL product.
p_2	Probability of having a reusable component 2 from an EOL product.
r_1	Revenue obtained by selling one unit of component 1
r_2	Revenue obtained by selling one unit of component 2
c_p	Unit purchasing cost of EOL product
c_q	Unit quality control cost of EOL product
h_1	Holding cost per unit of component 1 per unit time
h_2	Holding cost per unit of component 2 per unit time
K	Fixed transportation cost
δ	Scale economy parameter for variable transportation cost ($0 < \delta < 1$)
$N(t)$	Number of arrivals up to time *t*
β	Expected long-run average profit of a control policy
m	Maximum number of products in a batch

It is seen in Table 3.1 that an EOL product includes reusable component 1 and component 2 with probabilities p_1 and p_2, that are assumed to be independent from each other. In addition, the batch size of an arrival is k with probability q_k, and m denotes the maximum number of products in a batch. Since a product is composed of two main components, let us define a new probability function $w_{i,j}$ such that $w_{i,j}$ denotes the probability that exactly i reusable component 1 and j reusable component 2 will be obtained from an arriving batch. Assuming independence between the components, this probability can be calculated by using p_1, p_2 and q_k as follows.

$$w_{i,j} = \sum_{k=\max(i,j)}^{m} q_k \binom{k}{i} \binom{k}{j} {p_1}^i (1-p_1)^{k-i} {p_2}^j (1-p_2)^{k-j} \tag{3.1}$$

It should be noted that it may be difficult or impossible to calculate $w_{i,j}$ values when m is very high due to the calculations involved in Equation 3.1. In our computational experiments, we observe that when m is less than 60, which is an acceptable upper bound for the batch sizes in real life, all $w_{i,j}$ values can be calculated in less than one hour on a computer with Intel i5 processor, 6 GB of RAM and Windows 10 operating system. However, as m increases, the computation time increases exponentially and some approximation algorithms might be needed in order to calculate $w_{i,j}$ approximately, instead of using equation 3.1.

The collection center obtains a certain revenue, denoted as $r_1 x + r_2 y$, every time it sells the components to the remanufacturer, where x denotes the amount of component 1 and y denotes the amount of component 2 sold. However, various costs, as explained below, also accumulate over time during the operation of the collection center. The costs faced by the collection center in this system can be summarized as below:

[1] Acquisition cost per unit of EOL product, denoted as c_p.

[2] Quality control and disassembly cost per unit of EOL product, denoted as c_q.

[3] Holding cost per unit per unit time for the components kept in the warehouse until they are dispatched to the production plant, denoted as h_1 and h_2 for components 1 and 2, respectively,

[4] Fixed transportation cost, denoted as K, that is independent of the amount transported and applied each time when a transportation is made from the warehouse of the collection center to the production plant.

[5] Variable transportation cost for the components dispatched from the warehouse to the production plant, denoted as $(ax + by)^{\delta}$ when x units of component 1 and y units of component 2 are dispatched, where δ denotes the scale economy parameter for transportation, and a and b are the variable transportation cost factors for components 1 and 2.

Considering that the revenues and costs accumulate over time, we aim to maximize the long-run average profit of this collection center per unit time. We first focus on the dispatching decisions for a predetermined and fixed acquisition fee and we develop a stochastic dynamic programming model in order to determine the optimal dispatching decisions. We also analyze time-based and total quantity-based dispatching heuristics under fixed acquisition fee. Then, we extend these models to integrate the optimal acquisition fee decisions assuming a static acquisition fee is decided at the beginning of the system which will be held constant throughout time. Finally, coordinated with the dispatching decisions, we analyze dynamic pricing for the acquisition fee that can be changed at any time depending on the state of the system instead of employing a static fee at all times.

3.2. Fixed and Predetermined Acquisition Fee (FPA Models)

In order to focus on the dispatching decisions, we first assume that the acquisition fee is predetermined and fixed. The acquisition fee is taken as a parameter of the problem in this section, however, in the next sections, we relax this assumption and analyze the coordinated dispatching and acquisition fee decisions.

3.2.1. Exact solution model (FPA-O)

In this subsection, we aim to determine the optimal timings of the shipments to the remanufacturer depending on the state of the system. For this purpose, we develop a continuous time infinite horizon average cost dynamic programming formulation as seen in Equation 3.2. In this formulation, the states are denoted as (x, y) that define the existing amounts of component 1 and component 2 at hand, respectively. At every time, existing inventory levels of component 1 and component 2 are checked and we decide whether to dispatch all the existing components that have accumulated until that time to the remanufacturer, or wait until the next arrival of EOL products.

Please see Bertsekas (2001) for detailed explanations on infinite horizon average cost dynamic programming formulations. As stated on page 194 in Bertsekas (2001), Bellman's equation for an infinite horizon average cost per stage problem can be written as: $\lambda^* + h^*(i) = min_u[g(i,u) + \sum_{j=1}^{n} p_{ij}(u)h^*(j)]$, where λ^* denotes the optimal average cost per stage and $h^*(i)$ is interpreted as the relative or differential cost for each state i.

Similar to the above formulation, in our model, β^* represents the optimal long-run average profit per unit time, and since λ is defined as the transition rate per unit time, 1/λ denotes the average length of a transition and thus $\frac{\beta^*}{\lambda}$ denotes the long-run average profit per transition associated with the optimal policy. $H^*(x,y)$ represents the relative (differential) value function for state (x,y).

$$\frac{\beta^*}{\lambda} + H^*(x,y) = max \begin{bmatrix} -E[Y](c_p + c_q) + r_1 x + r_2 y - K - (ax+by)^{\delta} + \sum_{i=0}^{m}\sum_{j=0}^{m}(w_{i,j})H^*(i,j), \\ -E[Y](c_p + c_q) - \frac{h_1}{\lambda}x - \frac{h_2}{\lambda}y + \sum_{i=0}^{m}\sum_{j=0}^{m}(w_{i,j})H^*(x+i,y+j) \end{bmatrix} \quad (3.2)$$

Then, on the right-hand side we have a maximization problem among two decisions: dispatch or no dispatch. The first equation on the right-hand side denotes the expected profit when the existing products are dispatched. In that equation, the first term is expected acquisition and quality control cost for the next arrival, the second term and the third term are the expected revenues obtained by selling all existing components 1 and 2, and the next two terms are for fixed and variable transportation costs. The last term denotes the expected future profit related to this decision. Note that when a dispatch decision is made at state (x,y), all the current components $(x+y)$ are sold (the state becomes (0,0) at that time which is implicitly known) and when the next arrival occurs, the system will go to state (i,j) with a probability of $w_{i,j}$. Therefore, expected future profit is the sum of all $(w_{i,j})H^*(i,j)$ values. Similarly, the second equation on the right-hand side denotes the expected profit if the existing products are not dispatched at this time and waiting for the next arrival is chosen. In that equation, the first term is expected acquisition and quality control cost for the next arrival, and the next two terms are the accumulated holding costs of component 1 and component 2, respectively, during this transition. Note that since h_i denotes the inventory holding cost per unit per unit time, h_i/λ denotes the average inventory holding cost per unit per transition. Finally, the last term is the expected future profit related to this decision. Note that since we keep the products in this case, the system goes from (x,y) to $(x+i,y+j)$ with a probability of $(w_{i,j})$.

We use a general-purpose programming language to solve the above model. Detailed numerical calculations can be seen in Section 3.5. We also prove the following results about the characteristics of the optimal solution of this model.

Proposition 1. There is a critical value $x_c(y)$ for any y such that we should dispatch the components if $x > x_c(y)$ and do not dispatch if x< $x_c(y)$. In addition, $x_c(y)$ is non-increasing in y. (Please see Appendix 1 for proof.)

Proposition 2. There is a critical value $y_c(x)$ for any x such that we should dispatch the components if $y > y_c(x)$ and do not dispatch if $y < y_c(x)$. In addition, $y_c(x)$ is non-increasing in x. (Please see Appendix 1 for proof.)

Proposition 1 and 2 can also be illustrated by critical dispatching decisions as seen in Figure 3.2. It is seen in Figure 3.2 that there is a critical y (and x) value for each x (and y) for the dispatching decisions and these values are non-increasing. For example, for $x = 2$ and $x = 3$ critical y is 16, and we give the dispatching decision if $y \geq 16$ however for $x = 4$, critical y value drops to 15.

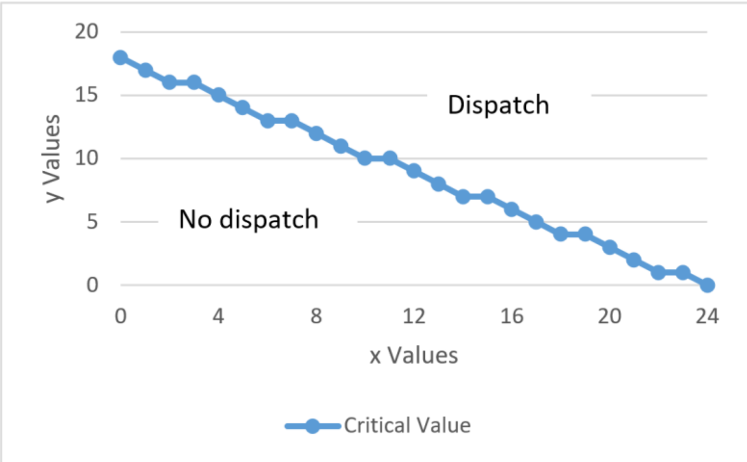


Figure 3.2. *Critical* $(\boldsymbol{x}, \boldsymbol{y})$ *values for dispatching decisions*

3.2.2. Total quantity-based dispatching heuristic (FPA-Q)

In the literature (e.g. Cetinkaya and Bookbinder 2003; Chen 2005) and in real life it is commonly observed that simpler dispatching policies are widely used for the shipments instead of employing the optimal policy due to its complexity. It is observed that instead of considering the individual quantities of the components, the total amount of components is commonly considered and the shipment decisions are based on the total amount of components. As an example, if there are two units of component 1 and three units of component 2, the optimal decision may be holding but if there are three units of component 1 and two units of component 2, the optimal decision may be dispatching. However, in this heuristic, the sum of products is five in both cases and the same policy is applied in both cases. In this section we aim to analyze and determine the performance of this commonly used heuristic.

Total quantity-based heuristic especially makes sense if the components are comparable in value and volume (quantity). In this heuristic, similar to the optimal policy, the inventory level is checked at every state (x, y). However, different from the optimal policy, the dispatching decision is not based on the inventory levels of component 1 and component 2 separately, but is based on the total inventory in the warehouse $(x + y)$. When the total inventory level (sum of reusable component 1 and component 2) becomes equal to or more than Q, they are dispatched. If not, they are held at least until the next arrival. Similar to the optimal policy, we model this heuristic using a continuous time infinite horizon average cost stochastic dynamic programming formulation that is similar to Equation 3.2. The only difference is that, on the right-hand side, instead of solving an optimization problem between two decisions, we check the total inventory amount and make a decision based on its value compared to Q. We aim to determine the optimal value of Q that maximizes the value of β^*, that represents the optimal value of the long-run average profit per unit time. The long-run average profit model is given in Equation 3.3. Note that *x* and *y* are the state variables denoting the level of inventories for components 1 and 2, respectively, and $H^*(x, y)$ denotes the relative value function for state (x, y).

$$\frac{\beta^*}{\lambda} + H^*(x,y) = \begin{cases} -E[Y](c_p + c_q) - \frac{h_1}{\lambda}x - \frac{h_2}{\lambda}y + \sum_{i=0}^{m}\sum_{j=0}^{m}(w_{i,j})H^*(x+i, y+j), & x + y < Q \\ -E[Y](c_p + c_q) + r_1 x + r_2 y - K - (ax + by)^{\delta} + \sum_{i=0}^{m}\sum_{j=0}^{m}(w_{i,j})H^*(i, j), & x + y \geq Q \end{cases} \tag{3.3}$$

3.2.3. Time-based dispatching heuristic (FPA-T)

Similar to the quantity-based heuristic, time-based dispatching policies are also commonly used in real life and in literature (e.g. Marklund, 2011; Cetinkaya and Lee, 2000). In this policy, different from the quantity-based policies, the shipments are made in constant time intervals independent of the quantities accumulated until that time. Reusable components are held until some certain time *T* and a shipment is made at every

T time units. We aim to determine the optimal value of T that maximizes the expected long-run average profit per unit time. This policy is commonly used in real life since the timings of the shipments are known in advance and thus planning and the management of the system is much easier considering the logistics constraints.

We propose a renewal-reward theory-based approach for this policy. First, we define the renewal process as the process of arrivals as shown in Figure 3.3. In this process, note that X_n values are assumed to be exponentially distributed. We define $N(t)$ as max$(n\colon S_n \leq t)$, that defines the number of arrivals until time t.

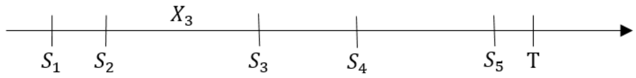


Figure 3.3. *Process of arrivals*

Note that every cycle has a length of T time units and the total holding times of the components in a cycle of length T can be written as follows.

$$Y_1(T - S_1) + Y_2(T - S_2) + \cdots Y_{N(T)}\left(T - S_{N(T)}\right) = E\left[T\sum_{i=1}^{N(T)} Y_i - \sum_{i=1}^{N(T)} Y_i S_i\right] \tag{3.4}$$

$$= TE[Y]E[N(T)] - E[Y]E\left[\sum_{i=1}^{N(T)} S_i\right] \tag{3.5}$$

$$= TE[Y]E[N(T)] - \frac{TE[Y]E[N(T)]}{2} \tag{3.6}$$

By conditioning on $N(T)$, the first summation is obtained as $TE[Y]E[N(T)]$ and since Y_i and S_i are independent from each other $E[Y_i S_i]$ can be written as $E[Y_i]E[S_i]$. Then, since we know that there are $N(T)$ arrivals up to time *T*, S_i values are uniformly distributed conditional on the number of arrivals up to time *T* (Ross, 2010, see theorem 5.2). By using this property, holding times are obtained as in Equation 3.7. Since the probabilities of obtaining reusable component 1 and component 2 are p_1 and p_2 respectively and since the holding costs are h_1 and h_2 per unit per unit time respectively, expected holding costs for a time period can be written as follows.

$$E[Holding\ Cost] = (p_1 h_1 + p_2 h_2)\frac{TE[Y]E[N(T)]}{2} \tag{3.7}$$

By a similar logic, expected transportation cost for a time period can be written as in Equation 3.8. In this equation, δ is the scale economy parameter and it allows a more realistic cost function instead of a linear cost function. By using δ, unit variable cost decreases when the quantity increases.

$$E[Transportation\ Cost] = K + E\left[((ap_1 + bp_2)YN(T))^{\delta}\right] \tag{3.8}$$

$$= K + (ap_1 + bp_2)^{\delta} E[Y^{\delta}]E[N(T)^{\delta}] \tag{3.9}$$

Moreover, expected acquisition and quality control cost can be written as follows.

$$E[Acquisition\ and\ Quality\ Control\ Cost] = \left(c_p + c_q\right)E[Y]E[N(T)] \tag{3.10}$$

Finally, the expected revenue for a time period T can be written as in Equation 3.11.

$$E[Revenue] = (r_1 p_1 + r_2 p_2)E[Y]E[N(T)] \tag{3.11}$$

By this context, expected long-run average profit per unit time can be written as in Equation 3.12.

$$\frac{\begin{pmatrix} (r_1 p_1 + r_2 p_2)E[Y]E[N(T)] - (p_1 h_1 + p_2 h_2)\dfrac{TE[Y]E[N(T)]}{2} \\ -K - (ap_1 + bp_2)^{\delta} E\left[Y^{\delta}\right]E\left[N(T)^{\delta}\right] - \left(c_p + c_q\right)E[Y]E[N(T)] \end{pmatrix}}{T} \tag{3.12}$$

Note that since arrival times are exponentially distributed with rate λ, $E[N(T)]$ is equal to λT. By using this fact, the long-run average profit per unit time can be simplified as follows.

$$\begin{aligned} &(r_1 p_1 + r_2 p_2)E[Y]\lambda - (p_1 h_1 + p_2 h_2)E[Y]\frac{\lambda T}{2} \\ &\qquad - \frac{K + (ap_1 + bp_2)^{\delta} E[Y^{\delta}]E[N(T)^{\delta}]}{T} - \left(c_p + c_q\right)E[Y]\lambda \end{aligned} \tag{3.13}$$

We determine the optimal T that maximizes the above function by searching the one-dimensional solution space over T.

3.3. Static Acquisition Fee (CSA Models)

Acquisition fee is an important parameter that affects the collected amounts and thus affects the dispatching decisions and the total system profit. In this section, we integrate the optimal acquisition fee decision with the dispatching decisions in order to maximize the total system profit. In other words, in this section, we consider the coordination of the dispatching and acquisition fee decisions under static pricing assumption (CSA Model). We assume that the acquisition fee, c_p, is a decision variable in the problem that needs to be decided at the beginning of the system and will be kept constant over time. Similar to the papers in the literature (e.g. Bakal and Akcali, 2006; Karakayali et al., 2007; Zheng et al. 2017), we assume that the rate of EOL arrivals, λ, is a function of the acquisition fee, c_p, such that when the acquisition fee increases, arrival rate also increases and vice versa. We aim to determine the optimal value of c_p integrated with the optimal dispatching decisions in order to maximize the expected value of the long-run average profit per unit time.

3.3.1. Exact solution model (CSA-O)

In this model, the value of c_p needs to be decided at the beginning of the system and it will be kept constant over time. Then, we also need to decide on the timings of the shipments to the remanufacturer depending on the state of the system. At every state (x, y), existing inventory levels of component 1 and component 2 are checked and a decision is made whether to dispatch all the existing components or wait until the next arrival.

We develop a dynamic programming model, as seen in Equation 3.14, similar to the one presented in section 3.1. In this formulation, different from the previous models, we develop a two-stage optimization problem such that for any given c_p, the optimal dispatching decisions are found and the value of $\beta^*(c_p)$ is obtained through the dynamic programming formulation. Then, we also aim to determine the optimal value of c_p that maximizes the value of $\beta^*(c_p)$.

$$max\ z = \beta^*(c_p) \tag{3.14}$$

$$s.t.$$

$$\frac{\beta^*(c_p)}{\lambda(c_p)} + H^*(x,y)$$

$$= max \begin{bmatrix} -E[Y](c_p + c_q) + r_1 x + r_2 y - K - (ax + by)^\delta + \sum_{i=0}^{m}\sum_{j=0}^{m}(w_{i,j})H^*(i,j), \\ -E[Y](c_p + c_q) - \frac{h_1}{\lambda(c_p)}x - \frac{h_2}{\lambda(c_p)}y + \sum_{i=0}^{m}\sum_{j=0}^{m}(w_{i,j})H^*(x+i, y+j) \end{bmatrix} \tag{3.15}$$

3.3.2. Total quantity-based dispatching heuristic (CSA-Q)

In this section, similar to the FPA-Q and CSA-O models, we present the total quantity-based dispatching heuristic integrated with the optimal dispatching decision. The problem is formulated in a similar manner to the previous cases as stated below.

$$\max z = \beta^*(c_p) \tag{3.16}$$

$$s.t$$

$$\frac{\beta^*(c_p)}{\lambda(c_p)} + H^*(x,y) = \begin{cases} -E[Y](c_p+c_q) - \frac{h_1}{\lambda(c_p)}x - \frac{h_2}{\lambda(c_p)}y + \sum_{i=0}^{m}\sum_{j=0}^{m}(w_{i,j})H^*(x+i,y+j), & x+y<Q \\ -E[Y](c_p+c_q) + r_1x + r_2y - K - (ax+by)^\delta + \sum_{i=0}^{m}\sum_{j=0}^{m}(w_{i,j})H^*(i,j), & x+y \geq Q \end{cases} \quad (3.17)$$

Similar to the previous dynamic programming-based models a general-purpose programming language can be used to determine the optimum Q and c_p values.

3.3.3. Time-based dispatching heuristic (CSA-T)

When we integrate the optimal acquisition fee decisions to the time-based dispatching heuristic, we obtain the equation for the long-run average profit per unit time as given in Equation 3.18, where $N(T)$ is a Poisson distributed random variable with rate $\lambda(c_p)T$. We use similar cost and profit functions to those used in Section 3.3 in order to obtain the equation for the expected profit per unit time under this heuristic.

$$E[Profit\ per\ unit\ time] = \frac{(r_1p_1+r_2p_2)E[Y]E[\lambda(c_p)]T}{T} - \frac{(c_p+c_q)E[Y]E[\lambda(c_p)]T + (p_1h_1+p_2h_2)\frac{TE[Y]E[\lambda(c_p)]T}{2} + K + (ap_1+bp_2)^\delta E[Y^\delta]E[N(T)^\delta]}{T} \quad (3.18)$$

After a basic calculation, Equation 3.18 can be simplified as follows.

$$E[Profit\ per\ unit\ time] = (r_1p_1+r_2p_2)E[Y]E[\lambda(c_p)] - (c_p+c_q)E[Y]E[\lambda(c_p)] - (p_1h_1+p_2h_2)\frac{E[Y]E[\lambda(c_p)]T}{2} - \frac{K+(ap_1+bp_2)^\delta E[Y^\delta]E[N(T)^\delta]}{T} \quad (3.19)$$

We determine the optimal c_p and T that maximize the above function by searching the two-dimensional solution space.

3.4. Dynamic Acquisition Fee (CDA-O Model)

In this section, coordinated with the dispatching decisions, we focus on dynamic acquisition fee decisions. Different from the previous section, here we assume that the acquisition fee is not constant at all times but can be changed at any time depending on the state of the system. The arrival rate of the products is again a function of the acquisition fee but since the acquisition fee changes over time, the arrival rate also changes over time. Thus, at every state (x, y), in addition to the dispatching decisions, the collection center also needs to determine the optimal value of the acquisition fee at that state, denoted as $c_{x,y}$, in order to maximize its profit. Also note that since the arrival rates of EOL products depend on the value of $c_{x,y}$, we let $\lambda_{x,y}$ denote the arrival rate at state (x, y) which is a function depending on the acquisition fee at that state. In order to analyze the optimal dynamic acquisition fee decisions coordinated with the dispatching decisions, we again propose a dynamic programming formulation for this system as follows.

$$\frac{\beta^*}{\bar{\lambda}} + H^*(x,y) = max \begin{bmatrix} \max_{c_{0,0}} \left[(r_1 x + r_2 y - K - (ax+by)^{\delta}) + \frac{\lambda_{0,0}}{\bar{\lambda}} \left(-E[Y](c_{0,0} + c_q) + \sum_{i=0}^{m} \sum_{j=0}^{m} (w_{i,j}) H^*(i,j) \right) + (\frac{\bar{\lambda} - \lambda_{0,0}}{\bar{\lambda}}) H^*(0,0) \right], \\ \max_{c_{x,y}} \left[-\frac{h_1 x}{\bar{\lambda}} - \frac{h_2 y}{\bar{\lambda}} + \frac{\lambda_{x,y}}{\bar{\lambda}} \left(-E[Y](c_{x,y} + c_q) + \sum_{i=0}^{m} \sum_{j=0}^{m} (w_{i,j}) H^*(x+i, y+j) \right) + (\frac{\bar{\lambda} - \lambda_{x,y}}{\bar{\lambda}}) H^*(x,y) \right] \end{bmatrix} \quad (3.20)$$

Note that in the above formulation, we decide on the value of $c_{x,y}$ at every state (x, y) and that affects the value of $\lambda_{x,y}$. Since the transition rates are non-uniform and state-dependent in this model, we apply the uniformization technique as explained between pages 254-261 in Bertsekas (2001). We first let $\bar{\lambda}$ denote a big enough value that defines an upper bound on the arrival rates such that $\bar{\lambda} \geq \lambda_{x,y}$ for all possible $\lambda_{x,y}$ values. In this uniformization technique, fictitious transitions from a state to itself are allowed. Roughly, a common transition rate per state $\bar{\lambda}$ is defined, but some of the transitions are real (the state is actually changed when the transition occurs, i.e. an arrival actually happened) with probability $\lambda_{x,y}/\bar{\lambda}$ and some of the transitions are fictitious (the state is unchanged, i.e no actual arrivals) with probability $(\bar{\lambda} - \lambda_{x,y})/\bar{\lambda}$. With this uniformization technique, now the model will be the same as the previous ones in which the common arrival (transition) rate is $\bar{\lambda}$, but the transition probabilities are redefined as stated above. In the above formulation, at state (x, y), if the decision is dispatching, we dispatch all the products (the state immediately after dispatching will be (0,0)) and with an acquisition fee offer, $c_{0,0}$, there will be actual arrivals with probability $\lambda_{0,0}/\bar{\lambda}$ in the next transition, and the system will go to state (i, j) with a probability of $w_{i,j}$, or there will be no arrivals (fictitious arrivals) in the next transition with probability $(\bar{\lambda} - \lambda_{0,0})/\bar{\lambda}$ and the system will stay at state (0,0). Similarly, if the decision is holding, we wait for the new arrivals at state (x, y) with an acquisition fee offer, $c_{x,y}$. There will be actual arrivals in the next transition with probability $\lambda_{x,y}/\bar{\lambda}$ and the system will go to state $(x +$

$i, y + j$) with a probability of $w_{i,j}$ or there will be no arrivals (fictitious arrivals) in the next transition with probability $(\bar{\lambda} - \lambda_{x,y})/\bar{\lambda}$ and the system will stay at state (x, y). The model determines the optimal acquisition fee, $c_{x,y}$, for all (x, y) pairs and gives the decision of either holding or dispatching for each state (x, y).

In proposition 3, we characterize the optimal decisions regarding the acquisition fees. We prove that as the amount of components at the warehouse of the collection center increases, the acquisition fee should also increase (or at least stay the same). The main reason for this structure is that as the inventory of components in the warehouse increase, the inventory holding cost accumulates in a faster manner. In order to avoid this high inventory cost accumulation, the collection center wants to dispatch these components as soon as possible and thus needs to acquire new components faster in order to reach the critical dispatching level of inventory sooner. Hence, the collection center increases the acquisition fee, which will increase the arrival rate of EOL products and the components in the warehouse will be dispatched sooner and the collection center will avoid the high inventory cost of the components in the warehouse.

Proposition 3: Let $\lambda'_{x,y}$ denote the derivative of the arrival rate function with respect to the acquisition fee, $c(x, y)$. Under the assumption that the function $\lambda_{x,y}/\lambda'_{x,y}$ is non-decreasing in $c_{x,y}$, for a fixed value of x (or y), the optimal acquisition fee $c(x, y)$ is monotonically non-decreasing in y (or x). (Please see Appendix 1 for proof.)

3.5. Computational Results

In this section, we present our computational results and discuss on the inferences and managerial implications of these results in different settings.

3.5.1. Base case problem

We first create a base case problem with the parameters as given in Table 3.2 and we use these base case parameters to test all the models developed above. Then, we compare these models under different parameter settings in the following subsections. We assume that $\lambda(c_p)$ is a linear function such that $\lambda(c_p) = \mu c_p$ where μ is a real number. For the batch size, Y, an empirical distribution is used with *m*=4 and the probabilities $q_1 = 0.30, q_2 = 0.30, q_3 = 0.25, q_4 = 0.15$, with the expected value as given below for the base case scenario.

Table 3.2. *Values of the parameters in base case instance*

c_p	c_q	h_1	h_2	K	λ	a	b	r_1	r_2	p_1	p_2	δ	$E[Y]$	m	μ
25	10	1	2	120	5	1	1	50	100	0,7	0,4	0,90	2.25	4	0.2

Computational results with the base case parameters are given in Table 3.3. In FPA models, we use acquisition fee value as $25 as given in Table 3.2. However, in CSA models, we allow the model to determine the optimal acquisition fee value. In Table 3.3, observe that its optimal value is found to be $31 in the CSA-T model, whereas in CSA-Q and CSA-O its optimal value is found to be $32. Finally, in the CDA model, the model determines a different c_p value for each state (x, y). Hence, we have written dynamic in Table 3.3 in the CDA row.

Table 3.3. *Computational results related to base case instance*

	Time-Based Heuristics (T)			**Total Quantity-Based Heuristics (Q)**			**Exact Model (O)**	
Approach	T	c_p	**Profit**	Q	c_p	**Profit**	c_p	**Profit**
FPA	3.821	25	377.939	53	25	389.819	25	389.850
CSA	3.435	31	393.104	64	32	408.848	32	408.877
CDA	-	-	-	-	-	-	Dynamic	409.256

We observe in Table 3.3 that time-based heuristics give the worst results in this scenario. It is seen that both FPA-T and CSA-T are the worst ones compared to other approaches. Total quantity-based heuristics and the exact model give very similar results in both FPA and CSA models. Similarly, it is seen that CSA-O and CDA-O models give very similar results when the base case parameters are used. In the next sections, we provide the results for different parameter settings in order to analyze the effects of the parameters on the system results.

We observe that the profits increase significantly in all policies if the collection center uses the optimal acquisition fee instead of the fixed base case acquisition fee value. This shows that determining and using the optimum acquisition fee can make a significant impact on the system profits.

In Table 3.4, we also present the dynamic acquisition fee values for some of the possible states, due to the limited space. As it is seen in Table 3.4, lower acquisition fees are offered when existing inventory levels are low and the acquisition fee offer increases as existing inventory increases. As stated in previously, the main reason for this structure is that as the inventory level increases, in order to avoid high inventory holding costs, the company aims to collect the EOL products faster in order to reach the dispatching level sooner. Thus, the acquisition fees are increased, products are collected faster and the current products at hand are dispatched sooner leading to less inventory costs. As an example, the acquisition fee is $30 for state $(0,0)$ but $32 for state $(8,15)$. Although it is not seen in Table 3.4, we observe in our numerical studies that, it increases to $35 in state $(40,50)$. We note that the optimal static acquisition fee is $32 in the CSA-O model, and CDA-O model shows that the dynamic acquisition fee ranges from $30 to $35. These two results support each other since $32 is nearly the average of the values between $30 and $35.

Table 3.4. *Acquisition fees for some* $(\boldsymbol{x}, \boldsymbol{y})$ *states (rows x, columns y)*

	0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
0	30	30	30	30	30	31	31	31	31	31	31	31	31	31	31	31
1	30	30	30	30	30	31	31	31	31	31	31	31	31	31	31	31
2	30	30	30	30	31	31	31	31	31	31	31	31	31	31	31	31
3	30	30	30	30	31	31	31	31	31	31	31	31	31	31	31	31
4	30	30	30	31	31	31	31	31	31	31	31	31	31	31	31	31
5	30	30	30	31	31	31	31	31	31	31	31	31	31	31	31	31
6	30	30	31	31	31	31	31	31	31	31	31	31	31	31	31	31
7	30	30	31	31	31	31	31	31	31	31	31	31	31	31	31	31
8	30	31	31	31	31	31	31	31	31	31	31	31	31	31	31	32
9	30	31	31	31	31	31	31	31	31	31	31	31	31	31	31	32
10	31	31	31	31	31	31	31	31	31	31	31	31	31	31	32	32
11	31	31	31	31	31	31	31	31	31	31	31	31	31	31	32	32
12	31	31	31	31	31	31	31	31	31	31	31	31	31	32	32	32
13	31	31	31	31	31	31	31	31	31	31	31	31	31	32	32	32
14	31	31	31	31	31	31	31	31	31	31	31	31	32	32	32	32
15	31	31	31	31	31	31	31	31	31	31	31	31	32	32	32	32

3.5.2. Sensitivity analysis

In this subsection, we analyze the system results under different parameter settings in order to observe the effects of the parameters in each model. In Table 3.5 and Table 3.6, we first focus on the dispatching policies and compare time-based, total quantity-based and the optimal dispatching policies under the fixed acquisition fee value. We think that the effect of parameters on the results of the dispatching policies can be better observed in FPA models compared to others, since acquisition fee is a fixed parameter in FPA models and only the dispatching policy related costs will be affected when a parameter is changed. Then, in Table 3.7, we analyze and compare the coordinated dispatching and acquisition fee models under static and dynamic pricing. In Table 3.5, 3.6 and 3.7, in order to observe the effect of each parameter independent of the others, we change the value of one of the parameters at a time while all other parameters remain unchanged. In both tables, the first row presents the results under the base case parameters and the following rows present the results when the value of a parameter is changed as given in that row while all others remain unchanged.

Under all fixed acquisition fee dispatching policies, since λ is predetermined and fixed, the expected amount of collected products per unit time is equal to $\lambda E[Y]$ and the cost of acquisition and quality control is equal to $\lambda E[Y](c_p + c_q)$. In addition, the expected amount of reusable components per unit time is equal to $\lambda E[Y]p_1$ and $\lambda E[Y]p_2$ for components 1 and 2, respectively. Then, the expected revenue obtained by the sale of these components is equal to $\lambda E[Y]p_1r_1 + \lambda E[Y]p_2r_2$. Note that these values are the same under all dispatching policies when the acquisition fee is predetermined and fixed. When the profit values are known, the policy-dependent costs of the system can be calculated using the equation: $Cost = \lambda E[Y]p_1r_1 + \lambda E[Y]p_2r_2 - \lambda E[Y](c_p + c_q) - Profit$. However, note that, in the coordinated dispatching and acquisition fee policies, since λ is also policy-dependent, all the values stated above will be different under each policy. Thus, as seen in Table 3.7, we present and compare only the profit values as defined in the previous sections. In order to be able to compare the results under fixed, variable and dynamic acquisition fee models, in Table 3.5 and 3.6, we present the profits in addition to the policy-dependent costs under each fixed acquisition fee dispatching policy. In that table, the first value in each cell under the Profit (Cost) column shows the profit and the second value in parentheses shows the policy-dependent cost. We also present the optimality gap percentages for the FPA-T and FPA-Q policies, denoting the percentage difference between the results of those policies and the optimal value obtained under the FPA-O model.

Table 3.5. *Comparison of fixed acquisition fee models (FPA models)*

Parameter	FPA-T		FPA-Q		FPA-O
	Profit (Cost)	**Gap**	**Profit (Cost)**	**Gap**	**Profit (Cost)**
Base Case	377.94 (72.06)	3.06% (19.80%)	389.82 (60.18)	0.01% (0.05%)	389.85 (60.15)
$h_1 = 0.04$ $h_2 = 0.08$	428.53 (21.47)	4.24% (762.43%)	447.50 (2.50)	0.00% (0.32%)	447.51 (2.49)

Table 3.6. *Comparison of FPA models (continues)*

Parameter	FPA-T		FPA-Q		FPA-O
	Profit (Cost)	Gap	Profit (Cost)	Gap	Profit (Cost)
$h_1 = 0.10$ $h_2 = 0.20$	422.38 (27.62)	3.83% (156.01%)	439.18 (10.82)	0.01% (0.25%)	439.21 (10.79)
$h_1 = 0.50$ $h_2 = 1.00$	396.87 (53.13)	3.74% (40.94%)	412.28 (37.72)	0.01% (0.06%)	412.30 (37.70)
$h_1 = 2$ $h_2 = 4$	351.28 (98.72)	3.18% (13.23%)	362.75 (87.26)	0.02% (0.08%)	362.82 (87.18)
$h_1 = 4$ $h_2 = 8$	313.69 (136.31)	4.41% (11.88%)	328.02 (121.98)	0.05% (0.12%)	328.17 (121.83)
$h_1 = 8$ $h_2 = 16$	260.65 (189.35)	7.98% (13.55%)	282.93 (167.07)	0.11% (0.19%)	283.25 (166.75)
$h_1 = 16$ $h_2 = 32$	185.76 (264.24)	17.74% (17.88%)	225.22 (224.78)	0.28% (0.28%)	225.84 (224.16)
$r_1 = 2.50$ $h_1 = 0.05$	20.28 (55.66)	30.02% (18.54%)	28.77 (47.17)	0.73% (0.46%)	28.98 (46.96)
$r_1 = 25$ $h_1 = 0.5$	189.09 (64.03)	5.15% (19.10%)	199.27 (53.86)	0.05% (0.17%)	199.36 (53.76)
$r_1 = 100$ $h_1 = 2$	758.09 (85.66)	1.93% (21.14%)	773.04 (70.71)	0.00% (0.00%)	773.04 (70.71)
$p_2 = 0.20$	163.58 (61.42)	5.89% (20.01%)	173.79 (51.21)	0.02% (0.07%)	173.82 (51.18)
$p_2 = 0.50$	485.59 (76.91)	2.25% (17.05%)	496.76 (65.74)	0.01% (0.04%)	496.79 (65.71)
$p_2 = 0.80$	809.82 (90.18)	1.81% (19.77%)	824.70 (75.31)	0.00% (0.02%)	824.71 (75.29)
$K = 80$	389.45 (60.55)	2.63% (20.98%)	399.92 (50.08)	0.01% (0.07%)	399.95 (50.05)
$K = 160$	368.21 (81.79)	3.43% (19.03%)	381.26 (68.74)	0.01% (0.05%)	381.29 (68.71)
$K = 200$	359.63 (90.37)	3.77% (18.47%)	373.69 (76.31)	0.01% (0.04%)	373.72 (76.28)
$(x + 2y)^{\delta}$	375.23 (74.77)	3.08% (18.95%)	387.11 (62.89)	0.01% (0.05%)	387.14 (62.86)
$(2x + y)^{\delta}$	373.25 (76.75)	3.09% (18.39%)	385.14 (64.86)	0.01% (0.05%)	385.17 (64.83)
$(x + 4y)^{\delta}$	370.02 (79.98)	3.12% (17.51%)	381.90 (68.10)	0.01% (0.04%)	381.93 (68.07)

We first analyze the effect of the inventory holding costs on the system results. In our base case scenario, we assume that the time unit is a month and the inventory holding costs for the components are about 2% of their sale value per month. In our models, the holding cost rates are thought as the rate per unit time, where the time unit can be chosen arbitrarily to be a day, a month, a year etc. The smaller holding cost values correspond to smaller time units, whereas the higher holding cost values correspond to longer time units. Note that, λ is also defined as the arrival rate of batches per unit time and thus when the time unit is changed, the arrival rate of the batches will also change. For the same arrival rate λ per unit time, when the holding cost is small (time unit is small), it corresponds to a system with faster arrivals of returns, and can be more suitable for fast moving products. On the other hand, a high holding cost value per unit time corresponds to a longer time unit and thus it corresponds to a system with slower collection rates. For example, in the second row of Table 3.5, the time unit is chosen to be a day, corresponding to a daily arrival rate of 5 batches, and the daily inventory holding costs of 0.04 and 0.08 are 0.08% of the sale value of the components per day. However, the holding cost values of 16 and 32 are the holding costs per unit time, when the time unit is chosen to be 16 months, corresponding to an arrival of 5 batches in a 16-month period. We observe that, for fixed λ, as longer time units are chosen, slower collection rates are realized, larger inventory holding costs are incurred per unit time and lower profits and higher policy-dependents costs are observed under all policies. When the time unit is chosen to be very high (meaning a small collection rate), the percentage gap between FPA-T and the optimal policy is also high and thus FPA-T performs poorly compared to the optimal policy. On the other hand, when the time unit is chosen to be small (meaning a high collection rate), the percentage gap between FPA-T and the optimal dispatching policy, based on policy-dependent costs, can be very high since the cost of the optimal dispatching policy per unit time is very small and a small difference in costs make a big influence on percentage gaps. When we compare FPA-Q and the optimal policy, we observe that FPA-Q performs very close to the optimal policy and the percentage gaps are very small under all settings.

We then analyze the system when the difference between the sale values of the components change. For this purpose, the sale value of the first component, r_1, and the inventory holding cost of that component, defined as 2% of the sale value per month, are changed. When r_1 is 2.5 and r_2 is 100, the components are significantly different from each other and we observe that FPA-T performs much worse in such a situation. The performance of FPA-Q also worsens in that case. However, as the products become similar in value, both policies perform closer to the optimal solution.

Finally, in the last rows of Table 3.6, we use different fixed transportation cost, K, values and different variable transportation cost functions. We observe that these values do not have a significant impact on the performances of the FPA-T and FPA-Q policies.

In summary, we can state that FPA-Q policy performs very close to the optimal policy in general, especially when different components are similar to each other, i.e. the parameters of different components are close to each other. However, the time-based dispatching policy performs much worse and there is an optimality gap of around 20%

on average compared to the optimal policy when the policy-dependent costs are considered.

Next, we analyze the coordinated dispatching and acquisition fee policies. In Table 3.7, we present the profit values obtained under the static acquisition fee models CSA-T, CSA-Q and CSA-O, and the dynamic acquisition fee model CDA-O. Note that in Table 3.7, the gap value refers to the percentage difference between the profit obtained under each policy and the profit value under the CDA-O model.

Table 3.7. *Comparison of static and dynamic acquisition fee models*

Parameter	CSA-T		CSA-Q		CSA-O		CDA-O
	Profit	Gap	Profit	Gap	Profit	Gap	Profit
Base Case	393.10	3.95%	408.85	0.10%	408.88	0.09%	409.26
$h_1 = 0.04, h_2 = 0.08$	449.96	5.91%	478.03	0.04%	478.04	0.04%	478.24
$h_1 = 0.10, h_2 = 0.20$	442.96	5.63%	469.10	0.06%	469.13	0.05%	469.37
$h_1 = 0.50, h_2 = 1.00$	414.22	5.34%	437.22	0.09%	437.24	0.08%	437.59
$h_1 = 2, h_2 = 4$	363.54	3.83%	377.37	0.17%	377.45	0.15%	378.01
$h_1 = 4, h_2 = 8$	322.34	5.02%	338.15	0.36%	338.30	0.32%	339.37
$h_1 = 8, h_2 = 16$	265.30	8.79%	288.35	0.86%	288.67	0.75%	290.85
$h_1 = 16, h_2 = 32$	186.74	19.35%	226.61	2.13%	227.23	1.86%	231.55
$r_1 = 2.50, h_1 = 0.05$	71.579	6.57%	75.626	1.29%	76.196	0.54%	76.611
$r_1 = 25, h_1 = 0.50$	192.82	4.59%	201.64	0.23%	201.73	0.18%	202.09
$r_1 = 100, h_1 = 2$	1000.46	3.61%	1037.48	0.04%	1037.48	0.04%	1037.94
$p_2 = 0.20$	170.99	4.83%	179.26	0.23%	179.30	0.21%	179.67
$p_2 = 0.50$	537.544	4.34%	561.591	0.07%	561.624	0.06%	561.957
$p_2 = 0.80$	1104.37	3.54%	1144.46	0.04%	1144.49	0.04%	1144.95
$K = 80$	405.90	3.36%	419.73	0.06%	419.76	0.06%	419.99
$K = 160$	382.29	4.47%	399.61	0.14%	399.65	0.13%	400.18
$K = 200$	372.74	4.95%	391.47	0.17%	391.50	0.17%	392.15
$(x + 2y)^{\delta}$	389.78	3.97%	405.43	0.11%	405.47	0.10%	405.89
$(2x + y)^{\delta}$	387.35	3.99%	403.00	0.11%	403.03	0.10%	403.45
$(x + 4y)^{\delta}$	383.39	4.02%	399.04	0.10%	399.07	0.09%	399.44

When we compare the CSA-O and CDA-O models in Table 3.7, we see that they generally give similar results. However, it is observed that dynamic acquisition fee becomes important if the rate of arrivals is smaller. For example, when the time unit is chosen to be a day as in the second row of Table 3.7, the collection rate is high and the gap between CSA-O and CDA-O is only 0.04%. However, when the time unit and thus the inventory holding cost rates are increased, the collection rate is decreased and the gap increases up to 1.86%. Collection of commonly used products such as household goods can be an example of a system with high collection rates, while collection of a rarely used product such as a specific type of an electronic product can be an example of a system with low collection rate. If the arrivals are frequent, static acquisition fee models can be used since they are easier to manage compared to the dynamic acquisition fee model. However, if arrivals are infrequent, dynamic acquisition fee model might provide significant improvements.

We observe that CSA-Q and CSA-O generally give very similar results but CSA-T always gives worse results. Actually, optimal policy and quantity-based policy have no difference if the holding costs and revenues of the components are the same. Significance of using the optimal policy increases as the differences between components increase. As the components become more different from each other, monitoring the components separately, instead of focusing only on the total inventory becomes much more important. It is seen in Table 3.7 that, when arrivals are less frequent and differences between holding costs are high, or when there are big differences between the sale values and the holding costs of the components, the gap between the quantity-based policy and the optimal policy increases. Briefly, we can state that if the difference between holding costs are less, total quantity-based policy can be used instead of the optimal policy since it is easier to manage in real life compared to the optimal policy. However, as the holding costs of the components become much different from each other, the optimal dispatching policy might provide significant savings compared to the total quantity-based dispatching policy.

When we consider the fixed transportation cost, we observe that all policies perform better when K is smaller and the percentage gaps increase as K increases. Finally, we observe that using different variable transportation cost functions does not have a significant impact on the results.

4. PRICING AND SUSTAINABILITY DECISIONS IN REMANUFACTURING SYSTEMS

Collection and remanufacturing of used products can be considered as one of the options to improve the sustainability of a manufacturing system. In this chapter of the thesis, we focus on pricing and sustainability level decisions in pure manufacturing and hybrid manufacturing-remanufacturing systems and compare the systemwide performances and the performances of supply chain actors under different settings with each other in terms of economic and environmental performance measures. In the first setting, no remanufacturing is made and only the manufactured products are sold, whereas in the second, the third and the fourth settings, the used products are collected and remanufactured by the manufacturer, retailer and a third-party remanufacturer, respectively. In all settings, we consider the environmental aspect of the supply chain and adopt the carbon tax policy. We propose stylized models under centralized and decentralized control of these settings and analyze the decisions obtained under optimal or equilibrium solution.

4.1. Problem Environment and the Analysis of Different SC Configurations

In this chapter, we consider a supply chain including a manufacturer, a remanufacturer, a retailer and customers and analyze the pricing and sustainability level decisions in pure manufacturing system and hybrid manufacturing-remanufacturing system. In pure manufacturing system, only the manufactured products are available in the market, whereas in the hybrid manufacturing-remanufacturing system, both manufactured and remanufactured products are available. In hybrid system, we consider the case in which manufactured and remanufactured products are sold in the same market and they are not perfect substitutes of each other, i.e. customers' valuations for manufactured and remanufactured products are different. Thus, in hybrid system, there is a competition between manufactured and remanufactured products.

Since our focus in this study is to observe pricing and sustainability level decisions under various types of decentralization and price-based competition among manufactured and remanufactured products, we consider a single period and we ignore all uncertainties in demand, return rate and return quality. We use linear demand functions for both manufactured and remanufactured products and assume that the demand depends on the selling price. If, only the manufactured products are available in the market, demand for manufactured products depends on the selling price of manufactured products only, whereas if both manufactured and remanufactured products are available in the market, due to the competition, demand for a type of products depends on both its selling price and competing product's selling price. Please refer to Table 4.1 for a list of parameters and decision variables used in this chapter.

Table 4.1. *Parameters and decision variables*

c_m	Unit manufacturing cost
c_r	Unit remanufacturing cost
c_p	Unit collection and testing cost
κ	Maximum amount of remanufacturable items available in the market
t	Unit carbon tax
a	Base unit emission
b	Sustainability level coefficient
Δ	Decrease in base unit emission by making remanufacturing
β	Substitution level, $0 < \beta < 1$
s	Sustainability level of manufacturer
$(a - bs)$	Unit emission of manufacturing in sustainability level s
$(a - bs - \Delta)$	Unit emission of remanufacturing in sustainability level s
$\bar{s}$	Maximum sustainability level, $\bar{s} < (a - \Delta)/\text{b}$
θs^2	Investment cost for sustainability level s
w_m	Unit wholesale price of manufactured products
w_r	Unit wholesale price of remanufactured products
p_m	Unit selling price of manufactured products
p_r	Unit selling price of remanufactured products
d_m	Demand for manufactured product
d_r	Demand for remanufactured product
$\pi_C^i(.)$	Systemwide profit in centralized case of Setting i
$\pi_D^i(.)$	Systemwide profit in decentralized case of Setting i
$\pi_M^i(.)$	Manufacturer's profit under Setting i
$\pi_R^i(.)$	Retailer's profit under Setting i
$\pi_Z^i(.)$	Remanufacturer's profit under Setting i

Referring to Ferguson and Toktay (2006), we normalize the market size to 1 and we use the inverse demand functions used in their study. If, only the manufactured products are available in the market, we use an inverse demand function, $p_m(d_m) = 1 - d_m$ for manufactured products, whereas if both manufactured and remanufactured products are available, we use an inverse demand function $p_m(d_m, d_r) = 1 - d_m - \beta d_r$ for the demand of manufactured product and $p_r(d_m, d_r) = \beta(1 - d_m - d_r)$ for the demand of remanufactured product. In these functions, β can be considered as the customer valuation or substitution level for remanufactured products. $\beta = 0$ means that customers give no valuation to remanufactured products and $\beta = 1$ means that customers give same valuation to the manufactured and remanufactured products, i.e. they are perfect substitutes of each other. In this study we assume that $0 < \beta < 1$. Please refer to Appendix B on page 366 of Ferguson and Toktay (2006) for the derivation of these demand functions.

Since in real-life used product quantity is generally limited, we assume that the amount of collected products cannot exceed a certain value; i.e., only a certain quantity of used products is available to collect and remanufacture.

In our problem environment, we also consider the emissions resulting from the manufacturing and remanufacturing processes and similar to Wang et al. (2018) we assume that unit emission of remanufacturing is less than or equal to the unit emission of manufacturing. A carbon tax is paid for each unit of the emissions, whereas the manufacturer has a sustainability level decision which affects the unit emission of manufacturing and remanufacturing processes, i.e. increasing the sustainability level decreases unit emission and vice versa. This sustainability level decision can be considered as a product design decision. Since we cannot remove the unit emission completely, we assume that the sustainability level can be increased up to a certain limit. Moreover, as seen in Table 4.1, we consider a quadratic cost function for sustainability level. As a result, increasing the sustainability level brings a lower marginal investment cost at lower levels and a higher marginal investment cost at higher levels.

In this context, we focus on four settings. Under Setting 1, the manufacturer produces a certain product such as household goods at a unit cost and unit CO_2 emission and pays a carbon tax for each unit of the emission. He has a sustainability level decision, which affects the emitted CO_2 in manufacturing process, whereas he incurs a sustainability investment cost to be in a certain sustainability level. After the manufacturing process, the manufacturer sells these products to the retailer at a unit wholesale price. Finally, the retailer sells these products to customers at a unit selling price. Under Setting 2, the manufacturer collects some of the remanufacturable used products to remanufacture and sell them to retailer as remanufactured units. He decides on the amount of collection by considering his total profit. He collects these products at a unit collection cost and remanufactures these products at a unit remanufacturing cost and emission. After the remanufacturing process, the manufacturer sells the remanufactured products to the same retailer, at a unit wholesale price and the retailer sells these remanufactured products to customers at a unit selling price. Finally, under

Setting 3 and Setting 4, the retailer and a third-party remanufacturer collects and remanufactures the used products.

We propose stylized models for the pure and hybrid manufacturing systems under centralized and decentralized control and compare the collection quantities, wholesale prices, selling prices, sustainability levels and sold product amounts with each other. The rest of this section is organized as follows. Models and analytical results for pure manufacturing system and hybrid manufacturing-remanufacturing system are given in Section 4.1.1 and 4.1.2 respectively. Section 4.1.1.1 and 4.1.1.2 are dedicated to pure manufacturing system under centralized control and decentralized control (Setting 1), respectively. Models and analytical result for hybrid manufacturing-remanufacturing system under centralized control, Setting 2, Setting 3 and Setting 4, are given in Section 4.1.2.1, 4.1.2.2, 4.1.2.3 and 4.1.2.4, respectively.

4.1.1. Pure manufacturing system

In pure manufacturing system, only the manufactured products are available for customers and no remanufacturing is made. We present the models under centralized and decentralized control of this system in the following subsections. In centralized control, a central authority makes all the decisions regarding the supply chain, i.e. both the manufacturer and retailer belong to the same company while in decentralized control the manufacturer and retailer make their own decisions by considering their own profits.

4.1.1.1. Pure system under centralized control

In this case, the central authority decides on the amount of manufactured product to sell, d_m and the sustainability level, s. Mathematical model for this case can be presented as follows.

$$\max_{\substack{d_m \geq 0 \\ p_m \geq 0 \\ 0 \leq s \leq \bar{s}}} \pi_C^1(d_m, s) = (p_m(d_m) - c_m)d_m - \theta s^2 - (a - bs)d_m t \tag{4.1}$$

In the objective function in equation (4.1), first part is the profit obtained by selling the products to customers, second part is the sustainability investment cost and third part is the carbon tax for manufactured products. In addition, the bounds on the decision variables guarantee that the demand for manufactured product, selling price of manufactured product and sustainability level must be greater than or equal to zero and the sustainability level must be less than a threshold, $\bar{s}$.

Theorem 1: Under centralized control of pure system, manufacturing quantity, d_m^* and sustainability level, s^* for the system can be characterized as in equation (4.2).

$$(d_m^*, s^*) = \begin{cases} \left(\dfrac{2\theta(1-c_m-at)}{4\theta-b^2t^2}, \dfrac{bt(1-c_m-at)}{4\theta-b^2t^2}\right) & \text{if } \dfrac{2\theta(1-c_m-at)}{4\theta-b^2t^2} > 0 \text{ and } \theta > \dfrac{b^2t^2}{4} \text{ and } \dfrac{bt(1-c_m-at)}{4\theta-b^2t^2} < \bar{s}, \\ \left(\dfrac{bt\bar{s}-at-c_m+1}{2}, \bar{s}\right) & \text{if } \dfrac{bt\bar{s}-at-c_m+1}{2} > 0 \text{ and } \dfrac{bt(1-c_m-at)-(4\theta-b^2t^2)\bar{s}}{2} \geq 0, \\ (0,0), & \text{otherwise.} \end{cases} \tag{4.2}$$

Proof: Please see Appendix 2.

4.1.1.2. Pure system under Setting 1 – no remanufacturing

Under this setting, the manufacturer and the retailer make their own decisions by considering their own profits. Product flows under this setting is illustrated in Figure 4.1.

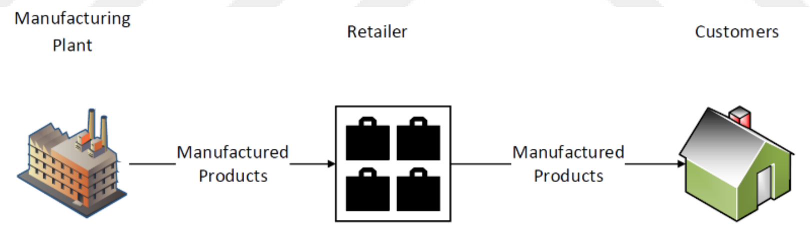


Figure 4.1. *Product flows under Setting 1*

The sequence of events is as follows.

1. Manufacturer decides on the wholesale price of manufactured product, w_m and sustainability level, s.
2. Retailer decides on the amount of manufactured product to sell, d_m.

We use backward induction to obtain the equilibrium solution. We first solve the retailer's problem for given manufacturer's wholesale price decision and obtain the retailer's best response. Then, we solve the manufacturer's problem given best response of the retailer to obtain the equilibrium solution.

Retailer's problem under setting 1 given manufacturer's wholesale price, w_m can be formulated as follows

$$\max_{\substack{d_m \geq 0 \\ p_m \geq 0}} \pi_R^1(d_m|w_m) = (p_m(d_m) - w_m)d_m \tag{4.3}$$

Objective function in equation (4.3) represents the total profit of retailer and bounds on the decision variables ensure that the demand for manufactured products and the selling price of manufactured products must be greater than or equal to zero.

Lemma 1: Best response of the retailer, in decentralized case of Setting 1 can be characterized as follows.

$$d_m^* = \begin{cases} \dfrac{1-w_m}{2} & \text{if } \dfrac{1-w_m}{2} > 0, \\ 0, & \text{otherwise.} \end{cases} \tag{4.4}$$

Proof: Please see Appendix 2.

Moreover, manufacturer's problem under Setting 1 can be formulated as in equation (4.5).

$$\max_{\substack{w_m \geq 0 \\ 0 \leq s \leq \bar{s}}} \pi_M^1(w_m, s|d_m) = (w_m - c_m)d_m - \theta s^2 - (a - bs)d_m t \tag{4.5}$$

In the objective function in equation (4.5), first part is the profit obtained by the manufacturer by selling the products to retailer, second part is the sustainability investment cost and finally the third part is the carbon tax. Bounds on the decision variables ensure that the wholesale price of manufactured product and the sustainability level must be greater than or equal to 0 and the sustainability level must be less than $\bar{s}$.

Plugging the best response of the retailer given in Lemma 1 into objective function of manufacturer's problem given in equation 4.5, we can obtain the following objective function for the manufacturer.

$$\max_{\substack{w_m \geq 0 \\ 0 \leq s \leq \bar{s}}} \pi_M^1(w_m, s) = \begin{cases} (w_m - c_m)\left(\dfrac{1-w_m}{2}\right) - \theta s^2 - (a - bs)\left(\dfrac{1-w_m}{2}\right)t & \text{if } \dfrac{1-w_m}{2} > 0, \\ -\theta s^2, & \text{otherwise.} \end{cases} \tag{4.6}$$

Theorem 2: Under Setting 1, equilibrium decisions of manufacturer w_m^*, s^* and the retailer, d_m^* can be characterized as follows.

$$(w_m^*, s^*, d_m^*) = \begin{cases} \left(\begin{array}{c} \dfrac{4\theta(1 + c_m + at) - b^2t^2}{8\theta - b^2t^2}, \\ \dfrac{bt(1 - c_m - at)}{8\theta - b^2t^2}, \dfrac{2\theta(1 - c_m - at)}{8\theta - b^2t^2} \end{array}\right) & \text{if } \begin{array}{l} \dfrac{2\theta(1 - c_m - at)}{8\theta - b^2t^2} > 0 \text{ and} \\ \theta > \dfrac{b^2t^2}{8} \text{ and} \\ \dfrac{bt(1 - c_m - at)}{8\theta - b^2t^2} < \bar{s}, \end{array} \\ \left(\begin{array}{c} \dfrac{1 + at + c_m - bt\bar{s}}{2}, \bar{s}, \\ \dfrac{bt\bar{s} - at - c_m + 1}{4} \end{array}\right) & \text{if } \begin{array}{l} \dfrac{bt\bar{s} - at - c_m + 1}{4} > 0 \text{ and} \\ \dfrac{bt(1 - c_m - at)}{8\theta - b^2t^2} \geq \bar{s}, \end{array} \\ (0,0,0), & \text{otherwise.} \end{cases} \tag{4.7}$$

4.1.2. Hybrid manufacturing-remanufacturing system

In this subsection, we present the models related to hybrid manufacturing-remanufacturing system. We first consider the centralized control, in which a central authority makes all the decisions regarding the system. Then, we consider the decentralized control in which the supply chain actors make their own decisions considering their own objectives.

4.1.2.1. Hybrid system under centralized control

Under centralized control of the hybrid system, the central authority decides on the amounts of manufactured and remanufactured products to sell, d_m, d_r and the sustainability level of manufacturer, s by considering the limited amount of returns. We can write the systemwide profit model as follows.

$$\begin{aligned} \max_{\substack{d_m \geq 0 \\ 0 \leq d_r \leq \kappa \\ 0 \leq s \leq \bar{s}}} \; & \pi_C^2(d_m, d_r, s) \\ &= (p_m(d_m) - c_m)d_m + (p_r(d_r) - c_r)d_r - (a - bs)d_m t \\ &\quad - (a - bs - \Delta)d_r t - c_p d_r - \theta s^2 \end{aligned} \tag{4.8}$$

In the objective function in equation (4.8), first and second terms represent the profits obtained by selling manufactured and remanufactured products to customers, third and fourth terms are the carbon taxes paid for manufacturing and remanufacturing processes respectively. Fifth term is the collection cost of used products and finally six term is the cost of sustainability investment.

Theorem 3*:* Under centralized control of the hybrid system, manufacturing and remanufacturing quantities, d_m^*, d_r^* and sustainability level, s^* for the system can be characterized as in equation (4.9) and (4.10).

If $\theta > \dfrac{b^2t^2}{4\beta}$

$$
(d_m^*, d_r^*, s^*) = \begin{cases}
\left(\dfrac{\beta + c_m - c_p - c_r + \Delta t - 1}{2(\beta - 1)}, \dfrac{-\begin{bmatrix} 4\theta(c_p + c_r - \beta c_m - \Delta t + at - \beta at) \\ + b^2t^2(\beta - 1 + \Delta t + c_m - c_p - c_r) \end{bmatrix}}{2(4\beta\theta - b^2t^2)(1-\beta)}, \dfrac{-bt(c_p - \beta + c_r - \Delta t + at)}{(4\beta\theta - b^2t^2)} \right) & \text{if } \dfrac{\beta + c_m - c_p - c_r + \Delta t - 1}{2(\beta - 1)} > 0 \text{ and } 0 < \dfrac{-\begin{bmatrix} 4\theta(c_p + c_r - \beta c_m - \Delta t + at - \beta at) \\ + b^2t^2(\beta - 1 + \Delta t + c_m - c_p - c_r) \end{bmatrix}}{2(4\beta\theta - b^2t^2)(1-\beta)} < \kappa \text{ and } \dfrac{-bt(c_p - \beta + c_r - \Delta t + at)}{(4\beta\theta - b^2t^2)} < \bar{s}, \\
\left(\dfrac{\beta + c_m - c_p - c_r + \Delta t - 1}{2(\beta - 1)}, \dfrac{-\begin{bmatrix} c_p + c_r - \beta c_m - \Delta t + \\ at - \beta at - b\bar{s}t + \beta b\bar{s}t \end{bmatrix}}{2\beta(1-\beta)}, \bar{s} \right) & \text{if } d_m = \dfrac{\beta + c_m - c_p - c_r + \Delta t - 1}{2(\beta - 1)} > 0 \text{ and } 0 < \dfrac{-\begin{bmatrix} c_p + c_r - \beta c_m - \Delta t + \\ at - \beta at - b\bar{s}t + \beta b\bar{s}t \end{bmatrix}}{2\beta(1-\beta)} < \kappa \text{ and } -\dfrac{bt(b\bar{s}t + \beta - c_p - c_r - \Delta t + at) + 4\beta\theta s}{2\beta} \geq 0, \\
\left(\dfrac{-[2\theta(at - 1 + c_m + 2\beta\kappa) - \kappa b^2t^2]}{4\theta - b^2t^2}, \kappa, \dfrac{-bt(c_m - 2\kappa + 2\beta\kappa + at - 1)}{4\theta - b^2t^2} \right) & \text{if } \dfrac{-[2\theta(at - 1 + c_m + 2\beta\kappa) - \kappa b^2t^2]}{4\theta - b^2t^2} > 0 \text{ and } \dfrac{-bt(c_m - 2\kappa + 2\beta\kappa + at - 1)}{4\theta - b^2t^2} < \bar{s} \text{ and } \dfrac{-\begin{bmatrix} 4\theta(c_p + c_r - \beta c_m + 2\beta\kappa - \Delta t + at - 2\beta^2\kappa - \beta at) \\ + b^2t^2(\beta - 1 + \Delta t + c_m - c_p - c_r - 2\kappa + 2\beta\kappa) \end{bmatrix}}{4\theta - b^2t^2} \geq 0, \\
\left(\dfrac{b\bar{s}t - 2\beta\kappa - at - c_m + 1}{2}, \kappa, \bar{s} \right) & \text{if } \dfrac{b\bar{s}t - 2\beta\kappa - at - c_m + 1}{2} > 0 \text{ and } \begin{bmatrix} \beta(c_m - 2\kappa + 2\beta\kappa - b\bar{s}t + at) \\ - c_r - c_p + \Delta t - at + b\bar{s}t \end{bmatrix} \geq 0 \text{ and } \dfrac{bt(1 + b\bar{s}t - c_m + 2\kappa - at - 2\beta\kappa) - 4\theta s}{2} \geq 0, \\
\left(\dfrac{-2\theta(cm + at - 1)}{4\theta - b^2t^2}, 0, \dfrac{bt(1 - c_m - at)}{4\theta - b^2t^2} \right) & \text{if } \dfrac{-2\theta(cm + at - 1)}{4\theta - b^2t^2} \geq 0 \text{ and } \dfrac{\begin{bmatrix} 4\theta(c_p + c_r - \beta c_m - \Delta t + at - \beta at) \\ + b^2t^2(\beta - 1 + \Delta t + c_m - c_p - c_r) \end{bmatrix}}{4\theta - b^2t^2} \geq 0 \text{ and } \dfrac{bt(1 - c_m - at)}{4\theta - b^2t^2} < \bar{s}, \\
\left(\dfrac{b\bar{s}t - at - c_m + 1}{2}, 0, \bar{s} \right) & \text{if } \dfrac{b\bar{s}t - at - c_m + 1}{2} > 0 \text{ and } c_p + c_r - \beta c_m - \Delta t + at - \beta at - b\bar{s}t + \beta b\bar{s}t \geq 0 \text{ and } \dfrac{bt(1 + b\bar{s}t - c_m - at) - 4\theta s}{2} \geq 0, \\
\left(0, \dfrac{-2\theta(c_p + c_r - \beta - \Delta t + at)}{4\beta\theta - b^2t^2}, \dfrac{-bt(c_p - \beta - \Delta t + c_r + at)}{4\beta\theta - b^2t^2} \right) & \text{if } \beta + c_m - c_p - c_r + \Delta t - 1 \geq 0 \text{ and } 0 < \dfrac{-2\theta(c_p + c_r - \beta - \Delta t + at)}{4\beta\theta - b^2t^2} < \kappa \text{ and } \dfrac{-bt(c_p - \beta - \Delta t + c_r + at)}{4\beta\theta - b^2t^2} < \bar{s}, \\
\left(0, \dfrac{-(c_p + c_r - \beta - \Delta t + at - b\bar{s}t)}{2\beta}, \bar{s} \right) & \text{if } 0 < \dfrac{-(c_p + c_r - \beta - \Delta t + at + b\bar{s}t)}{2\beta} < \kappa \text{ and } \beta + c_m - c_p - c_r + \Delta t - 1 \geq 0 \text{ and } \dfrac{-bt(-b\bar{s}t - \beta + c_p + c_r - \Delta t + at) - 4\beta\theta\bar{s}}{2\beta} \geq 0, \\
\left(0, \kappa, \dfrac{bt\kappa}{2\theta} \right) & \text{if } \dfrac{-[2\theta(c_p + c_r - \beta + 2\beta\kappa - \Delta t + at) - b^2t^2\kappa]}{2\theta} \geq 0 \text{ and } \dfrac{2\theta(at - 1 + c_m + 2\beta\kappa) - b^2t^2\kappa}{2\theta} \geq 0 \text{ and } \dfrac{bt\kappa}{2\theta} < \bar{s}. \\
(0, \kappa, \bar{s}) & \text{if } \beta - c_p - c_r + \Delta t - 2\beta\kappa - at + b\bar{s}t \geq 0 \text{ and } \beta\kappa t - 2\theta\bar{s} \geq 0 \text{ and } 2\beta\kappa + c_m + at - bst - 1 \geq 0, \\
(0,0,0), & \text{otherwise.}
\end{cases} \tag{4.9}
$$

If $\theta < \dfrac{b^2t^2}{4\beta}$

$$(d_m^*, d_r^*, s^*) = \begin{cases} \left(\dfrac{\beta + c_m - c_p - c_r + \Delta t - 1}{2(\beta - 1)}, \dfrac{-\begin{bmatrix} c_p + c_r - \beta c_m - \Delta t + \\ at - \beta at - b\bar{s}t + \beta b\bar{s}t \end{bmatrix}}{2\beta(1-\beta)}, \bar{s}\right) & \text{if } \begin{array}{l} d_m = \dfrac{\beta + c_m - c_p - c_r + \Delta t - 1}{2(\beta - 1)} > 0 \text{ and} \\ 0 < \dfrac{-\begin{bmatrix} c_p + c_r - \beta c_m - \Delta t + \\ at - \beta at - b\bar{s}t + \beta b\bar{s}t \end{bmatrix}}{2\beta(1-\beta)} < \kappa, \end{array} \\ \left(\dfrac{b\bar{s}t - 2\beta\kappa - at - c_m + 1}{2}, \kappa, \bar{s}\right) & \text{if } \begin{array}{l} \dfrac{b\bar{s}t - 2\beta\kappa - at - c_m + 1}{2} > 0 \text{ and} \\ \begin{bmatrix} \beta(c_m - 2\kappa + 2\beta\kappa - b\bar{s}t + at) \\ -c_r - c_p + \Delta t - at + b\bar{s}t \end{bmatrix} \geq 0, \end{array} \\ \left(\dfrac{b\bar{s}t - at - c_m + 1}{2}, 0, \bar{s}\right) & \text{if } \begin{array}{l} \dfrac{b\bar{s}t - at - c_m + 1}{2} > 0 \text{ and} \\ c_p + c_r - \beta c_m - \Delta t + at - \beta at - b\bar{s}t + \beta b\bar{s}t \\ \geq 0, \end{array} \\ \left(0, \dfrac{-(c_p + c_r - \beta - \Delta t + at - b\bar{s}t)}{2\beta}, \bar{s}\right) & \text{if } \begin{array}{l} 0 < \dfrac{-(c_p + c_r - \beta - \Delta t + at + b\bar{s}t)}{2\beta} < \kappa \text{ and} \\ \beta + c_m - c_p - c_r + \Delta t - 1 \geq 0, \end{array} \\ (0, \kappa, \bar{s}) & \text{if } \begin{array}{l} \beta - c_p - c_r + \Delta t - 2\beta\kappa - at + b\bar{s}t \geq 0 \text{ and} \\ \beta\kappa t - 2\theta\bar{s} \geq 0, \end{array} \\ (0,0,0), & \text{otherwise.} \end{cases} \quad (4.10)$$

Proof: Please see Appendix 2.

4.1.2.2. Hybrid system under Setting 2 – manufacturer remanufactures

Under this setting, the manufacturer collects and remanufactures some of the used products and sells them to the retailer together with the manufactured products. Product flows under this setting are presented in Figure 4.2.

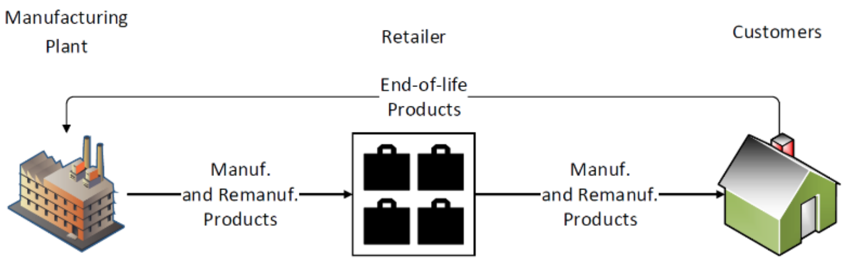


Figure 4.2. *Product flows under Setting 2*

The sequence of events is as follows.

1. Manufacturer decides on the wholesale prices of manufactured and remanufactured products, w_m, w_r and sustainability level, s by considering the limited amount of returns.
2. Retailer decides on the amount of manufactured and remanufactured products to sell, d_m, d_r.

We use backward induction to obtain the equilibrium solution. We first solve the retailer's problem for given manufacturer's wholesale price decisions and obtain the retailer's best response. Then, we solve the manufacturer's problem given best response of the retailer to obtain the equilibrium solution.

Retailer's problem under setting 2 given manufacturer's wholesale prices, w_m, w_r can be formulated as in equation (4.11).

$$\max_{\substack{d_m \geq 0 \\ 0 \leq d_r \leq \kappa}} \pi_R^2(d_m, d_r | w_m, w_r) = (p_m(d_m) - w_m)d_m + (p_r(d_r) - w_r)d_r \tag{4.11}$$

In the objective function of the retailer, first part represents the profit obtained by selling the manufactured products to customers and second part represents the profit obtained by selling the remanufactured products to customers.

Lemma 2: Under Setting 2, retailer's best response can be characterized as in equation (4.12).

$$(d_m^*, d_r^*) = \begin{cases} \left(\frac{\beta + w_m - w_r - 1}{2(\beta - 1)}, \frac{\beta w_m - w_r}{2\beta(1 - \beta)}\right) & \text{if } \frac{\beta + w_m - w_r - 1}{2(\beta - 1)} > 0 \text{ and } 0 < \frac{\beta w_m - w_r}{2\beta(1 - \beta)} < \kappa, \\ \left(\frac{1 - w_m - 2\beta\kappa}{2}, \kappa\right) & \text{if } \frac{1 - w_m - 2\beta\kappa}{2} > 0 \text{ and } \beta w_m - w_r - 2\beta\kappa(1 - \beta) > 0, \\ \left(\frac{1 - w_m}{2}, 0\right) & \text{if } \frac{1 - w_m}{2} > 0 \text{ and } w_r - \beta w_m > 0, \\ \left(0, \frac{\beta - w_r}{2\beta}\right) & \text{if } \beta + w_m - w_r - 1 > 0 \text{ and } 0 < \frac{\beta - w_r}{2\beta} < \kappa, \\ (0, \kappa) & \text{if } \beta - w_r - 2\beta\kappa > 0 \text{ and } w_m + 2\beta\kappa - 1 > 0, \\ (0,0), & \text{otherwise.} \end{cases} \tag{4.12}$$

Proof: Please see Appendix 2.

After characterizing the best response of the retailer based on the manufacturer's w_m, w_r decisions, we focus on the manufacturer's problem. Manufacturer's problem under Setting 2 can be presented as in equation (4.13).

$$\max_{\substack{w_m \geq 0 \\ w_r \geq 0 \\ 0 \leq s \leq \bar{s}}} \pi_M^2(w_m, w_r, s | d_m, d_r) = (w_m - c_m)d_m + (w_r - c_r)d_r - (a - bs)d_m t - (a - bs - \Delta)d_r t - c_p d_r - \theta s^2 \tag{4.13}$$

In the objective function in equation (4.13), first and second terms are the profits obtained by selling the manufactured and remanufactured products to retailer, third and fourth terms are the carbon taxes paid for manufacturing and remanufacturing processes.

Moreover, fifth term is the collection cost of end-of-life products and finally six term is the cost of sustainability investment.

Plugging the best response of the retailer given in Lemma 2 into objective function of manufacturer's problem given in equation 4.13, we can characterize the manufacturer's problem as in equation 4.14.

$$\max_{\substack{w_m \ge 0 \\ w_r \ge 0 \\ 0 \le s \le \bar{s}}} \pi_M^2(w_m, w_r, s) = \begin{cases} \max\limits_{\substack{w_m \ge 0 \\ w_r \ge 0 \\ 0 \le s \le \bar{s}}} \pi_{M,I}^2(w_m, w_r, s) & \text{if } \begin{array}{l} \frac{\beta + w_m - w_r - 1}{2(\beta - 1)} > 0 \text{ and} \\ 0 < \frac{\beta w_m - w_r}{2\beta(1-\beta)} < \kappa, \end{array} \\ \max\limits_{\substack{w_m \ge 0 \\ w_r \ge 0 \\ 0 \le s \le \bar{s}}} \pi_{M,II}^2(w_m, w_r, s) & \text{if } \begin{array}{l} \frac{1 - w_m - 2\beta\kappa}{2} > 0 \text{ and} \\ \beta w_m - w_r - 2\beta\kappa(1-\beta) > 0, \end{array} \\ \max\limits_{\substack{w_m \ge 0 \\ w_r \ge 0 \\ 0 \le s \le \bar{s}}} \pi_{M,III}^2(w_m, w_r, s) & \text{if } \begin{array}{l} \frac{1 - w_m}{2} > 0 \text{ and} \\ w_r - \beta w_m > 0, \end{array} \\ \max\limits_{\substack{w_m \ge 0 \\ w_r \ge 0 \\ 0 \le s \le \bar{s}}} \pi_{M,IV}^2(w_m, w_r, s) & \text{if } \begin{array}{l} \beta + w_m - w_r - 1 > 0 \text{ and} \\ 0 < \frac{\beta - w_r}{2\beta} < \kappa, \end{array} \\ \max\limits_{\substack{w_m \ge 0 \\ w_r \ge 0 \\ 0 \le s \le \bar{s}}} \pi_{M,V}^2(w_m, w_r, s) & \text{if } \begin{array}{l} \beta - w_r - 2\beta\kappa > 0 \text{ and} \\ w_m + 2\beta\kappa - 1 > 0, \end{array} \\ \max\limits_{\substack{w_m \ge 0 \\ w_r \ge 0 \\ 0 \le s \le \bar{s}}} \pi_{M,VI}^2(w_m, w_r, s), & \text{otherwise.} \end{cases} \tag{4.14}$$

where

$$\pi_{M,I}^2(w_m, w_r, s) = (w_m - c_m)\left(\frac{\beta + w_m - w_r - 1}{2(\beta - 1)}\right) + (w_r - c_r)\left(\frac{\beta w_m - w_r}{2\beta(1-\beta)}\right) - (a - bs)\left(\frac{\beta + w_m - w_r - 1}{2(\beta - 1)}\right)t - (a - bs - \Delta)\frac{\beta w_m - w_r}{2\beta(1-\beta)}t - c_p\left(\frac{\beta w_m - w_r}{2\beta(1-\beta)}\right) - \theta s^2$$

$$\pi_{M,II}^2(w_m, w_r, s) = (w_m - c_m)\left(\frac{1 - w_m - 2\beta\kappa}{2}\right) + (w_r - c_r)\boldsymbol{\kappa} - (a - bs)\left(\frac{1 - w_m - 2\beta\kappa}{2}\right)t - (a - bs - \Delta)\boldsymbol{\kappa t} - c_p\boldsymbol{\kappa} - \theta s^2$$

$$\pi_{M,III}^2(w_m, w_r, s) = (w_m - c_m)\left(\frac{1 - w_m}{2}\right) - (a - bs)\left(\frac{1 - w_m}{2}\right)t - \theta s^2$$

$$\pi_{M,IV}^2(w_m, w_r, s) = (w_r - c_r)\left(\frac{\beta - w_r}{2\beta}\right) - (a - bs - \Delta)\left(\frac{\beta - w_r}{2\beta}\right)t - c_p\left(\frac{\beta - w_r}{2\beta}\right) - \theta s^2$$

$$\pi_{M,V}^2(w_m, w_r, s) = (w_r - c_r)\kappa - (a - bs - \Delta)\kappa t - c_p\kappa - \theta s^2$$

$$\pi_{M,VI}^2(w_m, w_r, s) = -\theta s^2$$

The objective function of the model introduced in equation (4.14) is continuous but not continuously differentiable over the entire range of variables. The objective function over six ranges introduced in equation (4.14) are concave in decision variables over the corresponding range. Therefore, one can find the optimal solution to the overall problem by focusing on six different ranges objective function and treating the range on decision variables as constraints. Then, among these six alternative solutions, the equilibrium solution can be found by comparing them with respect to the objective function value. Concentrating on the optimization problem in each range in equation (4.14), alternative solutions to the problem are generated similar to equation (4.9). Since the expressions found are very tedious we are not providing them.

Alternatively, equilibrium decisions of the manufacturer can be obtained with a complete enumeration scheme since each of these decision variables have a lower and an upper bound ($0 \leq w_m \leq p_m \leq 1, 0 \leq w_r \leq p_r \leq 1, 0 \leq s \leq \bar{s}$). In our computational experiments, we implement this approach.

4.1.2.3. Hybrid system under Setting 3 – retailer remanufactures

Under Setting 3, the retailer collects and remanufactures the used products. Product flows under this setting are illustrated in Figure 4.3.

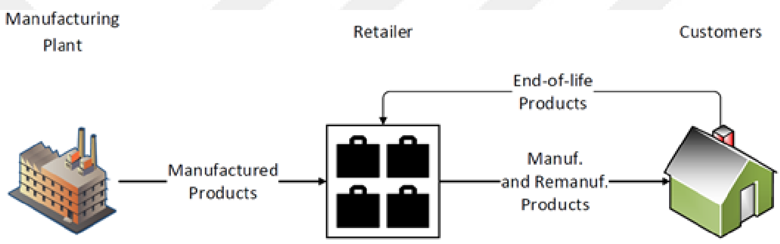


Figure 4.3. *Product flows under Setting 3*

The sequence of events is as follows.

1. Manufacturer decides on the wholesale price of manufactured products, w_m and sustainability level, s.
2. Retailer decides on the amount of manufactured and remanufactured products to sell, d_m, d_r.

Similar to Setting 2 decentralized case, we use backward induction to obtain the equilibrium solution. We first solve the retailer's problem for given manufacturer's wholesale price and sustainability level decisions and obtain the retailer's best response. Then, we solve the manufacturer's problem given best response of the retailer to obtain the equilibrium solution.

Retailer's problem under Setting 3 given manufacturer's wholesale price, w_m and sustainability level, s can be formulated as in equation (4.15).

$$\max_{\substack{d_m \geq 0 \\ 0 \leq d_r \leq \kappa}} \pi_R^3(d_m, d_r | w_m, s) = (p_m(d_m) - w_m)d_m + \big(p_r(d_r) - c_r - c_p\big)d_r - (a - bs - \Delta)d_r t \tag{4.15}$$

In the retailer's objective function, first part represents the profit obtained by selling the manufactured products to customers, second part represents the profit gained by selling the remanufactured products to customers. Finally, the last part is the carbon tax paid by the retailer for remanufacturing process. Bounds on the decision variables ensure that the amount of manufactured product must be greater than or equal to zero and the amount of remanufactured product to sell must be between 0 and κ.

Lemma 3: Under Setting 3, retailer's best response can be characterized as in equation (4.16).

$$(d_m^*, d_r^*) = \begin{cases} \left(\dfrac{\begin{pmatrix}\beta - c_p - c_r + w_m \\ +\Delta t - at + bst - 1\end{pmatrix}}{2(\beta-1)}, \dfrac{\begin{pmatrix} c_p + c_r - \Delta t \\ -\beta w_m + at - bst\end{pmatrix}}{2\beta(\beta-1)}\right) & \text{if } \dfrac{\begin{pmatrix}\beta - c_p - c_r + w_m \\ +\Delta t - at + bst - 1\end{pmatrix}}{2(\beta-1)} > 0 \text{ and } 0 < \dfrac{\begin{pmatrix} c_p + c_r - \Delta t \\ -\beta w_m + at - bst\end{pmatrix}}{2\beta(\beta-1)} < \kappa, \\ \left(\dfrac{1 - w_m - 2\beta\kappa}{2}, \kappa\right) & \text{if } \dfrac{1 - w_m - 2\beta\kappa}{2} > 0 \text{ and } \begin{pmatrix}\Delta t - c_r - 2\beta\kappa(1-\beta) \\ -c_p + \beta w_m - at + bst\end{pmatrix} > 0, \\ \left(\dfrac{1 - w_m}{2}, 0\right) & \text{if } \dfrac{1 - w_m}{2} > 0 \text{ and } \begin{pmatrix} c_p + c_r - \Delta t \\ -\beta w_m + \text{at} - \text{bst}\end{pmatrix} > 0, \\ \left(0, \dfrac{\begin{pmatrix}\beta - c_p - c_r \\ +\Delta t - at + bst\end{pmatrix}}{2\beta}\right) & \text{if } \dfrac{\begin{pmatrix}\beta - c_p - c_r \\ +\Delta t - at + bst\end{pmatrix}}{2\beta} > 0 \text{ and } 0 < \dfrac{\begin{pmatrix}\beta - c_p - c_r \\ +\Delta t - at + bst\end{pmatrix}}{2\beta} < \kappa, \\ (0, \kappa) & \text{if } \begin{pmatrix}\Delta t - at + bst \\ -c_r - 2\beta\kappa - c_p + \beta\end{pmatrix} > 0 \text{ and } w_m + 2\beta\kappa - 1 > 0, \\ (0,0), & \text{otherwise} \end{cases} \tag{4.16}$$

Proof: Please see Appendix 2.

After characterizing the best response of the retailer, we focus on the manufacturer's problem. Manufacturer's problem under this setting can be presented as in equation (4.17).

$$\max_{\substack{w_m \geq 0 \\ 0 \leq s \leq \bar{s}}} \pi_M^3(w_m, s | d_m) = (w_m - c_m)d_m - (a - bs)d_m t - \theta s^2 \tag{4.17}$$

In the objective function in equation (4.17), first term is the revenue obtained by selling the manufactured products to retailer, second term is the carbon tax paid for manufacturing process and finally third term is the cost of sustainability investment.

Plugging the best response of the retailer given in Lemma 3 into objective function of manufacturer's problem given in equation (4.17), we can characterize the manufacturer's problem as in equation (4.18).

$$\max_{\substack{w_m\geq 0\\ 0\leq s\leq \bar{s}}} \pi_M^3(w_m,s) = \begin{cases} \max\limits_{\substack{w_m\geq 0\\ 0\leq s\leq \bar{s}}} \pi_{M,I}^3(w_m,s) & \text{if } \dfrac{\begin{pmatrix}\beta - c_p - c_r + w_m\\ +\Delta t - at + bst - 1\end{pmatrix}}{2(\beta-1)} > 0 \text{ and } 0 < \dfrac{\begin{pmatrix}c_p + c_r - \Delta t\\ -\beta w_m + at - bst\end{pmatrix}}{2\beta(\beta-1)} < \kappa, \\ \max\limits_{\substack{w_m\geq 0\\ 0\leq s\leq \bar{s}}} \pi_{M,II}^3(w_m,s) & \text{if } \dfrac{1 - w_m - 2\beta\kappa}{2} > 0 \text{ and } \begin{pmatrix}\Delta t - c_r - 2\beta\kappa(1-\beta)\\ -c_p + \beta w_m - at + bst\end{pmatrix} > 0, \\ \max\limits_{\substack{w_m\geq 0\\ 0\leq s\leq \bar{s}}} \pi_{M,III}^3(w_m,s) & \text{if } \dfrac{1 - w_m}{2} > 0 \text{ and } \begin{pmatrix}c_p + c_r - \Delta t\\ -\beta w_m + \text{at} - \text{bst}\end{pmatrix} > 0, \\ \max\limits_{\substack{w_m\geq 0\\ 0\leq s\leq \bar{s}}} \pi_{M,IV}^3(w_m,s) & \text{if } \dfrac{\begin{pmatrix}\beta - c_p - c_r\\ +\Delta t - at + bst\end{pmatrix}}{2\beta} > 0 \text{ and } 0 < \dfrac{\begin{pmatrix}\beta - c_p - c_r\\ +\Delta t - at + bst\end{pmatrix}}{2\beta} < \kappa, \\ \max\limits_{\substack{w_m\geq 0\\ 0\leq s\leq \bar{s}}} \pi_{M,V}^3(w_m,s) & \text{if } \begin{pmatrix}\Delta t - at + bst\\ -c_r - 2\beta\kappa - c_p + \beta\end{pmatrix} > 0 \text{ and } w_m + 2\beta\kappa - 1 > 0, \\ \max\limits_{\substack{w_m\geq 0\\ 0\leq s\leq \bar{s}}} \pi_{M,VI}^3(w_m,s), & \text{otherwise} \end{cases} \tag{4.18}$$

where

$$\pi_{M,I}^3(w_m,s) = (w_m - c_m)\left(\frac{\beta - c_p - c_r + w_m + \Delta t - at + bst - 1}{2(\beta-1)}\right) - (a - bs)\left(\frac{\beta - c_p - c_r + w_m + \Delta t - at + bst - 1}{2(\beta-1)}\right)t - \theta s^2$$

$$\pi_{M,II}^3(w_m,s) = (w_m - c_m)\left(\frac{1 - w_m - 2\beta\kappa}{2}\right) - (a - bs)\left(\frac{1 - w_m - 2\beta\kappa}{2}\right)t - \theta s^2$$

$$\pi_{M,III}^3(w_m,s) = (w_m - c_m)\left(\frac{1 - w_m}{2}\right) - (a - bs)\left(\frac{1 - w_m}{2}\right)t - \theta s^2$$

$$\pi_{M,IV}^3(w_m,s) = \pi_{M,V}^3(w_m,s) = \pi_{M,VI}^3(w_m,s) = -\theta s^2$$

Concentrating on the optimization problem in each range in equation (4.18), alternative solutions to the problem are generated similar to equation (4.9). Since the expressions found are very tedious we are not providing them. We use a complete enumeration scheme to obtain the equilibrium decisions of the manufacturer and remanufacturer under this setting since each of these decision variables have a lower and an upper bound ($0 \leq w_m \leq p_m \leq 1, 0 \leq w_r \leq p_r \leq 1, 0 \leq s \leq \bar{s}$).

4.1.2.4. Hybrid system under Setting 4 – a third-party remanufactures

Under this setting, a third-party remanufacturer collects the used products to remanufacture and sell to retailer. Product flows under Setting 4 is illustrated in Figure 4.4.

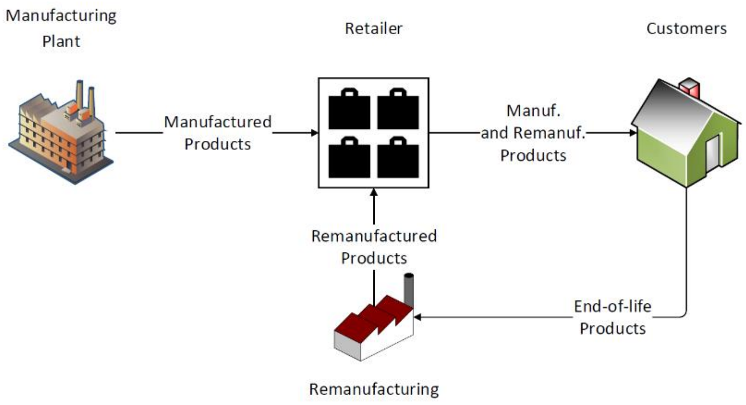


Figure 4.4. *Product flows under Setting 4*

The sequence of events is as follows.

1. The manufacturer and remanufacturer simultaneously decide on the wholesale prices of manufactured and remanufactured products and sustainability level, w_m, w_r and s by considering their own profits.
2. Retailer decides on the amount of manufactured and remanufactured products to sell, d_m, d_r.

Similar to Setting 2 and Setting 3 decentralized cases, we use backward induction to obtain the equilibrium solution. We first solve the retailer's problem for given manufacturer and remanufacturer's wholesale price decisions and obtain the retailer's best response. Then, we solve the manufacturer and remanufacturer's problems given best response of the retailer to obtain the equilibrium solution.

Retailer's problem under Setting 4 given manufacturer and remanufacturer's wholesale prices, w_m, w_r can be formulated as in equation (4.19).

$$\max_{\substack{d_m \geq 0 \\ 0 \leq d_r \leq \kappa}} \pi_R^4(d_m, d_r | w_m, w_r) = (p_m(d_m) - w_m)d_m + (p_r(d_r) - w_r)d_r \tag{4.19}$$

In the retailer's objective function, first and second terms are the profits obtained by selling the manufactured and remanufactured products respectively. Bounds on the decision variables ensure that the amount of manufactured products to sell must greater than or equal to zero and the amount of remanufactured products to sell must be between zero and κ.

Lemma 4: Under Setting 4, retailer's best response can be characterized as in equation (4.20).

$$(d_m^*, d_r^*) = \begin{cases} \left(\dfrac{\beta + w_m - w_r - 1}{2(\beta - 1)}, \dfrac{\beta w_m - w_r}{2\beta(1-\beta)}\right) & \text{if } \dfrac{\beta + w_m - w_r - 1}{2(\beta - 1)} > 0 \text{ and } 0 < \dfrac{\beta w_m - w_r}{2\beta(1-\beta)} < \kappa, \\ \left(\dfrac{1 - w_m - 2\beta\kappa}{2}, \kappa\right) & \text{if } \dfrac{1 - w_m - 2\beta\kappa}{2} > 0 \text{ and } \beta w_m - w_r - 2\beta\kappa(1-\beta) > 0, \\ \left(\dfrac{1 - w_m}{2}, 0\right) & \text{if } \dfrac{1 - w_m}{2} > 0 \text{ and } w_r - \beta w_m > 0, \\ \left(0, \dfrac{\beta - w_r}{2\beta}\right) & \text{if } \beta + w_m - w_r - 1 > 0 \text{ and } 0 < \dfrac{\beta - w_r}{2\beta} < \kappa, \\ (0, \kappa) & \text{if } \beta - w_r - 2\beta\kappa > 0 \text{ and } w_m + 2\beta\kappa - 1 > 0, \\ (0,0), & \text{otherwise.} \end{cases} \quad (4.20)$$

Proof: Please see Appendix 2.

After characterizing the best response of the retailer, we focus on the manufacturer's and remanufacturer's problems. We can present the manufacturer's problem as in equation (4.21).

$$\max_{\substack{w_m \geq 0 \\ 0 \leq s \leq \bar{s}}} \pi_M^4(w_m, s | d_m, d_r) = (w_m - c_m)d_m - (a - bs)d_m t - \theta s^2 \quad (4.21)$$

In the objective function in equation (4.21), first term is the revenue obtained by selling the manufactured products to retailer, second term is the carbon tax paid for manufacturing process and third term is the cost of sustainability investment.

Plugging the best response of the retailer given in Lemma 4 into objective function of manufacturer's problem given in equation (4.21), we can characterize the manufacturer's problem as in equation (4.22).

$$\max_{\substack{w_m \geq 0 \\ 0 \leq s \leq \bar{s}}} \pi_M^4(w_m, s | w_r) = \begin{cases} \max\limits_{\substack{w_m \geq 0 \\ 0 \leq s \leq \bar{s}}} \pi_{M,I}^4(w_m, s | w_r) & \text{if } \dfrac{\beta + w_m - w_r - 1}{2(\beta - 1)} > 0 \text{ and } 0 < \dfrac{\beta w_m - w_r}{2\beta(1-\beta)} < \kappa, \\ \max\limits_{\substack{w_m \geq 0 \\ 0 \leq s \leq \bar{s}}} \pi_{M,II}^4(w_m, s | w_r) & \text{if } \dfrac{1 - w_m - 2\beta\kappa}{2} > 0 \text{ and } \beta w_m - w_r - 2\beta\kappa(1-\beta) > 0, \\ \max\limits_{\substack{w_m \geq 0 \\ 0 \leq s \leq \bar{s}}} \pi_{M,III}^4(w_m, s | w_r) & \text{if } \dfrac{1 - w_m}{2} > 0 \text{ and } w_r - \beta w_m > 0, \\ \max\limits_{\substack{w_m \geq 0 \\ 0 \leq s \leq \bar{s}}} \pi_{M,IV}^4(w_m, s | w_r) & \text{if } \beta + w_m - w_r - 1 > 0 \text{ and } 0 < \dfrac{\beta - w_r}{2\beta} < \kappa, \\ \max\limits_{\substack{w_m \geq 0 \\ 0 \leq s \leq \bar{s}}} \pi_{M,V}^4(w_m, s | w_r) & \text{if } \beta - w_r - 2\beta\kappa > 0 \text{ and } w_m + 2\beta\kappa - 1 > 0, \\ \max\limits_{\substack{w_m \geq 0 \\ 0 \leq s \leq \bar{s}}} \pi_{M,VI}^4(w_m, s | w_r), & \text{otherwise.} \end{cases} \quad (4.22)$$

where

$$\pi_{M,I}^4(w_m, s|w_r) = (w_m - c_m)\left(\frac{\beta + w_m - w_r - 1}{2(\beta - 1)}\right) - (a - bs)\left(\frac{\beta + w_m - w_r - 1}{2(\beta - 1)}\right)t - \theta s^2$$
$$\pi_{M,II}^4(w_m, s|w_r) = (w_m - c_m)\left(\frac{1 - w_m - 2\beta\kappa}{2}\right) - (a - bs)\left(\frac{1 - w_m - 2\beta\kappa}{2}\right)t - \theta s^2$$
$$\pi_{M,III}^4(w_m, s|w_r) = (w_m - c_m)d_m - (a - bs)d_m t - \theta s^2$$
$$\pi_{M,IV}^4(w_m, s|w_r) = \pi_{M,V}^4(w_m, s) = \pi_{M,VI}^4(w_m, s) = -\theta s^2$$

Finally, we can present the remanufacturer's problem as in equation (4.23).

$$\max_{w_r \geq 0} \pi_Z^4(w_r|d_r) = (w_r - c_r)d_r - (a - bs - \Delta)d_r t - c_p d_r \tag{4.23}$$

In the objective function of the remanufacturer, first term is the revenue obtained by selling remanufactured products to retailer, second term is the carbon tax paid for remanufacturing process. Finally, third term is the collection cost of used products.

Plugging the best response of the retailer given in Lemma 4 into objective function of remanufacturer's problem given in equation (4.23), we can characterize the remanufacturer's problem as in equation (4.24).

$$\max_{w_r \geq 0} \pi_Z^4(w_r|w_m, s) = \begin{cases} \max_{w_r \geq 0} \pi_{Z,I}^4(w_r|w_m, s) & \text{if } \frac{\beta + w_m - w_r - 1}{2(\beta - 1)} > 0 \text{ and } 0 < \frac{\beta w_m - w_r}{2\beta(1 - \beta)} < \kappa, \\ \max_{w_r \geq 0} \pi_{Z,II}^4(w_r|w_m, s) & \text{if } \frac{1 - w_m - 2\beta\kappa}{2} > 0 \text{ and } \beta w_m - w_r - 2\beta\kappa(1 - \beta) > 0, \\ \max_{w_r \geq 0} \pi_{Z,III}^4(w_r|w_m, s) & \text{if } \frac{1 - w_m}{2} > 0 \text{ and } w_r - \beta w_m > 0, \\ \max_{w_r \geq 0} \pi_{Z,IV}^4(w_r|w_m, s) & \text{if } \beta + w_m - w_r - 1 > 0 \text{ and } 0 < \frac{\beta - w_r}{2\beta} < \kappa, \\ \max_{w_r \geq 0} \pi_{Z,V}^4(w_r|w_m, s) & \text{if } \beta - w_r - 2\beta\kappa > 0 \text{ and } w_m + 2\beta\kappa - 1 > 0, \\ \max_{w_r \geq 0} \pi_{Z,VI}^4(w_r|w_m, s) & \text{otherwise.} \end{cases} \tag{4.24}$$

where

$$\pi_{Z,I}^4(w_r|w_m, s) = (w_r - c_r)\left(\frac{\beta w_m - w_r}{2\beta(1 - \beta)}\right) - (a - bs - \Delta)\left(\frac{\beta w_m - w_r}{2\beta(1 - \beta)}\right)t - c_p\left(\frac{\beta w_m - w_r}{2\beta(1 - \beta)}\right)$$
$$\pi_{Z,II}^4(w_r|w_m, s) = (w_r - c_r)\kappa - (a - bs - \Delta)\kappa t - c_p\kappa$$
$$\pi_{Z,III}^4(w_r|w_m, s) = \pi_{Z,VI}^4(w_r) = 0$$
$$\pi_{Z,IV}^4(w_r|w_m, s) = (w_r - c_r)d_r - (a - bs - \Delta)d_r t - c_p d_r$$
$$\pi_{Z,V}^4(w_r|w_m, s) = (w_r - c_r)d_r - (a - bs - \Delta)d_r t - c_p d_r$$

In order to find the Nash equilibrium between manufacturer and remanufacturer, we first solve the manufacturer's problem based on the remanufacturer's fixed $w_r = 0$ decision and we find the w_m, s values for the manufacturer. Then, by using the found w_m, s values, we solve the remanufacturer's problem and find the new w_r value. We continue solving the manufacturer and remanufacturer's problem in respective order until there is no difference between $w_m, , w_r, s$ values obtained in last and previous steps.

Concentrating on the optimization problem in each range in equations (4.22) and (4.24), alternative solutions to the problem are generated similar to equation (4.9). Since the expressions found are very tedious we are not providing them. We use a complete enumeration scheme to obtain the equilibrium decisions of the manufacturer and remanufacturer under this setting since each of these decision variables have a lower and an upper bound ($0 \leq w_m \leq p_m \leq 1, 0 \leq w_r \leq p_r \leq 1, 0 \leq s \leq \bar{s}$).

4.2. Computational Study

In this section, we provide a computational study that we conduct to compare the systemwide profits, profits of supply chain actors, sustainability levels and remanufactured product quantities in pure manufacturing and hybrid manufacturing-remanufacturing systems. We first focus on a base case instance and compare the financial and environmental performance measures in both pure and hybrid systems. Then we extend our analysis by making sensitivity analyses regarding the parameters. The values of parameters for the base case instance is presented in Table 4.2.

Table 4.2. *Values of the parameters in base case instance*

Parameter	c_m	c_r	a	b	Δ	t	c_p	κ	β	θ
Base Value	0.40	0.10	2.00	0.20	0.30	0.05	0.05	0.30	0.60	0.001

Computational results corresponding to base case instance are provided in Table 4.3. Note that here and in the rest of the study, we present the computational results obtained in optimal or equilibrium solution. We observe from Table 4.3 that highest systemwide profit is observed in hybrid remanufacturing system under centralized control. When we focus on the systems under decentralized control, we observe that Setting 3 and Setting 4 achieves higher systemwide profit compared to Setting 1 and Setting 2. The reason of this fact is actually the competition between the manufacturer and the retailer (under Setting 3) or the third-party remanufacturer (under Setting 4. Due to this competition, selling prices of both manufactured and remanufactured products decrease and a systemwide profit that is close to centralized control is achieved under Setting 3 and Setting 4.

Table 4.3. *Computational results related to base case instance*

	d_m	d_r	w_m	w_r	p_m	p_r	s	$\pi_M^*(.)$	$\pi_Z^*(.)$	$\pi_R^*(.)$	SWP*
PSC	0.256	-	-	-	0.744		1.282	-	-	-	0.064
S1	0.127	-	0.747	-	0.873		0.633	0.032	-	0.016	0.048
HSC	0.169	0.149	-	-	0.742	0.410	1.587	-	-	-	0.069
S2	0.084	0.071	0.746	0.414	0.873	0.507	0.777	0.034	-	0.017	0.051
S3	0.084	0.220	0.568	-	0.784	0.418	0.000	0.006	-	0.058	0.064
S4	0.124	0.132	0.593	0.292	0.797	0.446	0.620	0.012	0.008	0.046	0.066

PSC: Pure system under centralized control; HSC: Hybrid system under centralized control;
S1: Setting 1; S2: Setting 2; S3: Setting 3; S4: Setting 4; SWP: Systemwide profit

Moreover, it is observed from Table 4.3 that lowest selling prices are achieved under Setting 3. Thus, from the customer perspective Setting 3 may be considered as the best setting. When we focus on the profit of manufacturer, we observe that the manufacturer achieved the highest profit under Setting 2. It is also obvious that collection and remanufacturing of used products either by the retailer or a third-party remanufacturer significantly deteriorates the profit of manufacturer. Finally, when we focus on the profit of the retailer, we observe that its profit significantly increases under the settings in which either the retailer itself or a third-party remanufacturer collects and remanufactures the used products (Setting 3 and Setting 4).

4.2.1. Sensitivity analysis

In this subsection, we present a sensitivity analysis to see the effects of parameters on performance measures under the optimal or equilibrium solution. For this purpose, in each instance, we change the value of one parameter at a time and kept the remaining parameters unchanged. We decrease and increase the value of each parameter by 20%, 40% and 60% compared to the value in base case instance. Since we have ten parameters and each parameter includes 7 instances (including the base case instance), we have 70 instances in total.

4.2.1.1. Systemwide profit

We compare the systemwide profits under Setting 1, Setting 2, Setting 3 and Setting 4 and present the computational results in Figure 4.5.

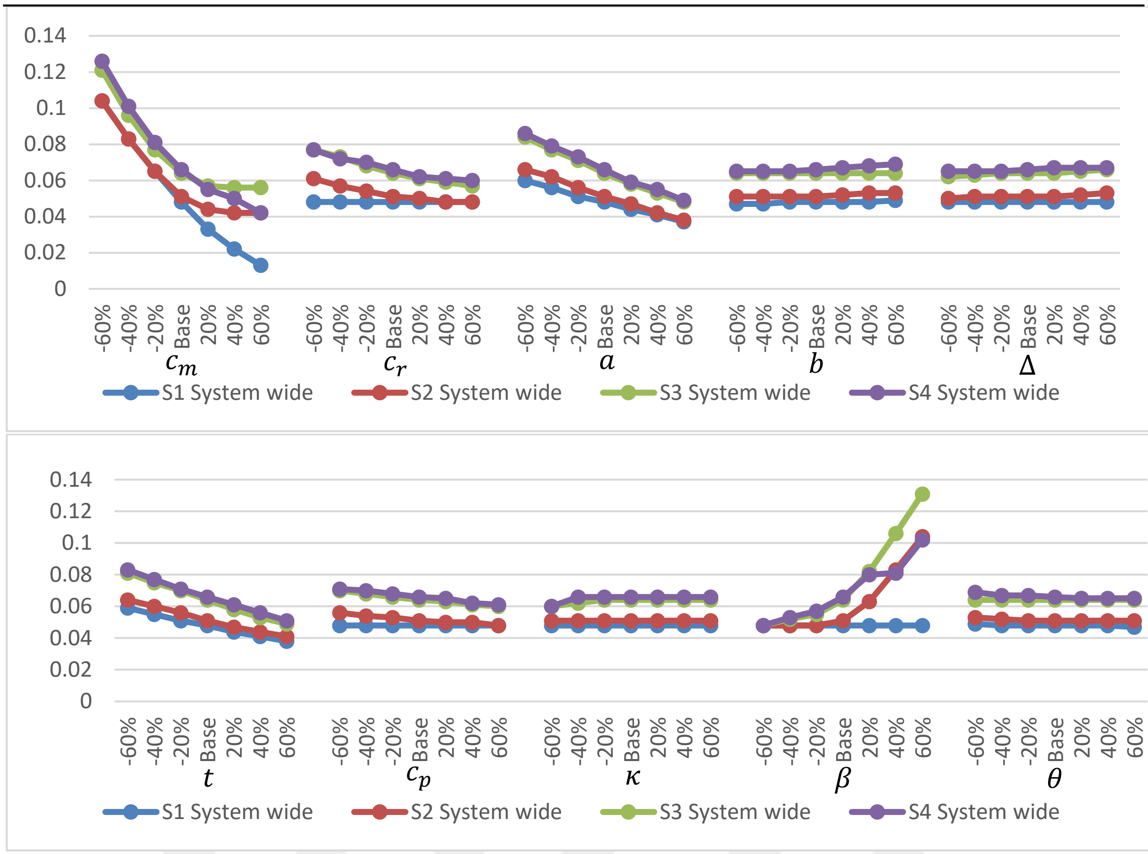


Figure 4.5. *Systemwide profit in different instances*

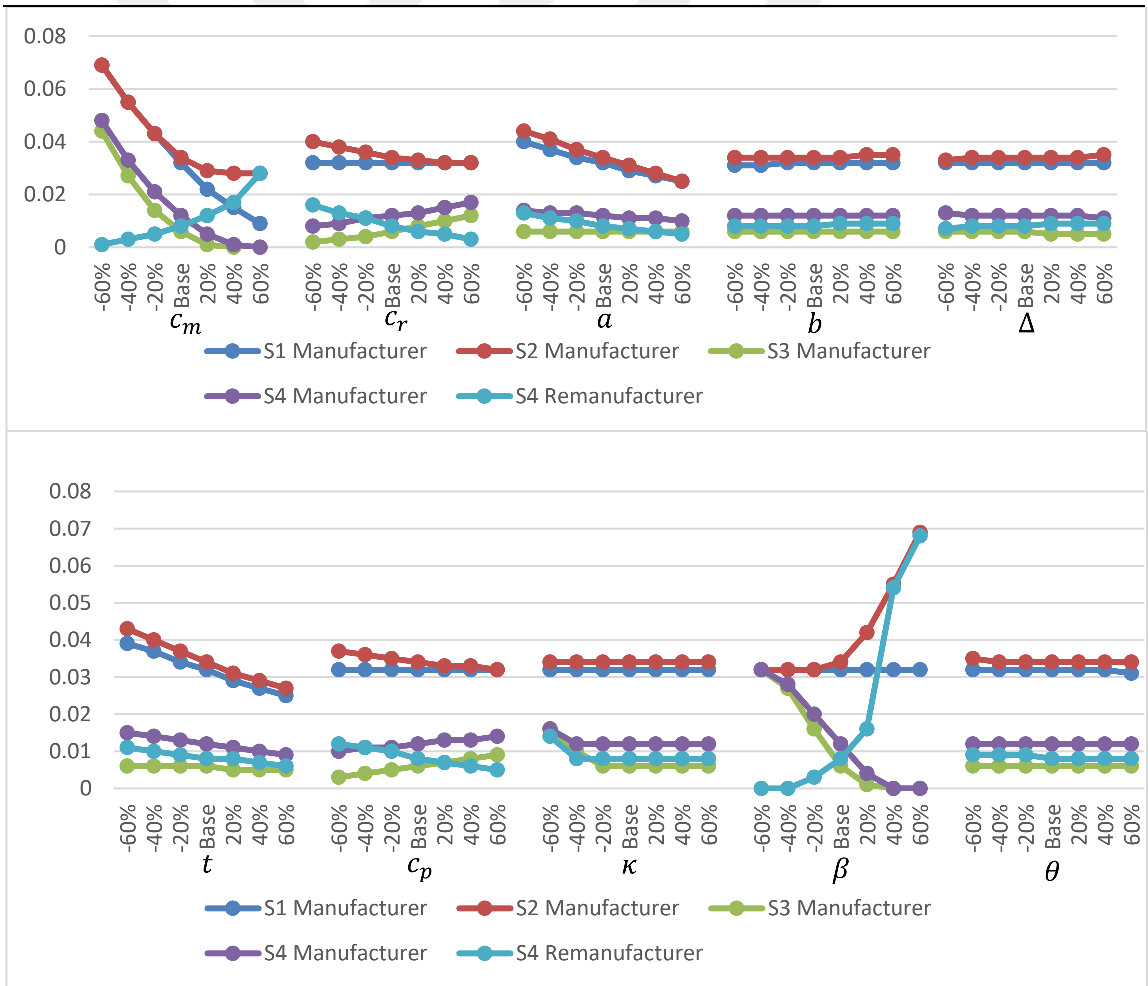
Various inferences can be made based on Figure 4.5. When we focus on the effects of parameters, we observe that unit manufacturing cost, c_m and substitution level, β have the most significant effect on systemwide profit under all settings. As expected, as the c_m value increases, systemwide profit decreases in all settings, whereas this decrease is higher under Setting 1 since under Setting 1 only manufactured products are sold and thus unit manufacturing cost has substantial effect on systemwide profit. In addition, as the β value increases, since customers see less difference between manufactured and remanufactured products, demand for remanufactured products increases and as a result systemwide profit under Setting 2, Setting 3 and Setting 4 increase while systemwide profit under pure manufacturing system (Setting 1) remains as the same. Based on this observation, we can infer that remanufacturing may especially be beneficial if the manufacturing cost is very high or the customers valuations to manufactured and remanufactured products are close to each other, i.e. they are perfect substitutes of each other.

When we compare the systemwide profits under different settings, it is observed that Setting 3 and Setting 4 give generally higher systemwide profit compared to Setting

1 and Setting 2. Therefore, it is obvious that if the remanufacturing operation is done either by the retailer or a third-party remanufacturer, systemwide profit becomes higher compared to the setting in which remanufacturing operation is done by the manufacturer. It is actually the result of competition between the manufacturer and the supply chain actor which collects and remanufactures the used products. Under Setting 2, the manufacturer considers this competition and its negative effect on the demand of manufactured products, whereas the retailer and the third-party remanufacturer do not consider this effect and focus only on their own profits.

4.2.1.2. Manufacturer, remanufacturer and retailer's profits

In this subsection, we analyze the profits of the manufacturer, remanufacturer and retailer and present the computational results in Figure 4.6.



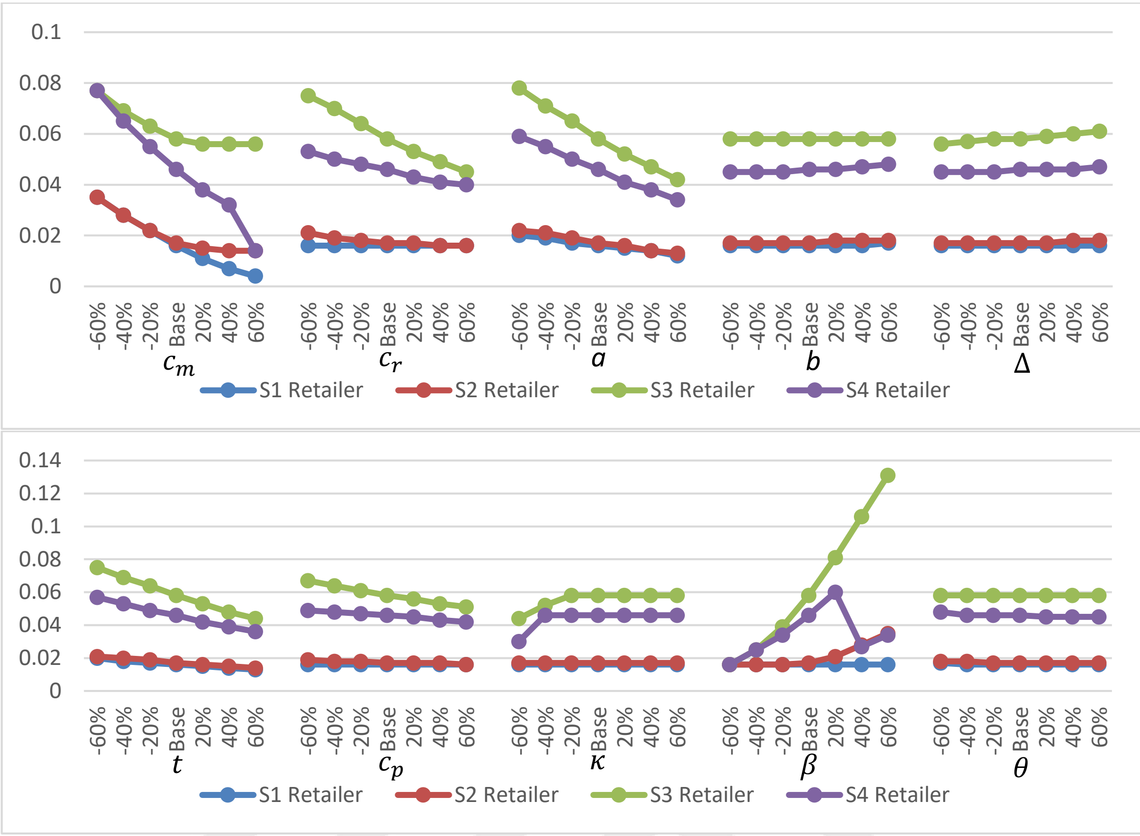


Figure 4.6. *Profits of the manufacturer, remanufacturer and retailer*

When we focus on the effects of parameters, we observe that unit manufacturing cost, c_m, unit remanufacturing cost, c_r, base emission value, a, and substitution level, β have a prominent effect on manufacturer, remanufacturer and retailer's profit while the effects of other parameters can be considered as limited. As the c_m value increases, manufacturer and retailer's profit decrease and remanufacturer's profit (in Setting 4) increases since as the c_m value increases the manufacturer sells the products at a higher wholesale prices to the retailer and the retailer sells it at a higher selling prices which consequently decreases the demand of manufactured products and increases the demand of remanufactured products. Moreover, when we focus on the unit remanufacturing cost, c_r, we observe that an increase in this value yields a decrease in the profit of both retailer and remanufacturer. It also decreases the profit of manufacturer under Setting 2 since under Setting 2, the manufacturer remanufactures the used products. On the other hand, since under Setting 3 and Setting 4 increasing the c_r value, yields an increase in the cost of manufacturer's competitor, its competitor increases the selling price and thus the manufacturer gain more customers for manufactured products. Hence, under Setting 3 and Setting 4, increasing the c_r value yields an increase in the profit of manufacturer.

When we focus on the base emission, a, it is observed that an increase in the value of a yields a decrease in manufacturer, remanufacturer and retailer's profit since as it increases, more carbon tax is paid for manufactured and remanufactured products. Finally, when we focus on the effect of value of β, we observe that as β increases, profit of the manufacturer under Setting 2 increases since in that setting manufacturer makes remanufacturing, whereas profit of the manufacturer under Setting 3, and Setting 4 decreases as β increases, since in those settings, the retailer or a third-party remanufacturer makes remanufacturing. Since under Setting 1 no remanufacturing is made, β has no effect on manufacturer's cost under Setting 1. Moreover, as expected an increase in β yields a prominent increase in the profit of remanufacturer under Setting 4 since it increases the demand of remanufactured products. β has also a prominent effect on retailer's profit. As the value of β increases, profit of the retailer under Setting 3 also increases since in that setting, remanufacturing is done by the retailer.

When we focus on the profit of the manufacturer, we observe that manufacturer achieves the lowest profit under Setting 3 and highest profit under Setting 2. It is obvious that if the retailer or a third-party remanufacturer makes remanufacturing, manufacturer's profit prominently deteriorates in all instances. When we focus on the profit of retailer, we observe that the retailer achieves highest profits under the settings where the remanufacturing is done either by the retailer or a third-party remanufacturer since in those settings, the manufacturer decreases the wholesale price of manufactured products due to competition. Finally, we observe that under Setting 1 and Setting 2 retailer's profit is generally less than the manufacturer's profit but under Setting 3 and Setting 4 retailer obtains a higher profit compared to the manufacturer.

4.2.1.3. Sustainability level

In this subsection, we analyze the values of sustainability level (s) in different instances and present the computational study in Figure 4.7.

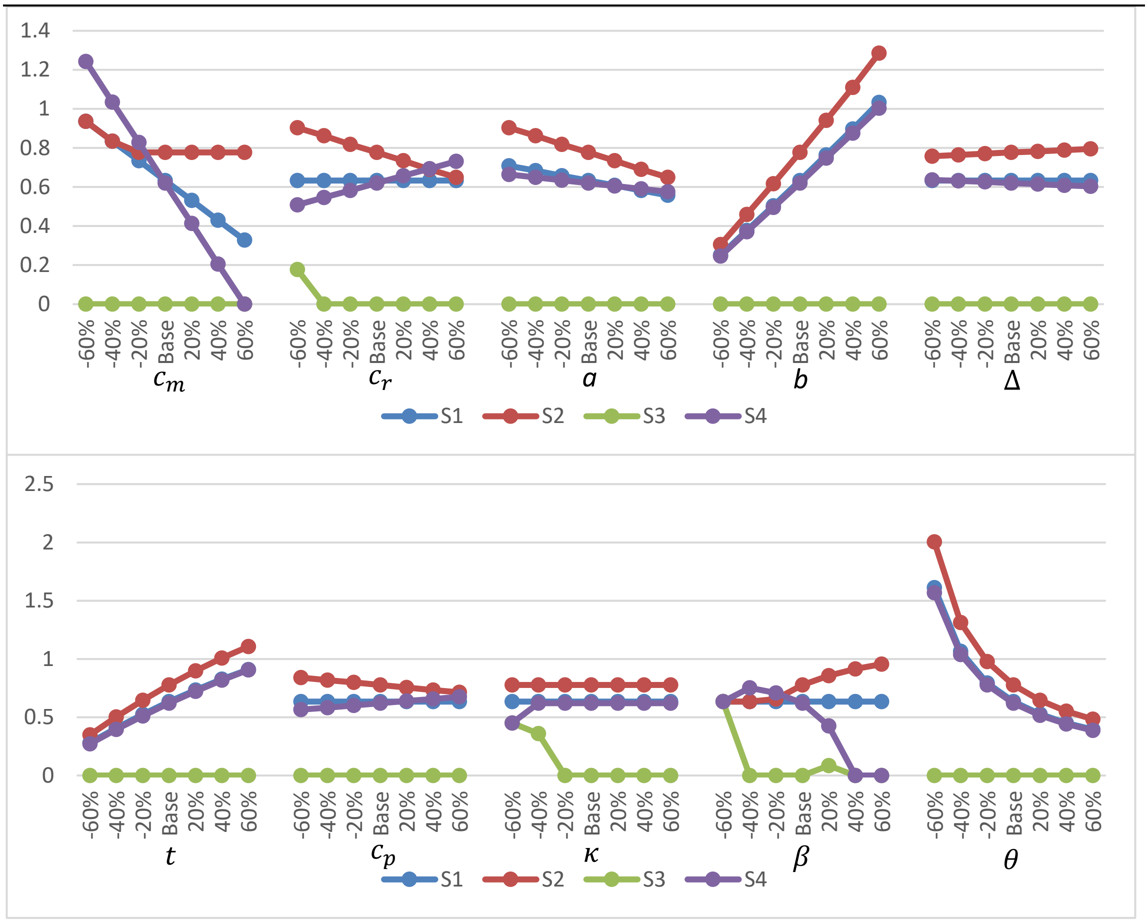


Figure 4.7. *Sustainability investments in different instances*

Figure 4.7 shows that as unit manufacturing cost, c_m, or unit remanufacturing cost, c_r increases, sustainability investment generally decreases under all settings since as one of these parameters increase, amount of manufactured or remanufactured products decreases and consequently higher sustainability investments become not profitable for manufacturer. Moreover, since unit emission is defined as $(a - bs)$ for manufactured products, paying the investment cost and increasing s may not be profitable for lower b values since lower b values bring less emission reductions and consequently less carbon tax reductions but it may be profitable to make that investment in higher b values since higher b values bring more emission reductions. Hence, as seen in Figure 4.7, as b increases, sustainability investment also increases. Finally, as expected we observe that an increase in sustainability investment cost yields a decrease in sustainability levels in all settings.

When we compare the sustainability levels under different settings, we observe that highest sustainability levels are achieved under Setting 2. An interesting observation here is that under Setting 4, the manufacturer makes no sustainability investment in many instances. The reason of this fact is that based on the retailer's best response under this setting, an increase in s value decreases the amount of manufactured products to sell and increases the amount of remanufactured products to sell. Thus, in most instances the manufacturer decides to keep the sustainability level at zero.

To sum up, considering the sustainability level, we can state that it is better for the environment if the manufacturer itself collects and remanufactures the used products compared to settings in which the remanufacturing is done by the retailer or a third-party remanufacturer.

4.2.1.4. Remanufactured product quantity

In this subsection, we analyze the remanufactured product quantity (d_r values) under Setting 2, Setting 3 and Setting 4 and present the computational results in Figure 4.8.

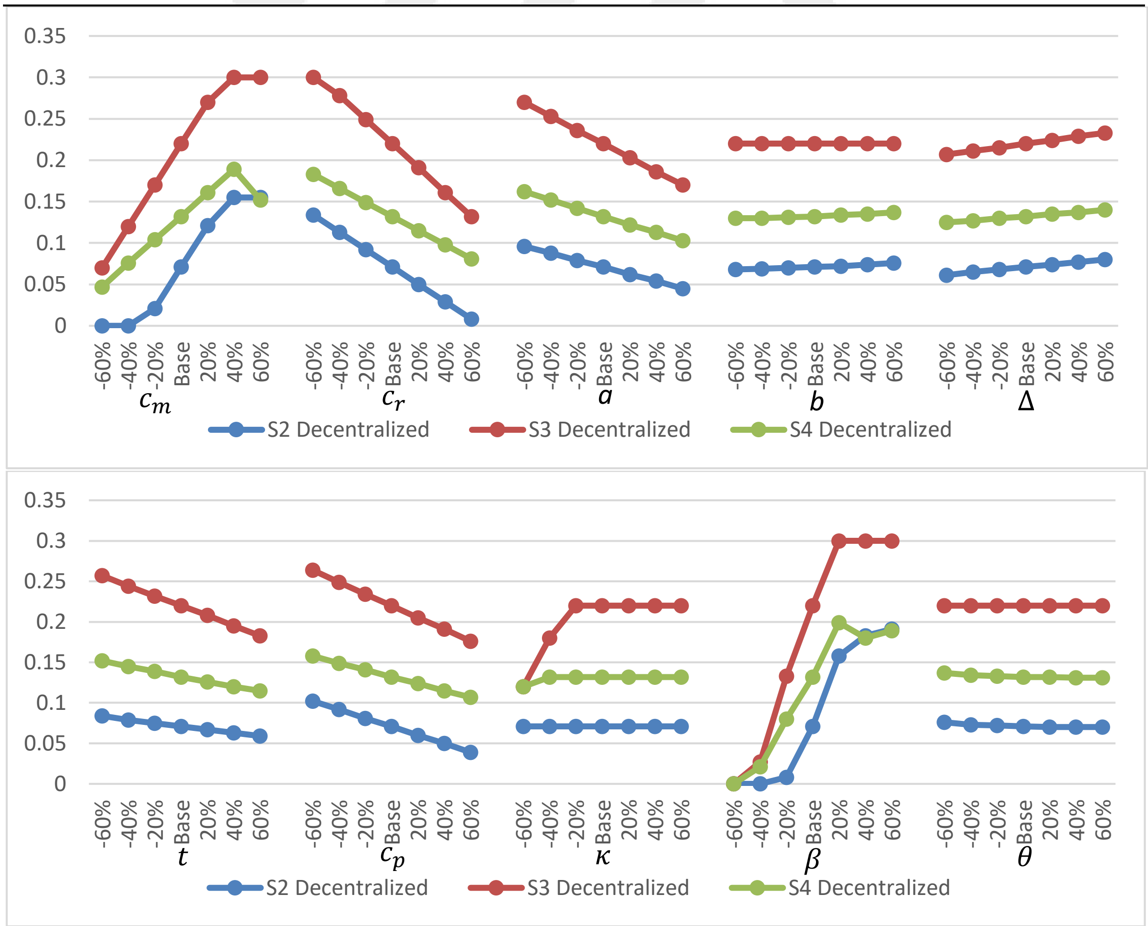


Figure 4.8. *Amount of remanufactured product in different instances*

It is observed from Figure 4.8 that especially unit manufacturing cost, c_m, unit remanufacturing cost, c_r and substitution level, β have significant effects on the remanufactured product quantities in all settings. As c_m increases, more remanufacturing is made and consequently remanufactured product quantity increases, whereas as c_r increases less remanufacturing is made and remanufactured product quantity decreases. Finally, we observe that as β increases remanufactured product quantity also increases since as β increases, customers see less difference between manufactured and remanufactured products and consequently demand for remanufactured products increases.

When we compare the d_r values under different settings, we observe that highest d_r values are achieved under Setting 3 in all experiments. An immediate inference that can be made based on this observation is that if the retailer makes the remanufacturing, highest amount of product can be collected and remanufactured. Moreover, it is seen that higher d_r values are achieved under Setting 4 compared to Setting 2 since the manufacturer considers the negative effect of competition on the demand of manufactured products and makes less remanufacturing compared to the third-party remanufacturer. Briefly, it is clear that higher amounts of remanufacturing may not be profitable for the manufacturer but (in the same parameter setting), it may be profitable for remanufacturer or retailer. In addition, as seen in Figure 4.8, in some instances d_r values are zero under Setting 2 but greater than zero under Setting 3 and Setting 4. In other words, the manufacturer prefers not to collect and remanufacture in those instances but it is profitable for remanufacturer or retailer to do remanufacturing. On the other hand, as we see in Figure 4.6, if the remanufacturing operation is done by the retailer or a third-party remanufacturer, profit of the manufacturer prominently deteriorates.

It is also observed in Figure 4.8 that in highest values of unit manufacturing cost and substitution level and in lowest value of unit remanufacturing cost, collection quantity increases up to 0.3 under Setting 3, which is the maximum possible collection quantity, whereas it is less than 0.3 in all other instances. In other words, in other instances, the supply chain actor decides to collect and remanufacture only a fraction of all available remanufacturable items and thus an increase in collection quantity do not yield to a change on the decisions of supply chain actors.

To sum up, from the perspective of the manufacturer the highest threat is the retailer's decision to collect and remanufacture the used products and second important threat is the decision of a third-party remanufacturer to collect and remanufacture the used products. These two decisions do not only deteriorate the profit of the manufacturer, but also decrease the sustainability investment. Thus, the manufacturer must take action to deter the collection and remanufacturing of retailer and third-party remanufacturer.

5. NETWORK DESIGN FOR CLOSING THE LOOP IN SUPPLY CHAINS

Over the past years, companies started to close the loop in their supply chains to comply with the regulations and increase the sustainability of their system. By this context, in this part of thesis, we focus on the financial and environmental effects of closing the loop in supply chains. We consider demand, return rate and returned product quality uncertainties simultaneously and propose a set of two-stage stochastic programming models for both forward and closed-loop supply chains to compare the optimal supply chain costs, supply chain emissions and model decisions with each other. We make various sensitivity analyses to see the effects of parameters. We also study three well-known and widely-used emission policies; carbon cap, carbon cap-and-trade and carbon tax together with the case of no emission regulation and compare the forward and closed-loop supply chains under these policies.

5.1. Problem Definition

In order to investigate the financial and environmental effects of closing the loop in supply chains, we focus on the supply chain of a product composed of multiple components. One unit of the final product is manufactured by using G different components. We construct this supply chain both as a forward supply chain and as a closed-loop supply chain to make the comparison between FSC and CLSC.

In FSC, components are procured and shipped from suppliers to manufacturing plants. After the manufacturing process in manufacturing plants, manufactured products (finished goods) are shipped from manufacturing plants to distribution centers. Finally, those products are handled in distribution centers and shipped from distribution centers to customers to satisfy their demands. Demands of customers must be fully met. The material flow in FSC is illustrated in Figure 5.1.

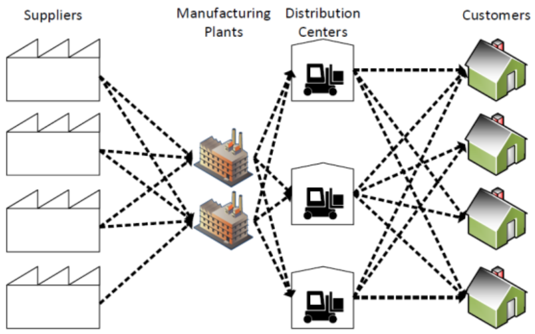


Figure 5.1. *Forward supply chain*

In CLSC, a fraction of end-of-use products are returned back to company. The ratio of returned products to all products is referred as *return rate*. We assume that the company must accept all of the returned products (Talaei et al., 2016). Due to these returned products, there are also some reverse supply chain processes in addition to FSC processes. Returned products are collected from customers in exchange for a unit acquisition fee and shipped from customers to collection centers via company owned vehicles. In other words, shipment costs of returned products from customers to collection centers are paid by the company. In collection centers, an initial test is made and repairable products are determined. The ratio of repairable products to returned products is referred as *product recovery rate*. Those repairable products are sent from collection centers to repair centers and after the repair operation in repair centers they are sent to distribution centers to be handled and to be sent to customers. Repaired and brand-new products are indifferent for customers (Üster and Hwang, 2016).

On the other hand, unrepairable products in collection centers are shipped from collection centers to disassembly centers for disassembly process. After the disassembly process in disassembly centers, reusabilities of components are checked. The ratio of disassembled products, which can provide a reusable component, is referred as *component recovery rate*. Component recovery rate is allowed to be non-identical for each component. Moreover, reusabilities of the components are assumed to be independent from each other. Those reusable components are sent from disassembly centers to manufacturing plants to be used in manufacturing process. Unreusable components are sent to landfill for disposal. Recovered components are assumed to be perfectly substitutable with the brand-new components procured from suppliers. The material flow in CLSC is illustrated in Figure 5.2.

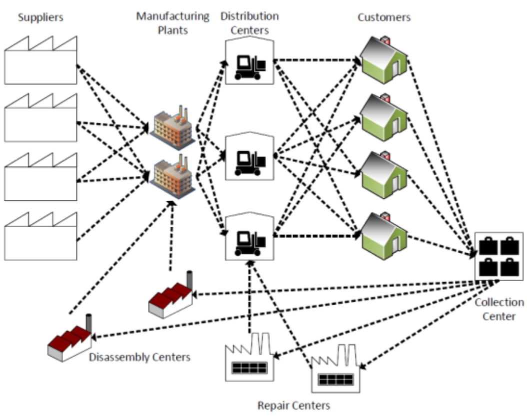


Figure 5.2. *Closed-loop supply chain*

We assume that the locations of suppliers and customers, and the capacities of suppliers are fixed. Potential locations of manufacturing plants, distribution centers, collection centers, repair centers and disassembly centers are also known (Ramezani et al., 2013). Unit procurement cost and unit procurement emission of components supplied by different suppliers, and capacities of suppliers are allowed to be non-identical. Manufacturing plants, distribution centers, collection centers, repair centers and disassembly centers have an initial capacity, if they are decided to be opened. However, we assume that their capacities can be expanded up to a certain capacity expansion limit incurring a unit capacity expansion cost. By this context, each facility has a fixed cost per period and variable capacity expansion cost. Fixed cost of a facility is independent from the operations and includes the costs such as rental costs, insurance costs and amortized costs. Although fixed cost and unit capacity expansion cost are allowed to be non-identical across different facilities, unit cost and unit emission of an operation is assumed to be identical in all facilities, i.e. unit manufacturing cost is assumed to be the same in all manufacturing plants. Finally, we consider a unit cost and unit emission per unit.km for shipments between two facilities.

Nowadays, faced with increasing amounts of waste, many governments have reviewed available policy options and concluded that placing the responsibility for the post-consumer phase of certain goods on producers could be an option. Extended Producer Responsibility (EPR) is a policy approach under which producers are given a significant responsibility (financial and/or physical) for the treatment or disposal of post-consumer products (OECD.org). Considering this policy and other policies about disposal of used products, in this study, either the disposal operation is made by the company or by a third-party firm, we assume that the company is responsible for the cost and emission of disposal operations. In FSC, we assume that the products are disposed after they are used by the customers. On the other hand, in CLSC, in addition to the uncollected products that are used by customers, we assume that the products that are collected but not recovered are also disposed.

In this problem setting, we propose a set of two-stage stochastic programming models to investigate the financial and environmental effects of closing the loop in supply chains under demand, return rate, product recovery rate and component recovery rate uncertainties. In a standard two-stage stochastic programming model, decision variables are divided into two groups; namely, first stage and second stage variables. First stage variables are decided upon before the actual realization of the random parameters. Once the uncertain events have unfolded, further design or operational adjustments can be made through values of the second-stage or alternatively called recourse variables at a particular cost (Al-Qahtani and Elkamel, 2011). Based on the two-stage programming approach, in our models, locations of facilities and suppliers to work with are determined in the first stage, capacity expansion, flow and shipment decisions as well as emission-related decisions in carbon cap-and-trade policy are made in the second stage.

Moreover, we modify our models to three well-known and widely-used carbon policies; carbon cap, carbon cap-and-trade and carbon tax to compare the FSC and CLSC under these policies. Under carbon cap policy, there is an emission limit called carbon cap such that the total supply chain emission cannot exceed this limit. In carbon cap-and-trade policy, similar to carbon cap policy there is a predetermined carbon emission limit called carbon cap. However, under carbon cap-and-trade policy the total supply chain emission may exceed this emission limit. In this case, the company must purchase carbon credits at a certain unit price. Similarly, if the total supply chain emission of the company is below the emission limit, they can sell the remaining carbon credits at the same unit price. As an example to systems using carbon-cap-and-trade policy, we can give the EU Emissions Trading System (EU ETS). The EU ETS remains the world's biggest emissions trading market operating in about 30 countries including the EU countries (The EU ETS Factsheet). Finally, under carbon tax policy, the companies pay a certain fee for each unit of their carbon emission. This fee is called as carbon tax. As an example to a place using carbon tax policy, we can mention the British Columbia, a province of Canada. In 2008, the province implemented North America's first broad-based carbon tax, proving that it is possible to reduce emissions while growing the economy (gov.bc.ca).

5.2. Mathematical Models

Sets, parameters and decision variables used in our models can be presented as follows.

<u>Sets</u>

G: Set of components, indexed by g

H: Set of suppliers, indexed by h

I: Set of potential locations of manufacturing plants, indexed by i

J: Set of potential locations of distribution centers, indexed by j

K: Set of customers, indexed by k

L: Set of potential locations of collection centers, indexed by l

M: Set of potential locations of repair centers, indexed by m

N: Set of potential locations of disassembly centers, indexed by n

O: Set of operations (in respective order; manufacturing, handling, collection and testing, repair, disassembly, disposal), indexed by *o*

S: Set of scenarios, indexed by s

Deterministic Parameters

ds_{hi}: *Distance between supplier h and manufacturing plant i (km)*

dm_{ij}: *Distance between manufacturing plant i and distribution center j (km)*

dd_{jk}: *Distance between distribution center j and customer k (km)*

dc_{kl}: *Distance between customer k and collection center l (km)*

da_{lm}: *Distance between collection center l and repair center m (km)*

db_{ln}: *Distance between collection center l and disassembly center n (km)*

dr_{mj}: *Distance between repair center m and distribution center j (km)*

de_{ni}: *Distance between disassembly center n and manufacturing plant i (km)*

cs_{hg}: *Capacity of supplier h for component g (unit per period)*

cm_i: *Capacity of manufacturing plant i (unit per period)*

cd_j: *Capacity of distribution center j (unit per period)*

cc_l: *Capacity of collection center l (unit per period)*

cr_m: *Capacity of repair center m (unit per period)*

ca_n: *Capacity of disassembly center n (unit per period)*

lm_i: *Upper limit of capacity expansion in manufacturing plant i (unit per period)*

ld_j: *Upper limit of capacity expansion in distribution center j (unit per period)*

lc_l: *Upper limit of capacity expansion in collection center l (unit per period)*

lr_m: *Upper limit of capacity expansion in repair center m (unit per period)*

la_n: *Upper limit of capacity expansion in disassembly center n (unit per period)*

wm_i: *Capacity expansion cost of manufacturing plant i (\$ per unit)*

wd_j: *Capacity expansion cost of distribution center j (\$ per unit)*

wc_l: *Capacity expansion cost of collection center l (\$ per unit)*

wr_m: *Capacity expansion cost of repair center m (\$ per unit)*

wa_n: *Capacity expansion cost of disassembly center* n *($ per unit)*

fm_i: *Fixed cost of manufacturing plant* i *($ per period)*

fd_j: *Fixed cost of distribution center* j *($ per period)*

fc_l: *Fixed cost of collection center* l *($ per period)*

fr_m: *Fixed cost of repair center* m *($ per period)*

fa_n: *Fixed cost of disassembly center* n *($ per period)*

uv: *Unit cost of shipment ($ per unit.km)*

uo_o: *Unit cost of operation* o *($ per unit)*

us_{hg}: *Unit procurement cost of component* g *procured from supplier* h *($ per unit)*

ev: *Unit emission of shipment (ton* CO_2 *per unit.km)*

eo_o: *Unit emission of operation* o *(ton* CO_2 *per unit)*

es_{hg}: *Emission, dedicated to production of component* g *in supplier* h *(ton* CO_2 *per unit)*

mc: *Carbon cap (ton* CO_2*)*

mp: *Carbon price in carbon cap-and-trade policy ($ per ton* CO_2*)*

mt: *Carbon tax in carbon tax policy ($ per ton* CO_2*)*

p^s: *Probability that the scenario* s *will occur.*

Random Parameters

rd_k^s: *Demand of customer* k *under scenario* s *(unit)*

rr_k^s: *Return rate of customer* k *under scenario* s

rp^s: *Product recovery rate under scenario* s

rq_g^s: *Component recovery rate for component* g *under scenario* s

Decision Variables

TS_{hig}^s: *Flow of component* g*, from supplier* h *to manufacturing plant* i *under scenario* s *(unit)*

TM_{ij}^s: *Flow of product from manufacturing plant* i *to distribution center* j *under scenario* s *(unit)*

TD_{jk}^s: *Flow of product from distribution center* j *to customer* k *under scenario* s *(unit)*

TC_{kl}^s: *Flow of returned product from customer* k *to collection center* l *under scenario* s *(unit)*

TA_{lm}^{s}: *Flow of returned product from collection center* l *to repair center* m *under scenario s (unit)*

TB_{ln}^{s}: *Flow of returned product from collection center* l *to disassembly center* n *under scenario s (unit)*

TR_{mj}^{s}: *Flow of returned product from repair center* m *to distribution center* j *under scenario s (unit)*

TE_{nig}^{s}: *Flow of returned component* g *from disassembly center* n *to manufacturing plant* i *under scenario s (unit)*

EM_{i}^{s}: *Amount of capacity expansion in manufacturing plant* i *under scenario s (unit)*

ED_{j}^{s}: *Amount of capacity expansion in distribution center* j *under scenario s (unit)*

EC_{l}^{s}: *Amount of capacity expansion in collection center* l *under scenario s (unit)*

ER_{m}^{s}: *Amount of capacity expansion in repair center* m *under scenario s (unit)*

EA_{n}^{s}: *Amount of capacity expansion in disassembly center* n *under scenario s (unit)*

CP^{s}: *Amount of purchased carbon credits in carbon cap-and-trade policy under scenario s (ton)*

CS^{s}: *Amount of sold carbon credits in carbon cap-and-trade policy under scenario s (ton)*

XM_{i}: *Binary variable, 1 if a manufacturing plant is opened in candidate location* i *and 0 otherwise.*

XD_{j}: *Binary variable, 1 if a distribution center is opened in candidate location* j *and 0 otherwise.*

XC_{l}: *Binary variable, 1 if a collection center is opened in candidate location* l *and 0 otherwise.*

XR_{m}: *Binary variable, 1 if a repair center is opened in candidate location* m *and 0 otherwise.*

XA_{n}: *Binary variable, 1 if a disassembly center is opened in candidate location* n *and 0 otherwise.*

5.2.1. A two-stage stochastic programming model for FSC

Let FC^{s} be the supply chain cost in FSC occurring in scenario s, which can be written as follows.

$$FC^s = \sum_{i=1}^{I} fm_i XM_i + \sum_{j=1}^{J} fd_j XD_j + \sum_{i=1}^{I} wm_i EM_i^s + \sum_{j=1}^{J} wd_j ED_j^s + \sum_{i=1}^{I}\sum_{j=1}^{J} uo_1 TM_{ij}^s$$
$$+ \sum_{j=1}^{J}\sum_{k=1}^{K} uo_2 TD_{jk}^s + \sum_{k=1}^{K} uo_6 rd_k^s + \sum_{h=1}^{H}\sum_{i=1}^{I}\sum_{g=1}^{G} TS_{hig}^s ds_{hi} uv$$
$$+ \sum_{i=1}^{I}\sum_{j=1}^{J} TM_{ij}^s dm_{ij} uv + \sum_{j=1}^{J}\sum_{k=1}^{K} TD_{jk}^s dd_{jk} uv$$
$$+ \sum_{h=1}^{H}\sum_{i=1}^{I}\sum_{g=1}^{G} TS_{hig}^s us_{hg} \tag{5.1}$$

In respective order, FC^s includes the fixed costs of facilities, variable capacity expansion costs of facilities, variable costs of operations (manufacturing, handling, disposal), variable costs of shipments and finally the procurement costs of components. By this context, the model can be written as follows.

$$\min z = \sum_{s=1}^{S} p^s FC^s \tag{5.2}$$

$$\textit{subject to}$$

$$\sum_{h=1}^{H} TS_{hig}^s = \sum_{j=1}^{J} TM_{ij}^s \qquad \forall i, g, s \tag{5.3}$$

$$\sum_{i=1}^{I} TM_{ij}^s = \sum_{k=1}^{K} TD_{jk}^s \qquad \forall j, s \tag{5.4}$$

$$\sum_{j=1}^{J} TD_{jk}^s = rd_k^s \qquad \forall k, s \tag{5.5}$$

$$\sum_{i=1}^{I} TS_{hig}^s \leq cs_{hg} \qquad \forall h, g, s \tag{5.6}$$

$$\sum_{j=1}^{J} TM_{ij}^s \leq cm_i XM_i + EM_i^s \qquad \forall i, s \tag{5.7}$$

$$\sum_{k=1}^{K} TD_{jk}^s \leq cd_j XD_j + ED_j^s \qquad \forall j, s \tag{5.8}$$

$$EM_i^s \leq lm_i XM_i \quad \forall i, s \tag{5.9}$$

$$ED_j^s \leq ld_j XD_j \quad \forall j, s \tag{5.10}$$

$$TS_{hig}^s, TM_{ij}^s, TD_{jk}^s, EM_i^s, ED_j^s \geq 0, XM_i, XD_j \in \{0,1\} \tag{5.11}$$

In the above model, Equation 5.2 is the objective function, which minimizes the expected supply chain cost. Equation 5.3 and 5.4 are the flow balance constraints for manufacturing plants and distribution centers respectively. Equation 5.5 guarantees that demands of all customers are satisfied. Equation 5.6, 5.7 and 5.8 are the capacity constraints for suppliers, manufacturing plants and distribution centers respectively. Equation 5.9 and 5.10 are the capacity expansion constraints. They ensure that if a facility is not opened, then not any capacity expansion can be made. If a facility is opened, the capacity can be expanded up to the expansion limit. Finally, Equation 5.11 sets the types and signs of the decision variables.

5.2.2. A two-stage stochastic programming model for CLSC

If we let CC^s be the supply chain cost in CLSC occurring in scenario s, then CC^s can be written as follows.

$$
\begin{aligned}
CC^s = &\sum_{i=1}^{I} fm_i XM_i + \sum_{j=1}^{J} fd_j XD_j + \sum_{l=1}^{L} fc_l XC_l + \sum_{m=1}^{M} fr_m XR_m + \sum_{n=1}^{N} fa_n XA_n \\
&+ \sum_{i=1}^{I} wm_i EM_i^s + \sum_{j=1}^{J} wd_j ED_j^s + \sum_{l=1}^{L} wc_l EC_l^s + \sum_{m=1}^{M} wr_m ER_m^s \\
&+ \sum_{n=1}^{N} wa_n EA_n^s + \sum_{i=1}^{I}\sum_{j=1}^{J} uo_1 TM_{ij}^s + \sum_{j=1}^{J}\sum_{k=1}^{K} uo_2 TD_{jk}^s \\
&+ \sum_{k=1}^{K}\sum_{l=1}^{L} uo_3 TC_{kl}^s + \sum_{l=1}^{L}\sum_{m=1}^{M} uo_4 TA_{lm}^s + \sum_{l=1}^{L}\sum_{n=1}^{N} uo_5 TB_{ln}^s \\
&+ \sum_{k=1}^{K} uo_6 (1 - rr_k^s) rd_k^s + \sum_{l=1}^{L}\sum_{n=1}^{N}\sum_{g=1}^{G} uo_6 (1 - rq_g^s) TB_{ln}^s \qquad (5.12) \\
&+ \sum_{h=1}^{H}\sum_{i=1}^{I}\sum_{g=1}^{G} TS_{hig}^s ds_{hi}\, uv + \sum_{i=1}^{I}\sum_{j=1}^{J} TM_{ij}^s dm_{ij}\, uv \\
&+ \sum_{j=1}^{J}\sum_{k=1}^{K} TD_{jk}^s dd_{jk} uv + \sum_{k=1}^{K}\sum_{l=1}^{L} TC_{kl}^s dc_{kl} uv + \sum_{l=1}^{L}\sum_{m=1}^{M} TA_{lm}^s da_{lm} uv \\
&+ \sum_{l=1}^{L}\sum_{n=1}^{N} TB_{ln}^s db_{ln} uv + \sum_{m=1}^{M}\sum_{j=1}^{J} TR_{mj}^s dr_{mj} uv \\
&+ \sum_{n=1}^{N}\sum_{i=1}^{I}\sum_{g=1}^{G} TE_{nig}^s de_{ni} uv + \sum_{h=1}^{H}\sum_{i=1}^{I}\sum_{g=1}^{G} TS_{hig}^s us_{hg}
\end{aligned}
$$

In respective order, it includes the fixed costs of facilities, variable capacity expansion costs of facilities, variable costs of operations (manufacturing, handling, collection and testing, repair, disassembly, disposal), variable costs of shipments and finally the procurement costs of components. By this context, the model for CLSC can be written as follows.

$$\min z = \sum_{s=1}^{S} p^s CC^s \tag{5.13}$$

$$subject\ to$$

$$\sum_{h=1}^{H} TS_{hig}^s + \sum_{n=1}^{N} TE_{nig}^s = \sum_{J=1}^{J} TM_{ij}^s \qquad \forall i, g, s \tag{5.14}$$

$$\sum_{i=1}^{I} TM_{ij}^s + \sum_{m=1}^{M} TR_{mj}^s = \sum_{k=1}^{K} TD_{jk}^s \qquad \forall j, s \tag{5.15}$$

$$\sum_{j=1}^{J} TD_{jk}^s = rd_k^s \qquad \forall k, s \tag{5.16}$$

$$\sum_{l=1}^{L} TC_{kl}^s = rd_k^s rr_k^s \qquad \forall k, s \tag{5.17}$$

$$rp^s \sum_{k=1}^{K} TC_{kl}^s = \sum_{m=1}^{M} TA_{lm}^s \qquad \forall l, s \tag{5.18}$$

$$(1 - rp^s) \sum_{k=1}^{K} TC_{kl}^s = \sum_{n=1}^{N} TB_{ln}^s \qquad \forall l, s \tag{5.19}$$

$$\sum_{l=1}^{L} TA_{lm}^s = \sum_{j=1}^{J} TR_{mj}^s \qquad \forall m, s \tag{5.20}$$

$$rq_g^s \sum_{l=1}^{L} TB_{ln}^s = \sum_{i=1}^{I} TE_{nig}^s \qquad \forall n, g, s \tag{5.21}$$

$$\sum_{i=1}^{I} TS_{hig}^s \leq cs_{hg} \qquad \forall h, g, s \tag{5.22}$$

$$\sum_{j=1}^{J} TM_{ij}^s \leq cm_i XM_i + EM_i^s \qquad \forall i, s \tag{5.23}$$

$$\sum_{k=1}^{K} TD_{jk}^s \leq cd_j XD_j + ED_j^s \qquad \forall j, s \tag{5.24}$$

$$\sum_{k=1}^{K} TC_{kl}^{s} \leq cc_l XC_l + EC_l^s \qquad \forall l, s \tag{5.25}$$

$$\sum_{l=1}^{L} TA_{lm}^{s} \leq cr_m XR_m + ER_m^s \qquad \forall m, s \tag{5.26}$$

$$\sum_{l=1}^{L} TB_{ln}^{s} \leq ca_n XA_n + EA_n^s \qquad \forall n, s \tag{5.27}$$

$$EM_i^s \leq lm_i XM_i \quad \forall i, s \tag{5.28}$$

$$ED_j^s \leq ld_j XD_j \quad \forall j, s \tag{5.29}$$

$$EC_l^s \leq lc_l XC_l \quad \forall l, s \tag{5.30}$$

$$ER_m^s \leq lr_m XR_m \quad \forall m, s \tag{5.31}$$

$$EA_n^s \leq la_n XA_n \quad \forall n, s \tag{5.32}$$

$$TS_{hig}^s, TM_{ij}^s, TD_{jk}^s, TC_{kl}^s, TA_{lm}^s, TB_{ln}^s, TR_{mj}^s, TE_{nig}^s, EM_i^s, ED_j^s, EC_l^s, ER_m^s, EA_n^s \geq 0 \tag{5.33}$$

$$XM_i, XD_j, XC_l, XR_m, XA_n \in \{0,1\} \tag{5.34}$$

In the above model, Equation 5.13 is the objective function, which minimizes the expected supply chain cost. Equation 5.14 and 5.15 are the flow balance constraints for manufacturing plants and distribution centers under each scenario respectively. Equation 5.16 guarantees that the demands of all customers are satisfied. Equation 5.17 is the reverse flow constraint for the products returned from customers to collection centers. Equations 5.18-5.21 are the reverse flow balance constraints for collection centers, repair centers and disassembly centers. Equations 5.22-5.27 are the capacity constraints for suppliers and facilities. Equation 5.28-5.32 are the capacity expansion constraints. They ensure that if a facility is not opened, then not any capacity expansion can be made. If a facility is opened, the capacity can be expanded up to the expansion limit. Finally, Equation 5.33 and 5.34 set the signs and types of decision variables.

5.2.3. Models with environmental considerations

Let FE^s be the total emission in FSC in a scenario s, then FE^s can be written as follows.

$$FE^s = \sum_{i=1}^{I}\sum_{j=1}^{J} eo_1 TM_{ij}^s + \sum_{j=1}^{J}\sum_{k=1}^{K} eo_2 TD_{jk}^s + \sum_{k=1}^{K} eo_6 rd_k^s$$
$$+ \sum_{h=1}^{H}\sum_{i=1}^{I}\sum_{g=1}^{G} TS_{hig}^s ds_{hi} ev + \sum_{i=1}^{I}\sum_{j=1}^{J} TM_{ij}^s dm_{ij} ev \quad (5.35)$$
$$+ \sum_{j=1}^{J}\sum_{k=1}^{K} TD_{jk}^s dd_{jk} ev + \sum_{h=1}^{H}\sum_{i=1}^{I}\sum_{g=1}^{G} TS_{hig}^s es_{hg}$$

In respective order, FE^s includes variable emissions of operations (manufacturing, handling, disposal), variable emissions of shipments and emissions dedicated to procured components.

Similarly, if we let CE^s be the total emission in CLSC in scenario s, then CE^s can be written as follows.

$$CE^s = \sum_{i=1}^{I}\sum_{j=1}^{J} eo_1 TM_{ij}^s + \sum_{j=1}^{J}\sum_{k=1}^{K} eo_2 TD_{jk}^s + \sum_{k=1}^{K}\sum_{l=1}^{L} eo_3 TC_{kl}^s + \sum_{l=1}^{L}\sum_{m=1}^{M} eo_4 TA_{lm}^s$$
$$+ \sum_{l=1}^{L}\sum_{n=1}^{N} eo_5 TB_{ln}^s + \sum_{k=1}^{K} eo_6 (1 - rr_k^s) rd_k^s$$
$$+ \sum_{l=1}^{L}\sum_{n=1}^{N}\sum_{g=1}^{G} eo_6 (1 - rq_g^s) TB_{ln}^s + \sum_{h=1}^{H}\sum_{i=1}^{I}\sum_{g=1}^{G} TS_{hig}^s ds_{hi}\, ev$$
$$+ \sum_{i=1}^{I}\sum_{j=1}^{J} TM_{ij}^s dm_{ij}\, ev + \sum_{j=1}^{J}\sum_{k=1}^{K} TD_{jk}^s dd_{jk} ev \quad (5.36)$$
$$+ \sum_{k=1}^{K}\sum_{l=1}^{L} TC_{kl}^s dc_{kl} ev + \sum_{l=1}^{L}\sum_{m=1}^{M} TA_{lm}^s da_{lm} ev$$
$$+ \sum_{l=1}^{L}\sum_{n=1}^{N} TB_{ln}^s db_{ln} ev + \sum_{m=1}^{M}\sum_{j=1}^{J} TR_{mj}^s dr_{mj} ev$$
$$+ \sum_{n=1}^{N}\sum_{i=1}^{I}\sum_{g=1}^{G} TE_{nig}^s de_{ni} ev + \sum_{h=1}^{H}\sum_{i=1}^{I}\sum_{g=1}^{G} TS_{hig}^s es_{hg}$$

In respective order, it includes variable emissions of operations (manufacturing, handling, collection and testing, repair, disassembly, disposal), variable emissions of shipments and emissions dedicated to procured components.

By this context, modifications in FSC and CLSC models for carbon cap, carbon cap-and-trade and carbon tax policies are given in Table 5.1.

Table 5.1. *Models with environmental considerations*

Policy	Model	Objective Function	Additional Constraints
Carbon Cap	FSC	$\min \sum_{s=1}^{S} p^s[FC^s]$	$FE^s \leq mc \quad \forall s$
	CLSC	$\min \sum_{s=1}^{S} p^s[CC^s]$	$CE^s \leq mc \quad \forall s$
Carbon Cap-and-Trade	FSC	$\min \sum_{s=1}^{S} p^s[FC^s + CP^s mp - CS^s mp]$	$FE^s - CP^s + CS^s \leq mc \quad \forall s$ $CP^s, CS^s \geq 0$
	CLSC	$\min \sum_{s=1}^{S} p^s[CC^s + CP^s mp - CS^s mp]$	$CE^s - CP^s + CS^s \leq mc \quad \forall s$ $CP^s, CS^s \geq 0$
Carbon Tax	FSC	$\min \sum_{s=1}^{S} p^s[FC^s + FE^s mt]$	-
	CLSC	$\min \sum_{s=1}^{S} p^s[CC^s + CE^s mt]$	-

As seen in Table 5.1, under carbon cap policy, objective functions are the same with the no environmental consideration cases. However, different from those models, there is an additional constraint which ensures that the total supply chain emission in each scenario will be less than or equal to the carbon cap, *mc*. Moreover, under carbon cap-and-trade policy, the objective functions include also the costs of purchased carbon credits and the revenues obtained from sold carbon credits. In this case, there is also two additional constraints. First constraint ensures that the remaining carbon credits may be sold if total carbon emission is less than the carbon cap and additional carbon credits are needed to be purchased if total carbon emission is greater than carbon cap. Second constraint guarantees that purchased or sold carbon credits should be greater than or equal to zero. Finally, under carbon tax policy there is not any additional constraint. However, the objective function includes additionally the cost of emitted CO_2.

5.3. Numerical Experiments

The proposed models are implemented to a base case problem first, considering a manufacturer in Turkey, with five potential suppliers, four candidate manufacturing plants, eight candidate distribution centers, three candidate collection centers, two candidate repair centers, two candidate disassembly centers and fifteen customer locations. Locations of potential suppliers and customers and candidate locations of facilities are selected among the cities of Turkey. Distances between these locations are obtained from Google Maps. Demands of customers are generated by considering the populations of these cities. Fixed costs of facilities are generated by taking the rental costs in each location into account. Values of other parameters such as costs and emissions of operations are determined by using the publicly available data and papers in the literature (i.e. Xu et al., 2017; State and Trends of Carbon Pricing, 2019).

We use three scenarios (low, medium, high) for demand, return rate, product recovery rate and component recovery rate. As a result, our models evaluate 81 scenarios simultaneously. Probability of each scenario is obtained by multiplying the probabilities of random parameters in that scenario. For instance, probability of Scenario 1 is obtained as 0.0098 by multiplying the probabilities of low demand (0.3), low return rate (0.3), low product recovery rate (0.33) and low component recovery rate (0.33). Values of base case parameters used in our experiments are given in Appendix 3, probabilities of demand scenarios and demand values for each scenario are given in Appendix 4. Further analysis about parameters are also made in sensitivity analysis section in order to analyze the optimal decisions and economic and environmental performance measures in different parameter settings.

5.3.1. Base case problem results

In the base case problem, we assume that the company is in an area where there is no emission regulation, i.e. there is no cost and upper limit for emitted CO_2. In such a case, we compare the optimal decisions, expected supply chain cost and corresponding emission in FSC and CLSC. Computational results are summarized in Table 5.2. Note that in that table and in the rest of the study, percentage cost and emission differences between forward and closed-loop supply chains are obtained by using the formula $100.(FSC\ Value - CLSC\ Value)/(FSC\ Value)$. It should also be noted that there are 81 scenarios and total emitted CO_2 under the optimal solution is scenario dependent. Here and in the rest of the study unless stated otherwise, corresponding emission refers to the expected emission under the minimum expected cost solution.

It is seen in Table 5.2 that CLSC performs better than FSC in terms of both economic and environmental performance measures in our base case problem. According to our base case parameters, it is possible to reduce the total supply chain cost by about 9% and total supply chain emission by about 20% by closing the loop in supply chains.

When we focus on the facility decisions, we see that additional facilities may be needed to close the loop in supply chains, i.e. the number of distribution centers is increased from 2 to 3 and additional facilities are opened for reverse supply chain operations. Opening these facilities brings additional costs to the company. However, despite these additional costs incurred for facilities and additional costs of reverse supply chain operations such as collection and testing, repair and disassembly, we see that CLSC may still bring less total cost compared to FSC.

Table 5.2. *Computational results related to base case instance*

	FSC Model	CLSC Model	Difference
Optimal Cost ($)	2,182,186.39	1,976,345.84	9.43%
Corresponding Emission (ton CO_2)	41,889.21	33,632.42	19.71%
Selected Suppliers for Component 1	2	2 and 5	-
Selected Suppliers for Component 2	2	2 and 5	-
Opened Manufacturing Plants	1 and 4	1 and 3	-
Opened Distribution Centers	1 and 6	4, 5 and 6	-
Opened Collection Centers	-	2 and 3	-
Opened Repair Centers	-	2	-
Opened Disassembly Centers	-	2	-

Finally, when we focus on the selected suppliers, we see that the company works with an additional supplier in CLSC for each component. In fact, less raw material is needed in CLSC compared to FSC, since in CLSC some of the products are reused. By this context, it is possible to claim that the reason of working with an additional supplier is not the capacity problem. Instead, distance of existing supplier to new manufacturing plant is the reason of this fact.

5.3.2. Benefit of utilizing stochastic programming approach

In this subsection, we investigate the benefit of putting the uncertainties into account. For this purpose, we consider the CLSC and we first solve the deterministic model of CLSC by using the expected values of uncertain parameters. All location decisions (facilities that are opened and capacities of opened facilities) of deterministic model are then fixed in stochastic programming model and the stochastic programming model is solved according to those fixed location decisions. By this way, we investigate the effects of using deterministic model decisions in an uncertain environment. Numerical experiments are presented in Table 5.3.

An immediate inference that can be made based on Table 5.3 is that there are instances in which ignoring the uncertainty may bring wrong decisions on facilities and consequently a higher cost and emission to company.

Table 5.3. *Benefit of utilizing stochastic programming approach*

	Deterministic Model Decisions under Uncertainty	Two-Stage Stochastic Model Decisions under Uncertainty	Difference
Total Supply Chain Cost	2,152,698.01	1,976,345.84	8.92%
Corresponding Emission	34,152.59	33,632.42	1.54%
Selected Suppliers for Comp. 1	2	2 and 5	-
Selected Suppliers for Comp. 2	2	2 and 5	-
Opened Manufacturing Plants	1	1 and 3	-
Opened Distribution Centers	1,4 and 6	4, 5 and 6	-
Opened Collection Centers	2 and 3	2 and 3	-
Opened Repair Centers	2	2	-
Opened Disassembly Centers	2	2	-

Moreover, in order to see the effect of level of uncertainty we make the same comparison in different variance values of demand. It should be noted that in this analysis, we only change the variance of demand, mean of demand is same in all experiments. Please refer to Appendix 4 for values of demand parameters in different cases. Numerical experiments are presented in Table 5.4 as follows. In that table percentage cost and emission differences are obtained by using the deterministic model decisions under uncertainty and using the two-stage stochastic programming under uncertainty.

Table 5.4. *Effect of demand variance*

	Percentage Cost Difference	Percentage Emission Difference
Very Low Demand Variance	1.81%	0.61%
Low Demand Variance	4.79%	0.98%
Medium Demand Variance (Base Case)	8.92%	1.54%
High Demand Variance	11.52%	1.85%
Very High Demand Variance	Deterministic model decisions are infeasible in uncertain environment	

As it is seen in the Table 5.4, as the level of uncertainty (i.e. demand variance) increases, both percentage cost and emission differences also increase. Thus, handling uncertainty and using stochastic programming is especially important if there is a high level of uncertainty.

Moreover, in the last row of the table, it is seen that deterministic model decisions become infeasible in uncertain environment. The reason of this fact is capacity infeasibility. Since the variance is high in that case, the fixed capacities (and possible capacity expansions) of facilities become insufficient in higher values of demand. Thus, we can claim that, in real life cases, ignoring the uncertainty may also bring insufficient capacity problems in company's daily operations especially if the level of uncertainty is high.

Briefly, it is possible to claim that there are instances in which ignoring the uncertainty may bring either infeasible solutions or higher cost and emission values. Hence, it is important to put the uncertainties into account while designing the supply chain networks.

5.3.3. Effects of cost parameters

In this subsection, we investigate the effects of cost parameters on percentage cost difference between FSC and CLSC to determine in which cases closing the loop may be beneficial. For this purpose, we change the value of one parameter at a time and kept the remaining parameters constant. We first decrease the value of each parameter by 30%, 60% and 90% compared to base case value. Then, similarly, we increase the value of each parameter by 30%, 60% and 90% compared to base case value. In each setting, we make the comparison of optimal FSC and CLSC costs and determine the percentage cost difference. Computational results are presented in Figure 5.3. Note that in that figure P, S, M, C, R, O, D and H represent the unit procurement cost, unit shipment cost, unit manufacturing cost, unit collection and testing cost, unit repair cost, unit disposal cost, unit disassembly cost and unit handling cost respectively.

Figure 5.3. *Change in percentage cost difference*

Our analysis shows that increasing the values of unit procurement cost and unit manufacturing cost bring an increase in percentage cost difference between FSC and CLSC; while an increase in other cost parameters brings a decrease in percentage cost difference. Moreover, we see that the percentage cost difference between FSC and CLSC is not a result of only one parameter. Contrarily, all cost parameters have an effect on this difference. However, some parameters such as unit procurement cost or unit collection and testing cost are more effective, while the effects of some other parameters such as unit handling cost are very limited.

In order to see the effects of cost parameters, we also make an experimental design. In our design, we determine two levels for each parameter, in high level the parameter is increased by 90% compared to base case value, while in low level the parameter is decreased by 90% compared to base case value. Note that unit disposal cost, unit disassembly cost and unit handling cost bring less than 2% change when we change them between -90% and +90%. In other words, their effects are very limited. Thus, we kept them at their base case values and we make the experiments with the remaining five parameters. Since each parameter has two levels and our analysis includes five parameters, we make 2^5 experiments in total for both FSC and CLSC. Numerical results are presented in Table 5.5. In that table, (-) refers to a 90% decrease of base case value of that parameter and (+) refers to a 90% increase of base case value of that parameter. In % rows, values refer to the percentage cost difference between FSC and CLSC in that experiment, i.e. for the first one it is found as 11.8%.

Table 5.5. *Effects of cost parameters on percentage cost difference*

	1	2	3	4	5	6	7	8	9	10	11
P	+	+	+	+	+	+	+	+	+	+	+
S	+	+	+	+	+	+	+	+	-	-	-
M	+	+	+	+	-	-	-	-	+	+	+
C	+	+	-	-	+	+	-	-	+	+	-
R	+	-	+	-	+	-	+	-	+	-	+
%	11.8	13.9	14.7	16.8	5.5	8.4	9.9	12.7	20.1	22.6	23.8
	12	13	14	15	16	17	18	19	20	21	22
P	+	+	+	+	+	-	-	-	-	-	-
S	-	-	-	-	-	+	+	+	+	+	+
M	+	-	-	-	-	+	+	+	+	-	-
C	-	+	+	-	-	+	+	-	-	+	+
R	-	+	-	+	-	+	-	+	-	+	-
%	26.9	16.6	20.7	22.8	26.3	1.5	1.6	2.0	4.9	-27.9	-22.5
	23	24	25	26	27	28	29	30	31	32	
P	-	-	-	-	-	-	-	-	-	-	
S	+	+	-	-	-	-	-	-	-	-	
M	-	-	+	+	+	+	-	-	-	-	
C	-	-	+	+	-	-	+	+	-	-	
R	+	-	+	-	+	-	+	-	+	-	
%	-18.7	-13.2	5.1	9.11	11.17	15.3	-26.4	-21.5	-16.6	-4.3	

According to Table 5.5, main findings of our experiments can be summarized as follows.

- Closing the loop in supply chains does not always bring cost reduction. In some cases, it brings significant extra costs to companies. In 24 of our 32 experiments, we observe a cost reduction by closing the loop. However in remaining 8 experiments we observe a cost increase.
- Benefit of closing the loop depends more on unit procurement cost, unit shipment cost and unit manufacturing cost rather than the costs of reverse supply chain activities such as unit repairing cost or unit collection and testing cost.
- In the cases where P is high and S is low, closing the loop may bring significant cost reductions. Our experiments show cost reductions between about 16% and 27% in those experiments.
- Moreover, in the cases, where both P and S are high, closing the loop may still be beneficial especially in the cases where M is also high. On the other hand, if M is low while both P and S are high, benefit of closing the loop prominently decreases.
- Finally, in the cases where both P and M are low, closing the loop may bring significant extra costs to company. In those cases, we observe a cost increase between about 4% and 28% by closing the loop in supply chains.

5.3.4. Effects of return rate and returned product quality

In this subsection, we focus on the return rate and returned product quality in CLSC's. We mainly investigate two questions. First, what are the effects of changes in return rate and returned product quality on percentage cost and emission difference between FSC and CLSC? Second, do the return rate and returned product quality affect the location and allocation decisions? In order to investigate these questions, we test the model under various settings of return rate and returned product quality. As an indicator of returned product quality, we focus on both the product recovery rate and the component recovery rate. We present the percentage cost and emission difference in each parameter setting in Figure 5.4. In that figure, RR, PR and CR refer to return rate, product recovery rate and component recovery rate for both components, respectively.

Note that the FSC cost and emission is fixed in all parameter settings since a change in return rate or returned product quality does not affect them. Thus, a change in percentage cost or emission difference is the result of a change in CLSC cost or emission.

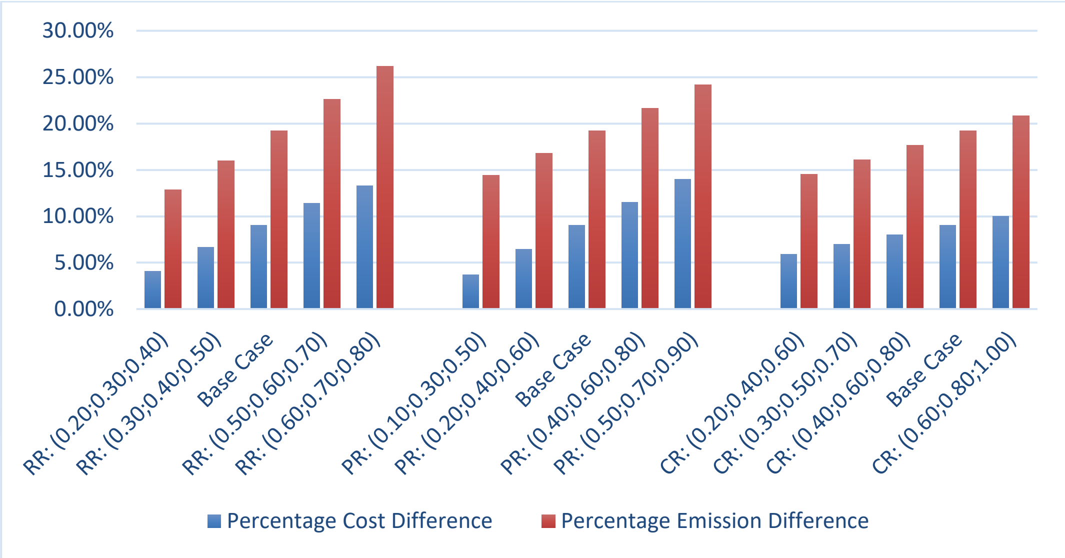


Figure 5.4. *Effects of return rate and returned product quality*

Figure 5.4 shows that although the return rate has more effect compared to product recovery rate and component recovery rate, both return rate and returned product quality have an observable effect on percentage cost and emission difference between FSC and CLSC. Thus, increasing the return rate or returned product quality can be a beneficial way for cost and emission reduction. Increasing the public awareness, providing incentives and return programs to customers may be the ways of increasing the return rate. On the other hand, returned product quality can be increased by using sustainable manufacturing technologies.

Moreover, our analysis shows that both return rate and returned product quality have an effect on location and allocation decisions. As the return rate or returned product quality change, the number and/or the locations of opened facilities also change. For example, when the product recovery rate is (0.40;0.60;0.80), the model selects distribution centers (4,5,6), collection centers (1,3) and repair center (2). However, when the product recovery rate is (0.50;0.70;0.90), selected facilities are distribution centers (1,4,6), collection center (2) and repair center (1) while in both cases manufacturing plants (1,3) and disassembly center (2) are selected.

5.3.5. Carbon cap policy

In this subsection, we focus on the effect of carbon cap and compare the optimal FSC and CLSC costs under different carbon caps. First, it should be noted that the carbon cap can be decreased only down to a certain value due to demand satisfaction constraint. Setting a carbon cap below that value brings an infeasible solution. That value is obtained as 54,853.76 ton CO_2 for FSC and 52,483.15 ton CO_2 for CLSC. Computational results are presented in Figure 5.5. Note that in that figure there is no FSC cost for the carbon cap values between 52,500 and 54,500 since in those values of carbon cap FSC model is infeasible.

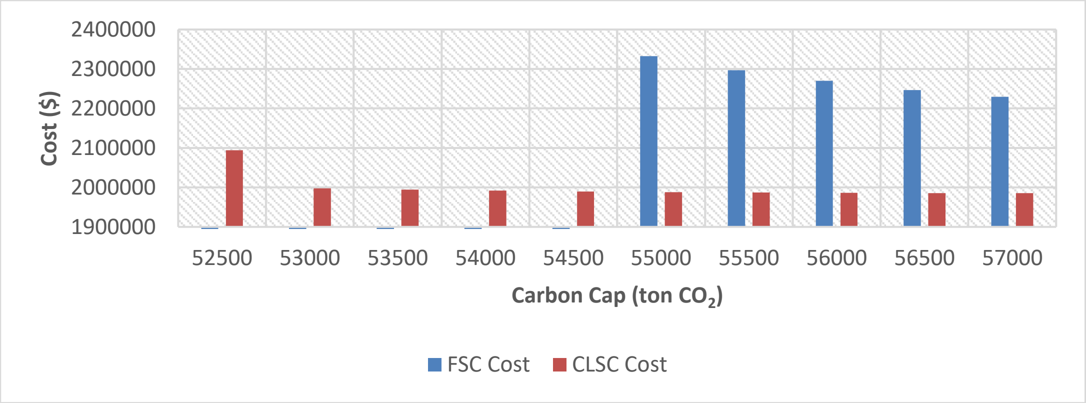


Figure 5.5. *Carbon cap policy*

Various inferences can be made by using Figure 5.5. First, we see that it is possible to work under lower carbon caps in CLSC compared to FSC. For example, if there is an emission regulation including a carbon cap of 53,000 or 54.000 ton CO_2, the company can comply with this regulation only if they have a CLSC. Therefore, CLSC may be better than FSC in terms of coping with strict carbon regulations. Secondly, it is seen that CLSC brings less cost compared to FSC under all carbon caps and percentage difference between FSC and CLSC costs increases as the carbon cap decreases. Thus, especially in lower carbon caps, closing the loop may bring significant cost reductions.

Finally, we observe that in both FSC and CLSC, in some cases it is possible to work under lower carbon caps with an acceptable additional cost. For instance, in FSC, the company can reduce its emission limit from 57,000 ton to 56,500 ton CO_2 with about $17,500 extra cost per period. However, as it is seen in figure, in both FSC and CLSC, additional cost increases prominently as the carbon cap decreases.

5.3.6. Carbon cap-and-trade policy

The European Climate Exchange data shows carbon price limits between $3.12/ton and $19.53/ton during 2009-2015. However, the price in the EU is anticipated to be up to $35/ton to fulfil its emission reduction target by 2020 (Xu et al., 2017). In this study considering the future increases we analyze carbon prices between $10 and $100.

Park et al. (2015) mention that the carbon cap-and-trade policy may not be effective when the supply of carbon emission allowance is greater than the demand. Hence, in our analysis we set a strict carbon cap, 25,000 ton CO_2. Numerical experiments for different carbon prices are provided in Figure 5.6. Note that since purchased and sold carbon amount is scenario dependent, emission trading percentage in that figure refers to the expected trading percentage.

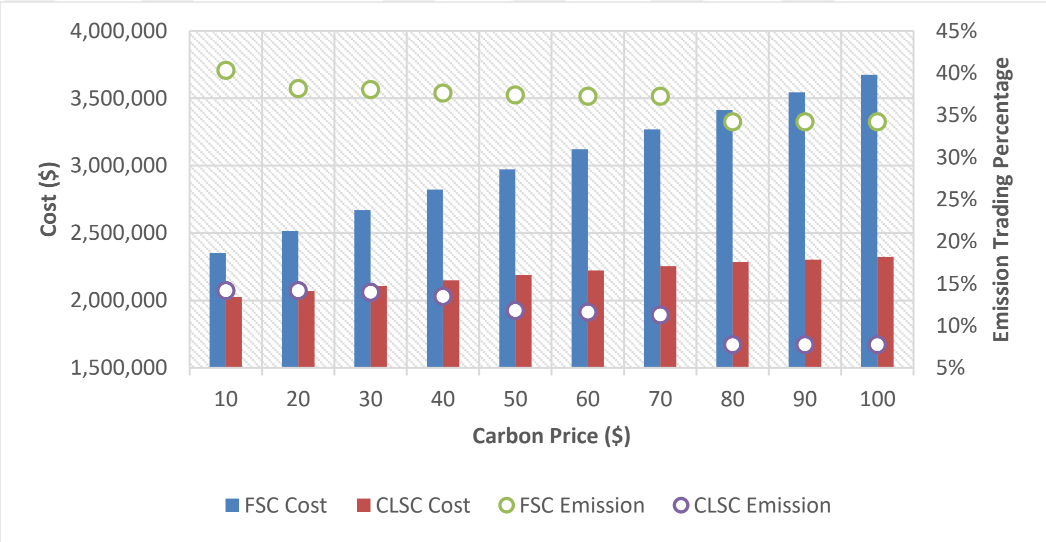


Figure 5.6. *Carbon cap-and-trade policy*

Figure 5.6 shows that CLSC brings less cost and emission compared to FSC in all carbon prices. Moreover, percentage cost difference between FSC and CLSC increases as the carbon price increases. Thus, especially in higher carbon prices, closing the loop may be more beneficial. Finally, it is observed that in both FSC and CLSC, higher carbon prices encourage the company to decrease its total emission. So that they decrease purchased carbon amount and avoid from higher emission-related costs.

In addition to this analysis, we also analyze the carbon cap of 15,000 ton CO_2 and 5,000 ton CO_2 and obtain similar results. Briefly, we can state that closing the loop in supply chains may be a beneficial option in terms of cost and emission in an environment where there is a carbon cap-and-trade policy. Especially in the cases where there is a strict carbon cap and high carbon price, closing the loop may bring significant cost reductions.

5.3.7. Carbon tax policy

Xu et al. (2017) mention that a carbon tax between $0 and $85 covers most of the carbon tax policies in the world. In this study considering the future increases, we analyze the carbon tax between $20 and $200. Optimal costs and corresponding emissions for FSC and CLSC in different carbon taxes are provided in Figure 5.7.

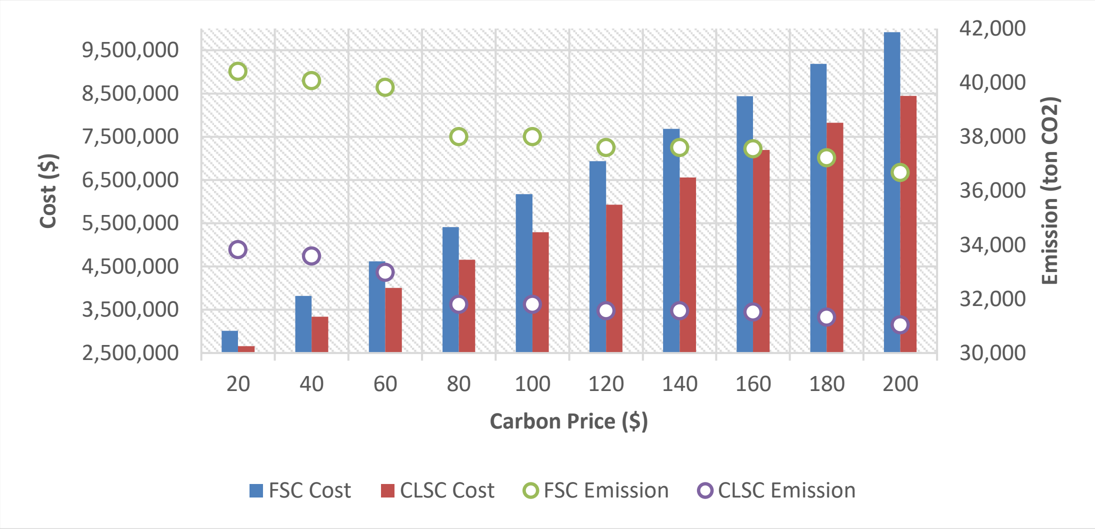


Figure 5.7. *Carbon tax policy*

Figure 5.7 shows that in both FSC and CLSC, higher carbon taxes bring significant extra costs to company. However, CLSC performs better than FSC in terms of cost and emission in all values of carbon tax. Moreover, when we focus on the percentage cost difference between FSC and CLSC, we observe that the percentage cost difference increases as the carbon tax increases and thus closing the loop becomes more beneficial in higher carbon taxes. Finally, it is seen that although increasing the carbon tax up to a value encourages the company to decrease the total emission, after that value increasing the carbon tax does not bring a significant emission reduction. Instead, it only brings a high extra cost to company.

6. CONCLUSION AND FUTURE WORK SUGGESTIONS

In recent years, product recovery gained considerable attention in both academia and industry due to its economic and environmental benefits. In this thesis, we mainly focus on two research questions regarding product recovery. First, in which cases product recovery may be a beneficial option for the entire supply chain or for a specific supply chain actor? Secondly, how can we develop appropriate policies for the supply chain actors to maximize their own benefits from product recovery? In order to investigate these questions, in Chapter 3 of this thesis, we consider collection centers that collect EOL products from end users, disassemble them to obtain reusable components, and sell the components to remanufacturing facilities. We determine the optimal dispatching and acquisition fee decisions in a coordinated manner under different cases. We also propose simpler policies in addition to the optimal solutions and analyze the performance of these policies. In addition, we compare static and dynamic pricing for the determination of the acquisition fee and present a sensitivity analysis in order to investigate the effects of the parameters on the system results.

Computational results in Chapter 3 bring various insights to us. We first observe that the optimal determination of the acquisition fee significantly affects the system profits. Second, time-based dispatching policies perform worse than quantity-based ones. Finally, the holding costs and arrival rates have a significant impact on the system results, and employing a dynamic acquisition fee becomes especially important when EOL product arrivals are less frequent or the components are much different from each other.

Our models in Chapter 3 can be extended as follows. Firstly, product-based acquisition fees can be used. In such systems, the acquisition fee can be determined based on different characteristics of the product, such as the age or working conditions. Higher acquisition fees can be offered for relatively new products since they are expected to have better reusable components. Similarly, lower fees will be offered for older products. Secondly, different collection systems that work under different contract mechanisms can be analyzed. Thirdly, the models can be extended to cases of EOL products with more than two components. However, in those cases, the state space of the dynamic programming formulations increases exponentially and it might take much longer to solve these models. Finally, different settings of the model can be studied such as finite or random demand for the components, or alternative assumptions/functions can be used for the relationship between the acquisition fee and the arrival rates/arrival batches.

In Chapter 4, we consider a supply chain including a manufacturer, a remanufacturer, a retailer and customers. We propose stylized models for both pure manufacturing system and hybrid manufacturing-remanufacturing systems to compare the systemwide performances and performances of supply chain actors under different settings with each other. We mainly focus on four settings. In the first setting, we focus on a forward supply chain in which no remanufacturing takes place and the retailer sells only the manufactured products, whereas in the second, third and fourth settings the manufacturer, the retailer and a third-party remanufacturer collect and remanufacture the used products, respectively. We also consider the environmental aspect of supply chain and adopt a well-known and widely-used emission policy, the carbon tax policy. Models and numerical experiments present various managerial insights to us.

When we focus on the systemwide profit or profit of the actors, we observe that highest systemwide profit is achieved under the settings where the products are collected and remanufactured by the retailer or a third-party remanufacturer. On the other hand, the manufacturer achieves the highest profit under the setting where the manufacturer himself collects and remanufactures the used products. We also observe that manufacturer's profit prominently deteriorates under the settings where either the retailer or a third-party remanufacturer collects and remanufactures the used products or no remanufacturing is realized. Finally, it is seen that the retailer achieves the highest profit under the settings where either the retailer himself or the third-party remanufacturer collects and remanufactures the used products.

When we focus on the collection quantity, it is observed that the highest collection quantity is achieved under the setting where the retailer collects and remanufactures the used products. The lowest collection quantity is attained under the setting where the manufacturer collects and remanufactures the used products. It is also seen that there are instances in which remanufacturing may not be profitable for the manufacturer, but it may be so for the retailer or the third-party remanufacturer. Since when the retailer or the third-party remanufacturer decides to make remanufacturing, the manufacturer's profit prominently decreases, the manufacturer should take action to deter the collection and remanufacturing decisions of the retailer or the third-party remanufacturer.

Finally, when we focus on the sustainability level, it is observed that the highest sustainability level is achieved under the setting where the manufacturer itself collects and remanufactures the used products, and the lowest sustainability level is attained in the setting where retailer collects and remanufactures the used products.

The following extensions can be considered for our problem environment and models in Chapter 4. First, we use linear demand functions and linear cost structures in our models. Use of nonlinear cost or demand functions may lead to much more complex equations, but at the same time may reflect the real-life cases better. Moreover, putting the uncertainties in demand, return rate or product recovery rate into account may also be an important extension. Finally, we consider the carbon tax policy as an emission regulation. Use of different emission regulations such as carbon cap or carbon cap-and-trade may also be an interesting extension.

In Chapter 5 of this thesis, we propose a set of two-stage stochastic programming models for the design of forward and closed loop supply chains (FSC and CLSC, respectively) to see the financial and environmental effects of closing the loop in supply chains. Our models simultaneously consider demand, return rate and returned product quality uncertainties and include capacity expansion decisions together with the location and allocation decisions. We make various sensitivity analyses to see the effects of problem parameters. We also investigate three well-known and widely-used emission policies (carbon cap, carbon cap-and-trade and carbon tax) in addition to the case of no emission regulation and compare the forward and closed-loop supply chains under these policies.

Our numerical experiments offer various insights regarding the forward and closed-loop supply chains. When we focus on the base case problem setting, we observe that closing the loop may still be beneficial for companies in terms of the total supply chain cost and emission despite the fact that it brings various additional costs such as the costs of additional facilities and reverse supply chain processes.

Secondly, sensitivity analyses about cost parameters show that almost all cost parameters have an effect on the percentage cost difference between FSC and CLSC. The benefit of closing the loop depends more on the unit procurement cost, unit shipment cost and unit manufacturing cost rather than the costs of reverse supply chain processes such as the unit repairing cost. It is also seen that closing the loop may be beneficial especially in the cases where unit procurement cost is high and unit shipment cost is low. On the other hand, it may contribute significant additional costs in the cases where both unit procurement cost and unit manufacturing cost are low.

Thirdly, our analysis about the return rate and returned product quality shows that as the return rate or returned product quality increases, both the total supply chain cost and emission decrease. Thus, it may be beneficial for the companies to take actions to increase both return rate and returned product quality. In addition, we also observe that both the return rate and returned product quality effect the number and locations of opened facilities. In other words, they have an observable effect on the design decisions.

We also obtain important insights regarding the FSC and CLSC under different emission policies. Our analysis in carbon cap policy shows that CLSCs can work under lower carbon caps compared to FSCs and the percentage cost difference between FSC and CLSC increases as the carbon cap decreases. Thus, closing the loop may be more beneficial in the cases where there is a strict carbon cap. Another observation about carbon cap policy is that companies can decrease their emissions and work under lower carbon caps with an acceptable additional cost, and this cost is less in CLSC compared to FSC. Secondly, when we focus on the carbon cap-and-trade policy, it is seen that CLSC performs better than FSC in terms of both cost and emission in all carbon prices and the percentage cost difference between FSC and CLSC increases as the carbon price increases. Finally, when we focus on the carbon tax policy, we observe that CLSC brings less cost and emission compared to FSC in all levels of carbon tax. We also observe that up to a certain level of carbon tax, increasing the carbon tax encourages the company to decrease the emission in both FSC and CLSC. However, after that level a further increase in tax does not provide a significant emission reduction. Instead, it only creates a high extra cost to the company.

Our study in Chapter 5 can also be extended in various ways in the future. First, applications of these models to a specific industry may provide deeper insights regarding the effects of closing the loop in supply chains in that industry. Secondly, considering the effect of time and modifying the models to a multi-period setting may be another interesting extension. Thirdly, it should be noted that we assume that repaired/remanufactured products are perfectly substitutable with the manufactured products. Relaxing this assumption and proposing models for that case may also stimulate interesting insights. Finally, uncertainties in the system can be handled by different approaches.

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APPENDIX 1: PROOFS OF THE PREPOSITIONS IN CHAPTER 3

Proof of Proposition 1

Assuming $a = b = 1$, we can write expected profit equation as below

$$\frac{\beta^*}{\lambda} + H^*(x, y) = \max[F(x, y), G(x, y)] \tag{A.1.1}$$

where $F(x, y)$ denotes the expected profit when the products are dispatched at state (x, y) such that

$$F(x, y) = -E[Y](c_p + c_q) + r_1 x + r_2 y - K - (x + y)^\delta + \sum_{i=0}^{m}\sum_{j=0}^{m}(w_{i,j})H^*(i, j) \tag{A.1.2}$$

and $G(x, y)$ denotes the expected profit when the products are not dispatched at state (x, y) such that

$$G(x, y) = -E[Y](c_p + c_q) - \frac{h_1}{\lambda}x - \frac{h_2}{\lambda}y + \sum_{i=0}^{m}\sum_{j=0}^{m}(w_{i,j})H^*(x + i, y + j) \tag{A.1.3}$$

For a given y, as x increases, let $\eta_1 = \frac{\partial F(x,y)}{\partial x}$, denote the increase rate of the function $F(x, y)$ with respect to x and observe that $\eta_1 \geq r_1 - 1$ since $0 < \delta < 1$. Similarly let $\eta_2 = \frac{\partial G(x,y)}{\partial x}$, denote the increase rate of the function $G(x, y)$ and observe that η_2 is at most $\eta_1 - h_1/\lambda$ since $H(x + 1, y) - H(x, y) \leq \eta 1$ for all x and y. For $x = 0$, when y is small, the value of $F(x, y)$ is less than $G(x, y)$ and the two equations will intersect at a single point, which is defined as $x_c(y) > 0$. Also, as y increases, since $F(x, y)$ increases with a rate that is more than the increase rate of $G(x, y)$, the intersection point of the two equations will occur at a smaller value of x. Thus, $x_c(y)$ will be non-increasing as y increases. However, when y is high, the value of $F(x, y)$ can already be more than $G(x, y)$ at $x = 0$ (the two equations will never intersect later) and the optimal decision will be to dispatch at that time, denoting that $x_c(y) = 0$ for such values of y.

Proof of Proposition 2

Proof is the same as the proof of Proposition 1.

Proof of Proposition 3

In our model, for a given policy and given acquisition fee values, the function $H(x, y)$ in can be written as follows.

$$H(x,y) = \max[F(x,y), G(x,y)] \tag{A.1.4}$$

where $F(x,y)$ relates to the dispatching decision and $G(x,y)$ relates to the holding decision, as given below:

$$F(x,y) = \frac{1}{\bar{\lambda}}\Bigg[\bar{\lambda}(r_1 x + r_2 y - K - (ax+by)^{\delta}) + \lambda_{0,0}\left(-E[Y](c_{0,0}+c_q) + \sum_{i=0}^{m}\sum_{j=0}^{m}(w_{i,j})H(i,j)\right) + (\bar{\lambda} - \lambda_{0,0})H(0,0) - \beta\Bigg] \tag{A.1.5}$$

$$G(x,y) = \frac{1}{\bar{\lambda}}\Bigg[-h_1 x - h_2 y + \lambda_{x,y}\left(-E[Y](c_{x,y}+c_q) + \sum_{i=0}^{m}\sum_{j=0}^{m}(w_{i,j})H(x+i,y+j)\right) + (\bar{\lambda} - \lambda_{x,y})H(x,y) - \beta\Bigg] \tag{A.1.6}$$

In order to obtain the optimal value of $c_{x,y}$ we take the derivative of $G(x,y)$ with respect to $c_{x,y}$ and when we set it to 0, we obtain the following equation.

$$(c_{x,y} + \lambda_{x,y}/\lambda'_{x,y})E[Y] = E[H(x+i,y+j)] - H(x,y) - E[Y]c_q \tag{A.1.7}$$

Then, we state the following lemmas 1 and 2 that will characterize the optimal acquisition fee decisions and present their proofs as below.

Lemma 1: $H(x,y)$ satisfies the following condition:

$$H(x+1,y) - H(x,y) \geq H(x,y) - H(x-1,y) \tag{A.1.8}$$

Proof: We can rewrite the above equation as follows.

$$H(x+1,y) + H(x-1,y) \geq 2H(x,y) \tag{A.1.9}$$

Let c^* denote the optimal fee at state (x,y). Let us assume that we apply the same fee at states $(x+1,y)$ and $(x-1,y)$, which are suboptimal for these states. For the same fee c^*, there can be four cases for the above statement.

<u>Case 1:</u> Dispatch decision is given for all three states $(x+1,y)$, $(x-1,y)$ and (x,y). In this case, if we use $F(x,y)$, we get:

$$H(x+1,y) + H(x-1,y) - 2H(x,y) = (-(x+1+y)^{\delta} - (x-1+y)^{\delta} + 2(x+y)^{\delta})/\bar{\lambda} \geq 0 \tag{A.1.10}$$

<u>Case 2:</u> Dispatch decision is given at states $(x+1,y)$ and (x,y) and no dispatch is chosen at state $(x-1,y)$. Due to the above decisions, $H(x+1,y) = F(x+1,y)$, $H(x,y) =$

$F(x,y)$ and $H(x-1,y) = G(x-1,y)$. We know from Case 1 that if we apply the first equation to all three cases, we have the following:

$$F(x+1,y) - F(x,y) \geq F(x,y) - F(x-1,y) \tag{A.1.11}$$

Since no dispatch decision is given at state $(x-1,y)$, this means that $G(x-1,y) > F(x-1,y)$. Then,

$$\begin{aligned} H(x+1,y) - H(x,y) = F(x+1,y) - F(x,y) &\geq F(x,y) - F(x-1,y) \\ \geq F(x,y) - G(x-1,y) &= H(x,y) - H(x-1,y) \end{aligned} \tag{A.1.12}$$

<u>Case 3:</u> No dispatch decision is given for all three states $(x+1,y)$, $(x-1,y)$ and (x,y). In this case, $G(x,y)$ will be applied for all three states. Let ξ denote a transformation function such that $H = \xi(H)$ where $\xi(H)$ denotes the second equation. Under this transformation function, observe that the property $H(x+1,y) - H(x,y) \geq H(x,y) - H(x-1,y)$ is preserved due to the induction hypothesis as below.

$$\begin{aligned} &H(x+1,y) - H(x,y) \\ &= \frac{1}{\bar{\lambda}}\Bigg[-h_1(x+1) - h_2 y \\ &+ \lambda_{x,y}\left(-E[Y](c_{x,y} + c_q) + \sum_{i=0}^{m}\sum_{j=0}^{m}(w_{i,j})H(x+1+i,y+j)\right) \\ &+ (\bar{\lambda} - \lambda_{x,y})H(x+1,y) - \beta + h_1 x + h_2 y \\ &- \lambda_{x,y}\left(-E[Y](c_{x,y} + c_q) + \sum_{i=0}^{m}\sum_{j=0}^{m}(w_{i,j})H(x+i,y+j)\right) \\ &- (\bar{\lambda} - \lambda_{x,y})H(x,y) + \beta\Bigg] \\ &= \frac{1}{\bar{\lambda}}\Bigg[-h_1 + \lambda_{x,y}\left(\sum_{i=0}^{m}\sum_{j=0}^{m}(w_{i,j})[H(x+1+i,y+j) - H(x+i,y+j)]\right) \\ &+ (\bar{\lambda} - \lambda_{x,y})(H(x+1,y) - H(x,y))\Bigg] \\ &\geq \frac{1}{\bar{\lambda}}\Bigg[-h_1 + \lambda_{x,y}\left(\sum_{i=0}^{m}\sum_{j=0}^{m}(w_{i,j})[H(x+i,y+j) - H(x-1+i,y+j)]\right) \\ &+ (\bar{\lambda} - \lambda_{x,y})(H(x,y) - H(x-1,y))\Bigg] = H(x,y) - H(x-1,y) \end{aligned} \tag{A.1.13}$$

<u>Case 4:</u> Dispatch decision is given at state $(x+1,y)$ and no dispatch is chosen at states (x,y) and $(x-1,y)$ Due to the above decisions, $H(x+1,y) = F(x+1,y)$, $H(x,y) =$

$G(x, y)$ and $H(x-1, y) = G(x-1, y)$. We know from Case 3 that if we apply the second equation to all three cases, we have the following:

$$G(x+1, y) - G(x, y) \geq G(x, y) - G(x-1, y) \tag{A.1.14}$$

Since dispatch decision is given at state $(x+1, y)$, this means that $F(x+1, y) > G(x+1, y)$. Then, we have

$$\begin{aligned} H(x+1, y) - H(x, y) = F(x+1, y) - G(x, y) \geq \ G(x+1, y) - G(x, y) \\ \geq G(x, y) - G(x-1, y) = H(x, y) - H(x-1, y) \end{aligned} \tag{A.1.15}$$

Lemma 2: $H(x, y)$ satisfies the following condition:

$$H(x, y+1) - H(x, y) \geq H(x, y) - H(x, y-1) \tag{A.1.16}$$

Proof: Same as the proof of Lemma 1.

Due to Lemma 1 and Lemma 2, the right-hand side of the equation below, that defines the optimal acquisition fee, is non-decreasing in x, and thus the left-hand side should also be non-decreasing in x. Since both $c_{x,y}$ and $\lambda_{x,y}/\lambda'_{x,y}$ are non-decreasing in $c_{x,y}$, we can state that $c_{x,y}$ should be monotonically non-decreasing as x increases.

$$(c_{x,y} + \lambda_{x,y}/\lambda'_{x,y})E[Y] = E[H(x+i, y+j)] - H(x, y) - E[Y]c_q \tag{A.1.17}$$

Similarly, we can state that $c_{x,y}$ is monotonically non-decreasing as y increases.

APPENDIX 2: PROOFS OF THE LEMMAS AND THEOREMS IN CHAPTER 4

In this section, we provide the proofs of the theorems and lemmas proposed in Chapter 4.

Proof of Theorem 1

Profit function for the pure manufacturing system under centralized control can be written as follows.

$$\max_{\substack{d_m \geq 0 \\ 0 \leq s \leq \bar{s}}} \pi_C^1(d_m, s) = (1 - d_m - c_m)d_m - (a - bs)d_m t - \theta s^2 \tag{A.2.1}$$

Hessian matrix corresponding to this function will be $H = \begin{bmatrix} -2 & bt \\ bt & -2\theta \end{bmatrix}$. Determinant of the principal minor (-2) is negative and determinant of the hessian matrix is $4\theta - b^2t^2$. If we assume that $\theta > \frac{b^2t^2}{4}$, this determinant is positive and the function is jointly concave with respect to d_m and s. In order to create an unconstrained problem, we write the Lagrangean function as follows.

$$\pi_{CL}^1(d_m, s, \lambda_1, \lambda_2) = (1 - d_m - c_m)d_m - (a - bs)d_m t - \theta s^2 + \lambda_1 d_m - \lambda_2(s - \bar{s}) \tag{A.2.2}$$

Partial derivatives of this Lagrangean function can be obtained as in equations (A2.3)-(A2.4).

$$\frac{\partial \pi_{CL}^1(d_m, s, \lambda_1, \lambda_2)}{\partial d_m} = 1 + \lambda_1 - c_m - 2d_m - (a - bs)t \tag{A.2.3}$$

$$\frac{\partial \pi_{CL}^1(d_m, s, \lambda_1, \lambda_2)}{\partial s} = d_m bt - 2\theta s - \lambda_2 \tag{A.2.4}$$

Necessary and sufficient conditions for optimality are that these partial derivatives are equal to zero, $\lambda_1 d_m = 0, \lambda_2(s - \bar{s}) = 0, \lambda_1 \geq 0$ and $\lambda_2 \geq 0$. Then, we may face with three different ranges. In Range I, suppose that $d_m > 0$ and $s < \bar{s}$. Then, since $\lambda_1 d_m = 0$, λ_1 will be zero and since $\lambda_2(s - \bar{s}) = 0$, λ_2 will be zero. In a similar manner, other ranges can also be obtained as in Table A.2.1.

Table A.2.1. *Ranges under Setting 1*

Range	d_m	s	λ_1	λ_2
I	> 0	$< \bar{s}$	0	0
II	> 0	$\bar{s}$	0	≥ 0
III	0	$< \bar{s}$	≥ 0	0

As seen in Table A.2.1, in each range we have two decision variables to determine, i.e. in first range we determine d_m and s. We can determine the values of these variables by using the partial derivatives in equations (A.2.3-A.2.4). For example, for the first range, if we set $\lambda_1 = 0$ and $\lambda_2 = 0$, partial derivatives will be as follows.

$$\frac{\partial \pi_{CL}^1(d_m, s, \lambda_1, \lambda_2)}{\partial d_m} = 1 - c_m - 2d_m - (a - bs)t \qquad \text{(A.2.5)}$$

$$\frac{\partial \pi_{CL}^1(d_m, s, \lambda_1, \lambda_2)}{\partial s} = d_m bt - 2\theta s \qquad \text{(A.2.6)}$$

Now, if we set these partial derivatives equal to 0, we have two equations and two decision variables. By solving these equations, we obtain the values of d_m and s as presented in equation (A.2.7). Based on Table A.2.1, since in first range, d_m must be greater than zero and s must be less than $\bar{s}$, we have two conditions in this range as $\frac{2\theta(1-c_m-at)}{4\theta-b^2t^2} > 0$ and $\frac{bt(1-c_m-at)}{4\theta-b^2t^2} < \bar{s}$ which are presented on the right-hand-side of equation (A.2.7). In a similar manner, we obtain the values of decision variables and conditions in other ranges and characterize the decisions as presented in equation (A.2.7).

If $\theta > \frac{b^2t^2}{4}$

$$(d_m^*, s^*) = \begin{cases} \left(\frac{2\theta(1-c_m-at)}{4\theta-b^2t^2}, \frac{bt(1-c_m-at)}{4\theta-b^2t^2}\right) & \text{if } \frac{2\theta(1-c_m-at)}{4\theta-b^2t^2} > 0 \text{ and } \frac{bt(1-c_m-at)}{4\theta-b^2t^2} < \bar{s}, \\ \left(\frac{bt\bar{s}-at-c_m+1}{2}, \bar{s}\right) & \text{if } \frac{bt\bar{s}-at-c_m+1}{2} > 0 \text{ and } \frac{bt(1-c_m-at)-(4\theta-b^2t^2)\bar{s}}{2} \geq 0, \\ (0,0), & \text{otherwise.} \end{cases} \qquad \text{(A.2.7)}$$

On the other hand, If $\theta < \frac{b^2t^2}{4}$, increasing the value of s will always increase the profit and hence s will go to infinity if it has no upper bound. In our problem, since it has an upper bound, $\bar{s}$, it will take this value and (w_m^*, s^*, d_m^*) decisions will be as follows.

$$(d_m^*, s^*) = \begin{cases} \left(\frac{bt\bar{s} - at - c_m + 1}{2}, \bar{s}\right) & \text{if } \frac{bt\bar{s} - at - c_m + 1}{2} > 0 \text{ and} \\ (0,0), & \text{otherwise.} \end{cases} \quad \text{(A.2.8)}$$

Proof of Lemma 1

We can write the retailer's profit problem under Setting 1 as in equation (A.2.9).

$$\max_{d_m \geq 0} \pi_R^1(d_m | w_m) = (1 - d_m - w_m)d_m \quad \text{(A.2.9)}$$

Since $\frac{\partial^2 \pi_R^1(d_m|w_m)}{\partial {d_m}^2} = -2$, the function is concave in d_m. We can obtain the best response of retailer by using the equation, $\frac{\partial \pi_R^1(d_m)}{\partial d_m} = 0$. As a result, best response of the retailer can be characterized as follows.

$$d_m^* | w_m = \begin{cases} \frac{1 - w_m}{2} & \text{if } \frac{1 - w_m}{2} > 0, \\ 0, & \text{otherwise.} \end{cases} \quad \text{(A.2.10)}$$

Proof of Theorem 2

Manufacturer's problem given Lemma 1 can be created as follows.

$$\max_{\substack{w_m \geq 0 \\ 0 \leq s \leq \bar{s}}} \pi_M^1(w_m, s) = \begin{cases} (w_m - c_m)\left(\frac{1 - w_m}{2}\right) - \theta s^2 - (a - bs)\left(\frac{1 - w_m}{2}\right)t & \text{if } \frac{1 - w_m}{2} > 0, \\ -\theta s^2, & \text{otherwise.} \end{cases} \quad \text{(A.2.11)}$$

Hessian matrix corresponding to the function, $(w_m - c_m)\left(\frac{1-w_m}{2}\right) - \theta s^2 - (a - bs)\left(\frac{1-w_m}{2}\right)t$ with respect to w_m and s is $H = \begin{bmatrix} -1 & -\frac{bt}{2} \\ -\frac{bt}{2} & -2\theta \end{bmatrix}$. Determinant of principal minor (-1) is negative and determinant of the hessian matrix is $2\theta - \frac{b^2t^2}{4}$. If we assume that $\theta > \frac{b^2t^2}{8}$, this determinant is positive and the function is jointly concave with respect to w_m and s. Optimal values of w_m and s can be obtained by using the equations $\frac{\partial \pi_M^1(w_m,s)}{\partial w_m} = 0$ and $\frac{\partial \pi_M^1(w_m,s)}{\partial s} = 0$. When we solve these two equations, we obtain $w_m =$

$\frac{4\theta(1+c_m+at)-b^2t^2}{8\theta-b^2t^2}$ and $s=\frac{bt(1-c_m-at)}{8\theta-b^2t^2}$ and by using these values, $d_m=\frac{2\theta(1-c_m-at)}{8\theta-b^2t^2}$ is obtained. Note that these values are valid only if $d_m=\frac{2\theta(1-c_m-at)}{8\theta-b^2t^2}>0$ and $s=\frac{bt(1-c_m-at)}{8\theta-b^2t^2}<\bar{s}$. If $d_m=\frac{2\theta(1-c_m-at)}{8\theta-b^2t^2}>0$ but $s=\frac{bt(1-c_m-at)}{8\theta-b^2t^2}\geq\bar{s}$, then, optimal s value will be $\bar{s}$ (Range II). In this range, values of other variables can be obtained as in equation (A.2.12). Finally, if $d_m=\frac{2\theta(1-c_m-at)}{8\theta-b^2t^2}\leq 0$, then optimal d_m value will be zero (Range III) and values of the other variables will be obtained accordingly as in equation (A.2.12).

If $\theta>\frac{b^2t^2}{8}$

$$(w_m^*,s^*,d_m^*)=\begin{cases}\left(\frac{4\theta(1+c_m+at)-b^2t^2}{8\theta-b^2t^2},\frac{bt(1-c_m-at)}{8\theta-b^2t^2},\frac{2\theta(1-c_m-at)}{8\theta-b^2t^2}\right) & \text{if } \frac{2\theta(1-c_m-at)}{8\theta-b^2t^2}>0 \text{ and } \frac{bt(1-c_m-at)}{8\theta-b^2t^2}<\bar{s},\\ \left(\frac{1+at+c_m-bt\bar{s}}{2},\bar{s},\frac{bt\bar{s}-at-c_m+1}{4}\right) & \text{if } \frac{bt\bar{s}-at-c_m+1}{4}>0 \text{ and } \frac{bt(1-c_m-at)}{8\theta-b^2t^2}\geq\bar{s},\\ (0,0,0), & \text{otherwise.}\end{cases} \quad \text{(A.2.12)}$$

On the other hand, $if\ \theta<\frac{b^2t^2}{8}$, increasing the value of s will always increase the profit and hence s will go to infinity if it has no upper bound. In our problem, since it has an upper bound, $\bar{s}$, it will take this value and (w_m^*,s^*,d_m^*) decisions will be as follows.

$$(w_m^*,s^*,d_m^*)=\begin{cases}\left(\frac{1+at+c_m-bt\bar{s}}{2},\bar{s},\frac{bt\bar{s}-at-c_m+1}{4}\right) & \text{if } \frac{bt\bar{s}-at-c_m+1}{4}>0\\ (0,0,0), & \text{otherwise.}\end{cases} \quad \text{(A.2.13)}$$

Proof of Theorem 3

We can write the profit of hybrid system under centralized control as in equation (A.2.14).

$$\max_{\substack{d_m\geq 0\\ 0\leq d_r\leq\kappa,\\ 0\leq s\leq\bar{s}}} \pi_C^2(d_m,d_r,s) = (1-d_m-\beta d_r-c_m)d_m+\big(\beta(1-d_m-d_r)-c_p-c_r\big)d_r - (a-bs)d_mt-(a-bs-\Delta)d_rt-\theta s^2 \quad \text{(A.2.14)}$$

Hessian matrix corresponding to this function with respect to d_m, d_r and s can be obtained as $H=\begin{bmatrix}-2 & -2\beta & bt\\ -2\beta & -2\beta & bt\\ bt & bt & -2\theta\end{bmatrix}$. Determinant of the first minor (-2) is negative and determinant of the second minor $(4\beta - 4\beta^2)$ is positive since $\beta < 1$. Finally, determinant of the matrix is $2(4\beta\theta - b^2t^2)(\beta - 1)$. If we assume that $\theta > \frac{b^2t^2}{4\beta}$, this determinant is negative. As a result, this function is jointly concave with respect to d_m, d_r and s. In order to create an unconstrained problem, we write the Lagrangean function as follows.

$$\begin{aligned}\pi_{CL}^2(d_m, d_r, s, \lambda_1, \lambda_2, \lambda_3, \lambda_4) \\ &= (1 - d_m - \beta d_r - c_m)d_m + d_r\big(\beta(1 - d_m - d_r) - c_p - c_r\big) \\ &- (a - bs)d_m t - (a - bs - \Delta)d_r t - \theta s^2 - \lambda_1(d_r - \kappa) + \lambda_2 d_m + \lambda_3 d_r \\ &- \lambda_4(s - \bar{s})\end{aligned} \tag{A.2.15}$$

Partial derivatives of this Lagrangean function, can be obtained as in equations (A2.16)-(A2.18).

$$\frac{\partial\pi_{CL}^2(d_m, d_r, s, \lambda_1, \lambda_2, \lambda_3, \lambda_4)}{\partial d_m} = 1 - c_m - 2d_m - 2\beta d_r - (a - bs)t + \lambda_2 \tag{A.2.16}$$

$$\begin{aligned}\frac{\partial\pi_{CL}^2(d_m, d_r, s, \lambda_1, \lambda_2, \lambda_3, \lambda_4)}{\partial d_r} \\ &= \lambda_3 - \lambda_1 - c_p - c_r - \beta d_m - \beta d_r - (a - bs - \Delta)t - \beta(d_m + d_r - 1)\end{aligned} \tag{A.2.17}$$

$$\frac{\partial\pi_{CL}^2(d_m, d_r, s, \lambda_1, \lambda_2, \lambda_3, \lambda_4)}{\partial s} = bt(d_m + d_r) - 2\theta s - \lambda_4 \tag{A.2.18}$$

Necessary and sufficient conditions for optimality are that these partial derivatives are equal to zero, $\lambda_1(d_r - \kappa) = 0$, $\lambda_2 d_m = 0$, $\lambda_3 d_r = 0$, $\lambda_4(s - \bar{s}) = 0$, $\lambda_1 \geq 0$, $\lambda_2 \geq 0$, $\lambda_3 \geq 0$ and $\lambda_4 \geq 0$. Then, we may face with eleven different ranges. In Range I, suppose that $d_m > 0$, $0 < d_r < \kappa$ and $s < \bar{s}$. Then, since $\lambda_1(d_r - \kappa) = 0$, λ_1 will be zero, since $\lambda_2 d_m = 0$, λ_2 will be zero, since $\lambda_3 d_r = 0$, λ_3 will be zero and since $\lambda_4(s - \bar{s}) = 0$, λ_4 will be zero. In a similar manner, other ranges can also be obtained as in Table A.2.2.

Table A.2.2. *Ranges under centralized control of hybrid system*

Range	d_m	d_r	s	λ_1	λ_2	λ_3	λ_4
I	> 0	$0 < d_r < \kappa$	$< \bar{s}$	0	0	0	0
II	> 0	$0 < d_r < \kappa$	$\bar{s}$	0	0	0	≥ 0
III	> 0	κ	$< \bar{s}$	≥ 0	0	0	0
IV	> 0	κ	$\bar{s}$	≥ 0	0	0	≥ 0
V	> 0	0	$< \bar{s}$	0	0	≥ 0	*0*
VI	> 0	0	$\bar{s}$	0	0	≥ 0	≥ 0
VII	0	κ	$< \bar{s}$	≥ 0	≥ 0	0	0
VIII	0	κ	$\bar{s}$	≥ 0	≥ 0	0	≥ 0
IX	0	$0 < d_r < \kappa$	$< \bar{s}$	0	≥ 0	0	0
X	0	$0 < d_r < \kappa$	$\bar{s}$	0	≥ 0	0	≥ 0
XI	0	0	$< \bar{s}$	0	≥ 0	≥ 0	0

As seen in Table A.2.2, in each range we have three decision variables to determine, i.e. in first range we determine d_m, d_r and s. We can determine the values of these variables by using the partial derivatives in equations (A2.16)-(A2.18). For example, for the first range, if we set $\lambda_1 = 0$, $\lambda_2 = 0$, $\lambda_3 = 0$ and $\lambda_4 = 0$, partial derivatives will be as follows.

$$\frac{\partial \pi_{CL}^2(d_m, d_r, s, \lambda_1, \lambda_2, \lambda_3, \lambda_4)}{\partial d_m} = 1 - c_m - 2d_m - 2\beta d_r - (a - bs)t \qquad \text{(A.2.19)}$$

$$\frac{\partial \pi_{CL}^2(d_m, d_r, s, \lambda_1, \lambda_2, \lambda_3, \lambda_4)}{\partial d_r} = -c_p - c_r - \beta d_m - \beta d_r - (a - bs - \Delta)t - \beta(d_m + d_r - 1) \qquad \text{(A.2.20)}$$

$$\frac{\partial \pi_{CL}^2(d_m, d_r, s, \lambda_1, \lambda_2, \lambda_3, \lambda_4)}{\partial s} = bt(d_m + d_r) - 2\theta s \qquad \text{(A.2.21)}$$

Now, if we set these partial derivatives equal to 0, we have three equations and three decision variables. By solving these equations, we obtain the values d_m, d_r and s and present in equation (A.2.22).

If $\theta > \frac{b^2t^2}{4\beta}$

$$(d_m^*, d_r^*, s^*) = \begin{cases} \left(\begin{array}{c} \frac{\beta + c_m - c_p - c_r + \Delta t - 1}{2(\beta - 1)}, \\ \frac{-\begin{bmatrix} 4\theta(c_p + c_r - \beta c_m - \Delta t + at - \beta at) \\ +b^2t^2(\beta - 1 + \Delta t + c_m - c_p - c_r) \end{bmatrix}}{2(4\beta\theta - b^2t^2)(1-\beta)}, \\ \frac{-bt(c_p - \beta + c_r - \Delta t + at)}{(4\beta\theta - b^2t^2)} \end{array} \right) & \text{if} \quad \begin{array}{l} \frac{\beta + c_m - c_p - c_r + \Delta t - 1}{2(\beta - 1)} > 0 \text{ and} \\ 0 < \frac{-\begin{bmatrix} 4\theta(c_p + c_r - \beta c_m - \Delta t + at - \beta at) \\ +b^2t^2(\beta - 1 + \Delta t + c_m - c_p - c_r) \end{bmatrix}}{2(4\beta\theta - b^2t^2)(1-\beta)} < \kappa \\ \text{and } \frac{-bt(c_p - \beta + c_r - \Delta t + at)}{(4\beta\theta - b^2t^2)} < \bar{s}, \end{array} \end{cases} \quad \text{(A.2.22)}$$

Values of decision variables in other ranges are also obtained in a similar manner and presented in equation (4.9). On the other hand, if $\theta < \frac{b^2t^2}{4\beta}$, increasing the value of s will always increase the profit and hence s will go to infinity if it has no upper bound. In our problem, since it has an upper bound, $\bar{s}$, it will take this value and (w_m^*, s^*, d_m^*) decisions will be as follows.

$$(d_m^*, d_r^*, s^*) = \begin{cases} \left(\frac{\beta + c_m - c_p - c_r + \Delta t - 1}{2(\beta - 1)}, \frac{-\begin{bmatrix} c_p + c_r - \beta c_m - \Delta t + \\ at - \beta at - b\bar{s}t + \beta b\bar{s}t \end{bmatrix}}{2\beta(1-\beta)}, \bar{s} \right) & \text{if} \quad \begin{array}{l} d_m = \frac{\beta + c_m - c_p - c_r + \Delta t - 1}{2(\beta - 1)} > 0 \text{ and} \\ 0 < \frac{-\begin{bmatrix} c_p + c_r - \beta c_m - \Delta t + \\ at - \beta at - b\bar{s}t + \beta b\bar{s}t \end{bmatrix}}{2\beta(1-\beta)} < \kappa, \end{array} \\ \left(\frac{b\bar{s}t - 2\beta\kappa - at - c_m + 1}{2}, \kappa, \bar{s} \right) & \text{if} \quad \begin{array}{l} \frac{b\bar{s}t - 2\beta\kappa - at - c_m + 1}{2} > 0 \text{ and} \\ \begin{bmatrix} \beta(c_m - 2\kappa + 2\beta\kappa - b\bar{s}t + at) \\ -c_r - c_p + \Delta t - at + b\bar{s}t \end{bmatrix} \geq 0, \end{array} \\ \left(\frac{b\bar{s}t - at - c_m + 1}{2}, 0, \bar{s} \right) & \text{if} \quad \begin{array}{l} \frac{b\bar{s}t - at - c_m + 1}{2} > 0 \text{ and} \\ c_p + c_r - \beta c_m - \Delta t + at - \beta at - b\bar{s}t + \beta b\bar{s}t \geq 0, \end{array} \\ \left(0, \frac{-(c_p + c_r - \beta - \Delta t + at + b\bar{s}t)}{2\beta}, \bar{s} \right) & \text{if} \quad \begin{array}{l} 0 < \frac{-(c_p + c_r - \beta - \Delta t + at + b\bar{s}t)}{2\beta} < \kappa \text{ and} \\ \beta + c_m - c_p - c_r + \Delta t - 1 \geq 0, \end{array} \\ (0, \kappa, \bar{s}) & \text{if} \quad \begin{array}{l} \beta - c_p - c_r + \Delta t - 2\beta\kappa - at + b\bar{s}t \geq 0 \text{ and} \\ \beta\kappa t - 2\theta\bar{s} \geq 0, \end{array} \\ (0,0,0), & \text{otherwise.} \end{cases} \quad \text{(A.2.23)}$$

Proof of Lemma 2

Retailer's problem under Setting 2 can be written as in equation (A.2.24).

$$\max_{\substack{d_m \geq 0 \\ 0 \leq d_r \leq \kappa}} \pi_R^2(d_m, d_r | w_m, w_r) = (1 - d_m - \beta d_r - w_m)d_m + (\beta(1 - d_m - d_r) - w_r)d_r \quad \text{(A.2.24)}$$

Hessian matrix corresponding to this function with respect to d_m, d_r can be obtained as $H = \begin{bmatrix} -2 & -2\beta \\ -2\beta & -2\beta \end{bmatrix}$. Determinant of the minor (-2) is negative and determinant of the matrix is $4\beta - 4\beta^2$. This determinant is positive since $\beta < 1$. As a result, this function is jointly concave with respect to d_m and d_r. In order to create an unconstrained problem, we can write the Lagrangean function as in equation (A.2.25).

$$\pi_{RL}^2(d_m, d_r, \lambda_1, \lambda_2, \lambda_3 | w_m, w_r)$$
$$= (1 - d_m - \beta d_r - w_m)d_m + (\beta(1 - d_m - d_r) - w_r)d_r - \lambda_1(d_r - \kappa) + \lambda_2 d_m + \lambda_3 d_r \quad \text{(A.2.25)}$$

Partial derivatives of this Lagrangean function can be obtained as in equations (A.2.26) and (A.2.27).

$$\frac{\partial \pi_{RL}^2(d_m, d_r, \lambda_1, \lambda_2, \lambda_3 | w_m, w_r)}{\partial d_m} = 1 - w_m - 2d_m - 2\beta d_r + \lambda_2 \quad \text{(A.2.26)}$$

$$\frac{\partial \pi_{RL}^2(d_m, d_r, \lambda_1, \lambda_2, \lambda_3 | w_m, w_r)}{\partial d_r} = \lambda_3 - \lambda_1 - w_r - \beta d_m - \beta d_r - \beta(d_m + d_r - 1) \quad \text{(A.2.27)}$$

Necessary and sufficient conditions for optimality are that these partial derivatives are equal to zero, $\lambda_1(d_r - \kappa) = 0$, $\lambda_2 d_m = 0$, $\lambda_3 d_r = 0$, $\lambda_1 \geq 0$, $\lambda_2 \geq 0$ and $\lambda_3 \geq 0$. Then, we may face with six different ranges. These ranges are presented in Table A.2.3.

Table A.2.3. *Ranges under Setting 2*

Range	d_m	d_r	λ_1	λ_2	λ_3
I	> 0	$0 < d_r < \kappa$	0	0	0
II	> 0	κ	≥ 0	0	0
III	> 0	0	0	0	≥ 0
IV	0	κ	≥ 0	≥ 0	0
V	0	$0 < d_r < \kappa$	0	≥ 0	0
VI	0	0	0	≥ 0	≥ 0

As seen in Table A.2.3, in each range we have two decision variables to determine, i.e. in first range d_m and d_r values are needed to be determined. We can determine the values of these variables by using the partial derivatives in equations (A.2.26)-(A.2.27). For example, for the first range, if we set $\lambda_1 = 0$, $\lambda_2 = 0$, $\lambda_3 = 0$, partial derivatives will be as follows.

$$\frac{\partial \pi_{RL}^2(d_m, d_r, \lambda_1, \lambda_2, \lambda_3 | w_m, w_r)}{\partial d_m} = 1 - w_m - 2d_m - 2\beta d_r \quad \text{(A.2.28)}$$

$$\frac{\partial \pi_{RL}^2(d_m, d_r, \lambda_1, \lambda_2, \lambda_3 | w_m, w_r)}{\partial d_r} = -w_r - \beta d_m - \beta d_r - \beta(d_m + d_r - 1) \quad \text{(A.2.29)}$$

Now, if we set these partial derivatives equal to 0, we have two equations and two decision variables. By solving these equations, we obtain $d_m = \frac{\beta + w_m - w_r - 1}{2(\beta - 1)}$ and $d_r =$

$\frac{\beta w_m - w_r}{2(\beta-\beta^2)}$. Values of decision variables in other ranges are determined in a similar manner and retailer's decisions are characterized as in equation (4.12).

Proof of Lemma 3

Retailer's profit under Setting 3 can be written as in equation (A.2.30).

$$\max_{\substack{d_m \geq 0 \\ 0 \leq d_r \leq \kappa}} \pi_R^3(d_m, d_r | w_m, s)$$
$$= (1 - d_m - \beta d_r - w_m) d_m + d_r\big(\beta(1 - d_m - d_r) - c_p - c_r\big) - (a - bs - \Delta) d_r t \tag{A.2.30}$$

Hessian matrix corresponding to this function with respect to d_m, d_r can be obtained as $H = \begin{bmatrix} -2 & -2\beta \\ -2\beta & -2\beta \end{bmatrix}$. Determinant of the minor (-2) is negative and determinant of the matrix is $4\beta - 4\beta^2$. This determinant is positive since $\beta < 1$. As a result, this function is jointly concave with respect to d_m and d_r. In order to create an unconstrained problem, we can write the Lagrangean function as in equation (A.2.31).

$$\pi_{RL}^3(d_m, d_r, \lambda_1, \lambda_2, \lambda_3 | w_m, s)$$
$$= (1 - d_m - \beta d_r - w_m) d_m + d_r\big(\beta(1 - d_m - d_r) - c_p - c_r\big) - (a - bs - \Delta) d_r t - \lambda_1(d_r - \kappa) + \lambda_2 d_m + \lambda_3 d_r \tag{A.2.31}$$

Partial derivatives of this Lagrangean function, can be obtained as follows.

$$\frac{\partial \pi_{RL}^3(d_m, d_r, \lambda_1, \lambda_2, \lambda_3 | w_m, s)}{\partial d_m} = 1 - w_m - 2d_m - 2\beta d_r + \lambda_2 \tag{A.2.32}$$

$$\frac{\partial \pi_{RL}^3(d_m, d_r, \lambda_1, \lambda_2, \lambda_3 | w_m, s)}{\partial d_r}$$
$$= \lambda_3 - \lambda_1 - c_p - c_r - \beta d_m - \beta d_r - \beta(d_m + d_r - 1) - (a - bs - \Delta)t \tag{A.2.33}$$

Similar to other settings, under this setting, necessary and sufficient conditions for optimality are that these first order derivatives are equal to zero, $\lambda_1(d_r - \kappa) = 0$, $\lambda_2 d_m = 0$, $\lambda_3 d_r = 0$, $\lambda_1 \geq 0$, $\lambda_2 \geq 0$ and $\lambda_3 \geq 0$. Then, we may face with six different ranges. In Range I, suppose that $d_m > 0$, and $0 < d_r < \kappa$. Then, since $\lambda_1(d_r - \kappa) = 0$, λ_1 will be zero, since $\lambda_2 d_m = 0$, λ_2 will be zero and since $\lambda_3 d_r = 0$, λ_3 will be zero. In a similar manner, other ranges can also be obtained as in Table A.2.4.

Table A.2.4. *Ranges under Setting 3*

Range	d_m	d_r	λ_1	λ_2	λ_3
I	>0	$0<d_r<\kappa$	0	0	0
II	>0	κ	≥ 0	0	0
III	>0	0	0	0	≥ 0
IV	0	κ	≥ 0	≥ 0	0
V	0	$0<d_r<\kappa$	0	≥ 0	0
VI	0	0	0	≥ 0	≥ 0

As seen in Table A.2.4, in each range we have two decision variables to determine. We can determine the values of these variables by using the partial derivatives in equations (A2.32-A.2.33). For example, for the first range, if we set $\lambda_1=0,\ \lambda_2=0, \lambda_3=0$, partial derivatives will be as follows.

$$\frac{\partial\pi_{RL}^3(d_m,d_r,\lambda_1,\lambda_2,\lambda_3|w_m,s)}{\partial d_m}=1-w_m-2d_m-2\beta d_r \tag{A.2.34}$$

$$\frac{\partial\pi_{RL}^3(d_m,d_r,\lambda_1,\lambda_2,\lambda_3|w_m,s)}{\partial d_r} = -c_p-c_r-\beta d_m-\beta d_r-\beta(d_m+d_r-1)-(a-bs-\Delta)t \tag{A.2.35}$$

Now, if we set these partial derivatives equal to 0, we have two equations and two decision variables. By solving these equations, we obtain $d_m=\frac{\beta-c_p-c_r+w_m+\Delta t-at+bst-1}{2(\beta-1)}$ and $d_r=\frac{c_p+c_r-\Delta t-\beta w_m+at-bst}{2\beta(\beta-1)}$. Values of decision variables in other ranges are obtained in a similar manner and presented in equation (4.16).

Proof of Lemma 4

Same as the proof of Lemma 2.

APPENDIX 3: VALUES OF THE PARAMETERS IN BASE CASE INSTANCE

Table A.3.1. *Unit cost ($/unit.km) and unit emission (ton CO_2/unit.km) of shipment*

Unit Cost of Shipment	Unit Emission of Shipment
0.085	0.00019

Table A.3.2. *Fixed costs of facilities ($/period)*

MP1	MP2	MP3	MP4	DC1	DC2	DC3	DC4	DC5	DC6
120,000	130,000	120,000	140,000	17,000	25,000	18,000	19,000	17,000	23,000
DC7	DC8	CC1	CC2	CC3	RC1	RC2	DisaC1	DisaC2	
21,000	20,000	10,000	20,000	15,000	40,000	30,000	50,000	40,000	

Table A.3.3. *Procurement costs ($/unit) and procurement emissions (ton CO_2/unit) of components (emissions are given in brackets)*

	Supplier 1	Supplier 2	Supplier 3	Supplier 4	Supplier 5
Component 1	55 (0.6)	45 (0.8)	55 (0.7)	50 (0.6)	45 (0.8)
Component 2	40 (1.0)	35 (1.2)	45 (0.8)	40 (0.9)	45 (0.7)

Table A.3.4. *Unit costs ($/unit) and unit emissions (ton CO_2/unit) of operations*

	Manuf.	Dist.	Col. and Test.	Repair	Disassembly	Disposal
Cost	80	5	15	20	10	10
Emission	1.75	0.50	0.60	0.70	0.40	0.70

Table A.3.5. *Values of return rate and returned product quality*

	Low Value (Probability)	Medium Value (Probability)	High Value (Probability)
Return rates of customers	0.40 (0.30)	0.50 (0.40)	0.60 (0.30)
Product recovery rate	0.30 (0.33)	0.50 (0.34)	0.70 (0.33)
Component recovery rates for both components	0.50 (0.33)	0.70 (0.34)	0.90 (0.33)

APPENDIX 4: MEANS AND VARIANCES OF DEMANDS OF CUSTOMERS

Table A.4.1. *Probabilities of demand scenarios*

Scenario	Low	Medium	High
Probability	0.3	0.4	0.3

Table A.4.2. *Demands of customers in low, medium and high scenario (base case values)*

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Low	200	400	350	150	250	180	300	280	400	340	280	300	180	280	250
Medium	400	800	700	300	500	360	600	560	800	680	560	600	360	560	500
High	600	1200	1050	450	750	540	900	840	1200	1020	840	900	540	840	750
Mean	400	800	700	300	500	360	600	560	800	680	560	600	360	560	500
Variance	24000	96000	73500	13500	37500	19440	54000	47040	96000	69360	47040	54000	19440	47040	37500

Table A.4.3. *Demands of customers in low, medium and high scenario (very low demand variance)*

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Low	360	720	630	270	450	324	540	504	720	612	504	540	324	504	450
Medium	400	800	700	300	500	360	600	560	800	680	560	600	360	560	500
High	440	880	770	330	550	396	660	616	880	748	616	660	396	616	550
Mean	400	800	700	300	500	360	600	560	800	680	560	600	360	560	500
Variance	960	3840	2940	540	1500	778	2160	1882	3840	2774	1882	2160	778	1882	1500

Table A.4.4. *Demands of customers in low, medium and high scenario (low demand variance)*

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Low	280	560	490	210	350	252	420	392	560	476	392	420	252	392	350
Medium	400	800	700	300	500	360	600	560	800	680	560	600	360	560	500
High	520	1040	910	390	650	468	780	728	1040	884	728	780	468	728	650
Mean	400	800	700	300	500	360	600	560	800	680	560	600	360	560	500
Variance	8640	34560	26460	4860	13500	6998	19440	16934	34560	24970	16934	19440	6998	16934	13500

Table A.4.5. *Demands of customers in low, medium and high scenario (high demand variance)*

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Low	120	240	210	90	150	108	180	168	240	204	168	180	108	168	150
Medium	400	800	700	300	500	360	600	560	800	680	560	600	360	560	500
High	680	1360	1190	510	850	612	1020	952	1360	1156	952	1020	612	952	850
Mean	400	800	700	300	500	360	600	560	800	680	560	600	360	560	500
Variance	47040	188160	144060	26460	73500	38102	105840	92198	188160	135946	92198	105840	38102	92198	73500

Table A.4.6. *Demands of customers in low, medium and high scenario (very high demand variance)*

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Low	40	80	70	30	50	36	60	56	80	68	56	60	36	56	50
Medium	400	800	700	300	500	360	600	560	800	680	560	600	360	560	500
High	760	1520	1330	570	950	684	1140	1064	1520	1292	1064	1140	684	1064	950
Mean	400	800	700	300	500	360	600	560	800	680	560	600	360	560	500
Variance	77760	311040	238140	43740	121500	62986	174960	152410	311040	224726	152410	174960	62986	152410	121500

RESUME

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Educational Background

Ph.D.	Industrial Engineering	Eskisehir Technical University	2015-2019
M.Sc.	Industrial Engineering	Anadolu University	2013-2015
B.Sc.	Industrial Engineering	Yildiz Technical University	2008-2013

Work Experience

Research and Teaching Assistant	Eskisehir Technical University Department of Industrial Engineering	2018-continues
Research and Teaching Assistant	Anadolu University Department of Industrial Engineering	2013-2018
Long-Term Project Intern	Mercedes-Benz Turk AS	2012-2012
Manufacturing Intern	Ford Otomotiv Sanayi AS	2011-2011

Teaching Experience

Course	*Language*	*Role*	*Experience*
ENM308 Production Planning and Control I	English	Teaching Assistant	5 Semesters
ENM401 Production Planning and Control II	English	Teaching Assistant	5 Semesters
PZL452 Revenue Management and Pricing	English	Teaching Assistant	2 Semesters
IST244 Engineering Probability	English	Teaching Assistant	2 Semesters
FIN201 Financial Analysis	Turkish	Teaching Assistant	1 Semester

Selected Publications

1. *Journal Paper:* Alegoz, M. and Kaya, O. (2017) Coordinated Dispatching and Acquisition Fee Decisions for a Collection Center in a Reverse Supply Chain. *Computers & Industrial Engineering*, 113, 475-486.

2. *Journal Paper:* Çelik, E., Gümüş, A. T., and Alegoz, M. (2014). A trapezoidal type-2 fuzzy MCDM method to identify and evaluate critical success factors for humanitarian relief logistics management. *Journal of Intelligent & Fuzzy Systems*. 27-6, 2847-2855.

3. *Working Paper:* Alegoz, M., Kaya, O. and Bayındır, Z. P. (2019). Closing the Loop in Supply Chains: Financial and Environmental Effects. *Computers & Industrial Engineering*, Under Editorial Review

4. *Working Paper:* Alegoz, M., Kaya, O. and Bayındır, Z. (2019). Pricing and Sustainability Level Decisions in Remanufacturing Systems.

5. *Conference Paper:* Dynamic Programming Models for Joint Incentive and Dispatching Decisions for Collection Centers in Remanufacturing, EURO2018 Valencia (Joint work with Onur KAYA)

6. *Conference Paper:* Financial and Environmental Effects of Closing the Loop in Supply Chains. Or2019 (Joint work with Onur KAYA and Z. Pelin BAYINDIR)

7. *Scientific Research Project:* Multi objective and Multi Echelon Solution Approaches for Supply Chain Network Design Problems. Anadolu University Scientific Research Project-AUBAP (Grant No: 1501F024). Researcher

8. *Scientific Research Project:* Supplier Selection and Order Allocation Decisions in a Supply Chain. Anadolu University Scientific Research Project-AUBAP (Grant No: 144F220). Researcher

Reviewing Experience

1. Computers & Industrial Engineering

2. Journal of Cleaner Production

3. Applied Soft Computing

4. Journal of Intelligent Manufacturing

Honors and Awards

1. First ranked student in the department, Yildiz Technical University, 2013
2. Third ranked student in the faculty, Yildiz Technical University, 2013
3. The Scientific and Technological Research Council of Turkey (TUBITAK) Scholarship, 2013-continues
4. Journal of Cleaner Production, Outstanding Contribution in Reviewing Certificate, 2018