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Facility location for a hybrid manufacturing/remanufacturing system with carbon costs

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**Facility location for a hybrid manufacturing/remanufacturing system
with carbon costs**

by

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A thesis submitted to the graduate faculty

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Program of Study Committee:
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ABSTRACT

This thesis addresses inventory management and facility location for a hybrid manufacturing/remanufacturing system where remanufacturing lead-time is different from production lead-time. We also investigate the impact of potential government regulation for carbon emission generated by transportation on a closed-loop supply chain (CLSC) network design. A two-stage optimization procedure is proposed in two cases of the different lead-times: The first stage optimizes the decisions on production and remanufacturing levels in each period based on a specific inventory management policy; the second stage optimizes the number and locations of factory, warehouse and collection centers. In a case of larger remanufacturing lead-time, the network is configured with a single plant, warehouse and collection center in the regions which minimize each investment considering the transportation cost. In the other case of larger production lead-time, the network is designed with multiple collection centers. With the consideration of the carbon emission cost, each storage facility first is located in the region closed to a plant with the highest investment, but as the emission cost increases, all facilities are centralized in the network to reduce the transportation costs. The proposed method results in lower combined costs of facility investment, holding inventory, transportation, and carbon emissions than a method that assumes equal manufacturing and remanufacturing lead-times.

CHAPTER 1 INTRODUCTION

1.1   Motivation

Over the last several decades, many countries have been aware of environmental issues due to the limited accessibility of resources. Some countries have legislated to encourage firms to be responsible for the products at the end of their life cycle after customer use to reduce waste [17]. As part of the responsibility of the products and the environment improvement, the firms have participated in reverse activities which are defined as collecting, inspecting, and remanufacturing the end of life products. The activities have generated new sources of profit to the firms [11]. Recently, there has been much research to develop a closed-loop supply chain (CLSC) management defined as "*the design, control, and operation of a system to maximize value creation over the entire life cycle of a product with dynamic recovery of value from different types and volumes of returns over time* [11]."

In addition, as the global climate change has accelerated recently, government regulation of the greenhouse gas emissions due to transportation has been another issue. According to the 2007 synthesis report of the Intergovernmental Panel on Climate Change [34], 13.1% of the greenhouse gas emission has come from the transportation sector, and it is responsible for the third-largest quantity of emissions. In addition, as a source of greenhouse gas emission in the U.S., transportation is in second place among sectors with 28% in 2011 [38]. Especially, carbon dioxide (CO_2) emission causes the

most serious problem among greenhouse gas emissions [34]. With this awareness of the environmental issue, the European Union instituted the Emission Trading Scheme (ETS) to reduce the greenhouse gas emission to 20% below its 1990 level by 2020 [5]. In 2011, Australia's government announced the details of a carbon tax of $24.65 per ton to lower the greenhouse gas emission by discouraging the use of fossil fuel [32]. Not only these countries, but several nations and regions including Kazakhstan, New Zealand, California in U.S., Québec in Canada, and Tokyo and Kyoto in Japan have participated in the movement to reduce the greenhouse gas emission [33]. These global movements ultimately motivate the firms to design their CLSC networks considering a potential government regulation on the carbon emission caused by transportation.

The product recovery is distinguished into three basic categories according to form of recovery: 1) recycling (material recovery), 2) repair, refurbishment, or reuse (product recovery), and 3) remanufacturing (component recovery) [1]. Especially, many firms view the remanufacturing as a technical operational problem [12], and define it as an activity which brings used products back to such a good condition as new ones [14]. A CLSC based on the product recovery consists of a traditional forward supply chain and a reverse supply chain. A reverse supply chain especially requires careful design, planning, and control because the returned items are uncertain in quality, quantity, and timing [12]. Such uncertainty for the returned items leads the remanufacturing to have different time sensitivity from traditional production [11]. Therefore, this thesis starts with an idea on the different processing lead-times required by a regular production and remanufacturing, and aims at building the CLSC network for a hybrid

manufacturing/remanufacturing system under a potential carbon emission regulation on the transportation.

1.2   Problem Statement

With the growing concern for the environmental issues and the awareness of the economic effects of the reverse activities, which are defined as product returns management, remanufacturing operational issues, and remanufactured products market development [11], the reverse supply chain has received a lot of attention from many researchers and firms. Especially, many firms have concentrated on the remanufacturing operational issues, which refer to reverse logistics, testing, sorting, disposition, repair, and remanufacturing for product returns [12]. Such issues are caused by different types of returns so that activities for the remanufacturing have different time sensitivity from the traditional forward activities [11]. However, many researchers have overlooked the fact that the remanufacturing lead-time may differ from the regular production lead-time when they build the CLSC network.

The CLSC network design aims to lead firms to achieve a successful long-term strategy for the huge amount of the investment in several types of facilities. Thus, the firms should consider not only the investment, but also all possible costs generated during the facility life span. However, estimating those costs requires network designers to anticipate the forward and the reverse flows as exactly as possible so that it is necessary for them to understand the nature of the remanufacturing which requires the

different processing time. A few studies have been proposed for the production planning and the inventory management on a recovery system where remanufacturing lead-time is different from a general manufacturing lead-time [1]. Especially, such research has implemented a simulation-based approach to optimize the flows with a control policy [1], [17], and [22]. Thus, we suggest a two-stage procedure involving a simulation-based and a mathematical optimization to design the CLSC network considering several costs generated over the facility life span.

In this thesis, therefore, we consider a CLSC network design for a hybrid manufacturing/remanufacturing system, with the different processing lead-times for the production and the remanufacturing, with a two-stage optimization approach. In the first stage, we optimize the production, remanufacturing, and inventory quantities based on a particular control policy in a simulation of the uncertain demands and returns. The second stage aims at optimizing the facility investments with the information obtained from the first stage. With the awareness of the environmental effects of the greenhouse gas emissions, we investigate the impact of potential government regulation for the carbon emission caused by transportation on the CLSC network design.

1.3 Thesis Organization

The rest of the thesis is organized as follows. In Chapter 2, an overview of the relevant academic literature to our problem is presented. Chapter 3 suggests a two-stage optimization for the CLSC network design with the model assumptions and notation. In

Chapter 4, we conduct a numerical analysis with estimated parameters. In Chapter 5, we draw a comprehensive conclusion of the thesis, and discuss future studies to overcome the limitations of our research.

CHAPTER 2 LITERATURE REVIEW

As the impact of supply chain on the environment and the economy has been emphasized for several decades, a variety of research on supply chain network design has been well-established (see [10], [23], and [28] for review). However, in the last 10 years, the importance of remanufacturing has been so stressed that many optimization-based approaches on reverse logistics, which are activities related to product returns in supply chain, have been suggested.

In the early work, Barros *et al*. [3] presented a two-echelon location problem solved by a mixed integer linear program (MILP) for sand recycling with capacity constraints, and considered a time period of one year and given constant demand set. Jayaraman *et al*. [16] presented a network design for remanufacturing and distribution facilities which minimizes the remanufacturing level, transportation costs, and holding cost of carrying remanufactured products. Starting with their leading work on the reverse logistics, several subsequent investigations have been proposed on different parameter settings [23].

Lu and Bostel [21] studied a CLSC network design for plants, remanufacturing facilities and intermediate centers for sorting and disposing, considering forward and reverse flow simultaneously. Their model assumed that the demands and the product returns are deterministic, and solved by MILP. Salema *et al*. [27] proposed the design of a reverse logistics network based on a warehouse location-allocation model with

capacity limits for all facilities and a multi-product system. Üster *et al*. [29] considered a multi-product CLSC network design problem for collection centers and remanufacturing facilities managed by an original equipment manufacturer (OEM) and solved their model by Benders decomposition. Listeş [20] presented a scenario-based stochastic model for the design of the CLSC network with uncertain nature of input parameters and solved it by a decomposition approach based on the branch-and-cut procedure. Ko and Evans [18] built a forward and reverse network design considering third party logistics providers solved by a genetic algorithm-based heuristic approach. Wang and Hsu [30] generalized the CLSC network design with integrated forward and reverse flows which share the same plant capacity, and solved it by a genetic algorithm. The above mentioned work has contributed to design the CLSC network for different parameter settings with various approaches. However, those papers have not mentioned the effect of different processing lead-times for regular production and remanufacturing on the CLSC network design.

Production planning and inventory management in a recovery system where regular manufacturing and remanufacturing lead-times are different has been studied by a few researchers since the late 1990's [1]. Inderfurth [15] first addressed a problem of product recovery management for a single product with a one-period lead-time difference between manufacturing and remanufacturing. In this paper, the recoverable inventory was not counted and the inventory policy was characterized by manufacturing-up-to level, remanufacturing-up-to level, and dispose-down-to level. In his further study [14], Inderfurth studied optimal policies for a recovery system where remanufactured products are significantly different from new ones which are used for substitutes when

remanufactured products are not available. Mahadevan *et al*. [22] presented production control and inventory management with a heuristically optimized inventory policy for a single manufacture-up-to level. Their model allowed all available returned items to be remanufactured at once in each period so that a manufacturing decision was dependent on the remanufacturing decision. Ferrer [8] studied a remanufacturing system where the yield of remanufacturing is random based on four scenarios analyzed, but with given demand for each period, and implemented an inventory policy with remanufacturing order quantity and manufacturing order quantity. Kiesmüller [17] presented a production control problem of a stochastic recovery system with two stocking points described by serviceable and recoverable inventories. He used separate inventory positions for the decisions on manufacturing and remanufacturing levels in each period under randomly distributed demands and returns instead of the traditional single inventory position for both decisions. The resulting policy is characterized by manufacturing-up-to level and remanufacturing-up-to level defined in terms of these inventory positions.

In this thesis, we apply the Kiesmüller inventory model to our first stage optimization problem to anticipate the forward and reverse flows in the CLSC network. This is because his model is not only fitted to our model, but also significantly reduced the cost compared to the result by the traditional approach. We review this model in depth in Section 3.4.

Furthermore, this thesis examines the influence on the CLSC network design of potential carbon emission regulations on the transportation sector. The policy instruments for the carbon emission control can be classified as price-based, which is

imposing a tax on the carbon emission, or quantity based, which is imposing a cap on emissions and allowing firms to trade emission permits [4]. Benjaafar *et al*. [4] presented the impact of various policy instruments of the carbon emission control on the lot-sizing model considering three types of carbon emission incurred by production, transportation, and inventory. Hoen *et al*. [13] investigated the effect of price-based and quantity-based policy instruments on the transportation mode selection decision. Gao [9] addressed the effect of two such policies characterized as uncertain parameters on the CLSC network design based on a robust optimization method. Cachon [6] presented a design of supply chain simultaneously considering retailer cost and customer cost based on the price-based policy for carbon emission. In this thesis, we concentrate on a price-based policy instrument which is defined as imposing a tax on the carbon emission and apply the unit transportation cost defined by Cachon [6] to our model because it considers not only uncertain carbon emission cost but also other parameters including fuel consumption, fuel price, non-fuel variable cost, and the amount of carbon emission by consumption of a unit of fuel.

This thesis starts with a different point of view from previous research because we first address the impact of the different manufacturing and remanufacturing lead-times on the CLSC network design. Second, we present various network configurations minimizing the total costs after incorporating uncertain carbon tax.

CHAPTER 3 METHODOLOGY

3.1   Assumptions

This section describes the assumptions used throughout this research to specify the scope of the study.

(i)   We consider a single product produced in a single factory. The remanufacturing process is integrated in a regular production environment, but the processing lead-time may be different.

(ii)   Production costs for manufacturing and remanufacturing are assumed to be the same.

(iii)   Stochastic demands, which are assumed to be independent in each period t, are satisfied from one type of stock point, serviceable inventory, which implies remanufactured items are as good as new ones.

(iv)   Stochastically returned items, whose distributions in each period are assumed to be independent of each other and of the demands, may be remanufactured at once or can be held in recoverable inventory for later use, but disposal option is not allowed.

(v)   Decisions on production and remanufacturing are periodically made, but the production decision occurs only when there is not enough stock available in recoverable inventory.

(vi)   There is one transportation mode available and the lead-time for distribution

between facilities is negligible.

3.2   Notation

In this section, we define the notation used throughout our research.

- **First Stage Notation**

  - **Sets**

    L Set of retailer locations which represent potential facility locations,

    T Set of time periods

  - **Indices**

    i Potential factory locations, $i \in L$

    j Potential warehouse locations, $j \in L$

    k Given retailer zones which represent potential facility locations, $k \in L$

    l Potential collection center locations, $l \in L$

    t Time periods, $t \in T$

  - **Cost Parameters**

    h^B Backorder cost rate ($\$/unit/period$)

    h^S Serviceable holding cost rate ($\$/unit/period$)

    h^R Recoverable holding cost rate ($\$/unit/period$)

  - **Input Parameters**

    $d_{k,t}$ Random demands placed by retailer k in period t, $k \in L, t \in T$

$r_{k,t}$ Random returns generated by retailer k in period t, $k \in L, t \in T$

D_t Total demands placed by all retailer sites in period t ($= \sum_{k \in L} d_{k,t}$), $t \in T$

R_t Total returns generated by all retailer sites in period t ($= \sum_{k \in L} r_{k,t}$), $t \in T$

Lp Production lead-time

Lr Remanufacturing lead-time

- **Intermediate Values**

IL_t Serviceable net-stock at the beginning of period t defined as serviceable inventory in period $t - 1$ minus backorders in period $t - 1$, $t \in T$

IP_t Inventory position including serviceable net-stock IL_t and all items on orders, $t \in T$

IPP_t Inventory position for production decision in period t, $t \in T$

IPU_t Inventory position for remanufacturing decision in period t, $t \in T$

- **Decision Variables**

S Production order-up-to level

M Remanufacturing order-up-to level

p_t Production ordering decision in period t, $t \in T$

u_t Remanufacturing ordering decision in period t, $t \in T$

Isf_t Stock-on-hand in serviceable inventory at the end of period t, $t \in T$

Irf_t Stock-on-hand in recoverable inventory at the end of period t, $t \in T$

Ibf_t Backorders at the end of period t, $t \in T$

- **Second Stage Notation**

  - **Sets**

    A Set of all the arcs in the network, $A \equiv \{(a,b): a, \text{ and } b \in L\}$

  - **Second Stage Parameters**

    ff_i Annualized fixed cost for a factory in potential location $i \in L$

    fw_j Annualized fixed cost for a warehouse in potential location $j \in L$

    fc_l Annualized fixed cost for a collection center in potential location $l \in L$

    c_{ab} Transportation cost between facilities a and b ($\$/unit$), $(a,b) \in A$

    ε Unit transportation cost ($\$/km/unit$)

    τ_{ab} Distance (km) from location a to b, $(a,b) \in A$

    v Non-fuel variable cost for the transportation mode ($\$/km$)

    f Fuel consumption (l/km)

    g Cost per unit of fuel ($\$/l$)

    θ Carbon emission by consumption of a unit of fuel (kg/l)

    e Carbon emission tax rate ($\$/kg$)

    q Transportation capacity defined as total units carried by a truck

    C Storage capacity of warehouse or collection center ($unit$)

    ρ Facility life span (year) ($= \frac{|T|}{52 weeks}$)

  - **Input Parameters from the First Stage**

    pu_t Total finished items to be distributed from a factory in period t, $t \in T$

         $(= p_{t-Lp} + u_{t-Lr})$,

Isf_0 Initial serviceable on-hand stock in all warehouses $j, j \in L$

Irr_0 Initial recoverable on hand stock in all collection center $l, l \in L$

- **Decision Variables**

$Is_{j,t}$ Stocks in warehouse j at the end of period $t, j \in L, t \in T$

$$(= \sum_J Is_{j,t} = Isf_t)$$

$Ib_{k,t}$ Backorders placed in retailer k at the end of period $t, k \in L, t \in T$

$$(= \sum_k Ib_{k,t} = Ibf_t)$$

$Ir_{l,t}$ Stocks in collection center l at the end of the period $t, l \in L, t \in T$

$$(= \sum_l Ir_{l,t} = Irf_t)$$

$\alpha_{i,j,t}$ Quantities distributed from factory i to warehouse j in period t,

   i and $j \in L, t \in T$

$\beta_{jk,t}$ Quantities distributed form warehouse j to retailer k in period t

   j and $k \in L, t \in T$

$\gamma_{kl,t}$ Returns delivered from retailer k to collection center l in period t

   k and $l \in L, t \in T$

$\delta_{li,t}$ Returns delivered form collection center l to a factory i in period t

   l and $i \in L, t \in T$

$x_i, y_j,$ and $z_l = \begin{cases} 1 & \text{if facility (factory } x, \text{warehouse } y, \text{collection } z) \text{is opened} \\ 0 & \text{otherwise} \end{cases}$,

   $i, j,$ and $l \in L$

3.3 Model Description: Two-Stage Optimization

In this section, we suggest a two-stage optimization process for the CLSC network design in a hybrid manufacturing/remanufacturing system where production and remanufacturing lead-times are different. The primary concern for the CLSC design is to determine facility locations to minimize several types of costs generated during the facility life span. This research considers three types of costs: 1) fixed costs of opening a factory, warehouses, and collection centers; 2) holding costs of carrying serviceable and recoverable inventory, and backorders; 3) transportation cost to move finished goods or returned items between facilities.

Generally, the investment in the facilities is significantly greater than the other costs, and occurs at a time point when a business is started so that the decision on the CLSC network design could be overwhelmed by the huge amount of the investment as ignoring the other costs. In this thesis, therefore, we annualize the investment in each facility, and compare it with the average annual cost for the others.

In this thesis, a two-stage optimization for the CLSC network design first aims at understanding the forward and reverse flows. Figure 3.1 illustrates the flows in a recovery system with different processing lead-times for the production and the remanufacturing. This model allows there to be multiple warehouses and collection centers in given retailer zones k, but only a single factory for the regular production and the remanufacturing is considered.
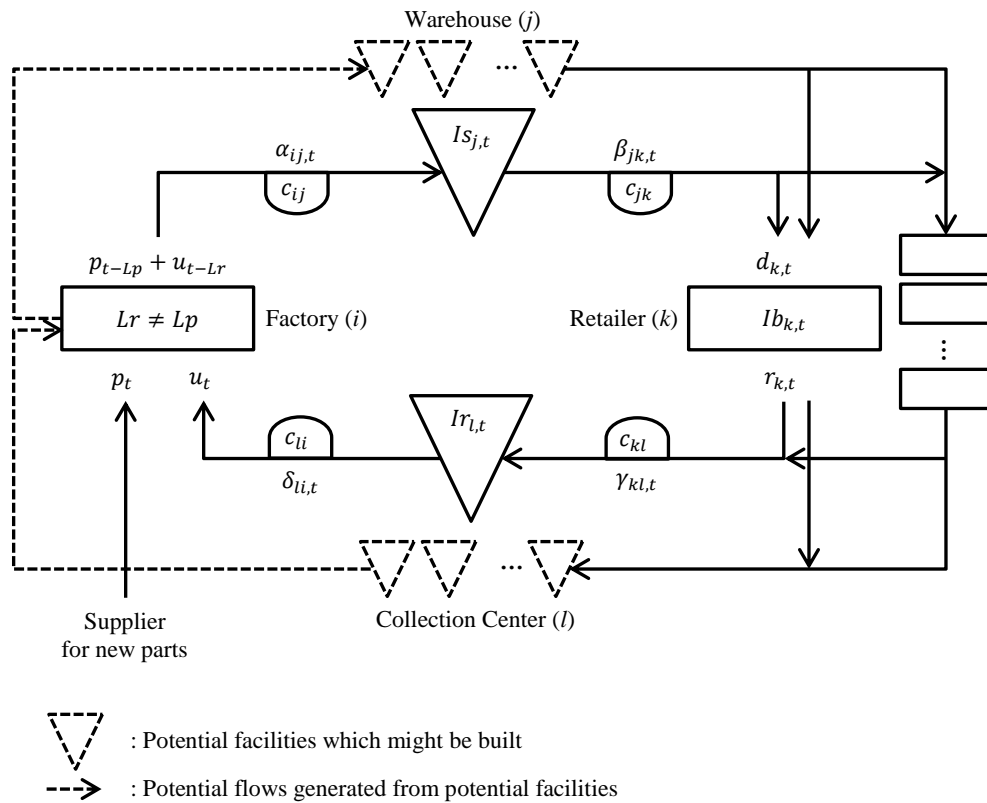
Figure 3.1 A hybrid manufacturing/remanufacturing system

With this primary assumption, demand $d_{k,t}$ generated in a given retailer zone k for a single product in a period t is satisfied from finished products $\beta_{j,k,t}$ delivered from the serviceable on-hand stock $Is_{j,t}$ in a potential warehouse location j. Backorders $Ib_{k,t}$ occur in the retailer zone k when the demands are not satisfied. The serviceable inventory is replenished by items $\alpha_{ij,t}$ distributed from a potential factory location i for each period t. The distributions $\alpha_{ij,t}$ include the newly manufactured products p_{t-Lp} and remanufactured items u_{t-Lr}.

Returned items $r_{k,t}$ generated by the retailer in zone k are shipped into potential collection center l for each period denoted by $\gamma_{kl,t}$. The returned items can be held in recoverable on-hand stock $Ir_{l,t}$ for later use, or they can be remanufactured at once for the needs u_t , which are satisfied with shipments $\delta_{li,t}$. Each shipment between facility a and b is distributed by a vehicle which incurs the unit cost c_{ab} under potential carbon emission regulations. This research, however, does not consider the third-party logistics for new parts coming into the factory from supplier for the regular production p_t.

With the understanding on the forward and the reverse flows in a recovery system, we here propose a two-stage optimization to design the CLSC network. In the first stage, with a simulation-based approach, we determine the quantities to be produced p_t and remanufactured u_t for each period according to uncertain demands $d_{k,t}$ and returns $r_{k,t}$ as minimizing the average holding and backorder costs over the entire period of a facility life span with a specific inventory management policy. In the second stage, the model configures the CLSC network based on the fundamental information, pu_t and u_t, obtained from the first stage as minimizing the annualized fixed costs and the average transportation costs accumulated per year. Here, it is important for the second stage to use the same values for the demand and the return as those of the first stage because the second stage is based on the results obtained from the simulation in the first stage. In this fashion, we can study empirically an asymptotic property with transition probabilities [24]. Finally, our model suggests different configurations of the network according to different amounts of carbon emission costs under the potential regulation. Figure 3.2 illustrates overall flows for our two-stage optimization problem.
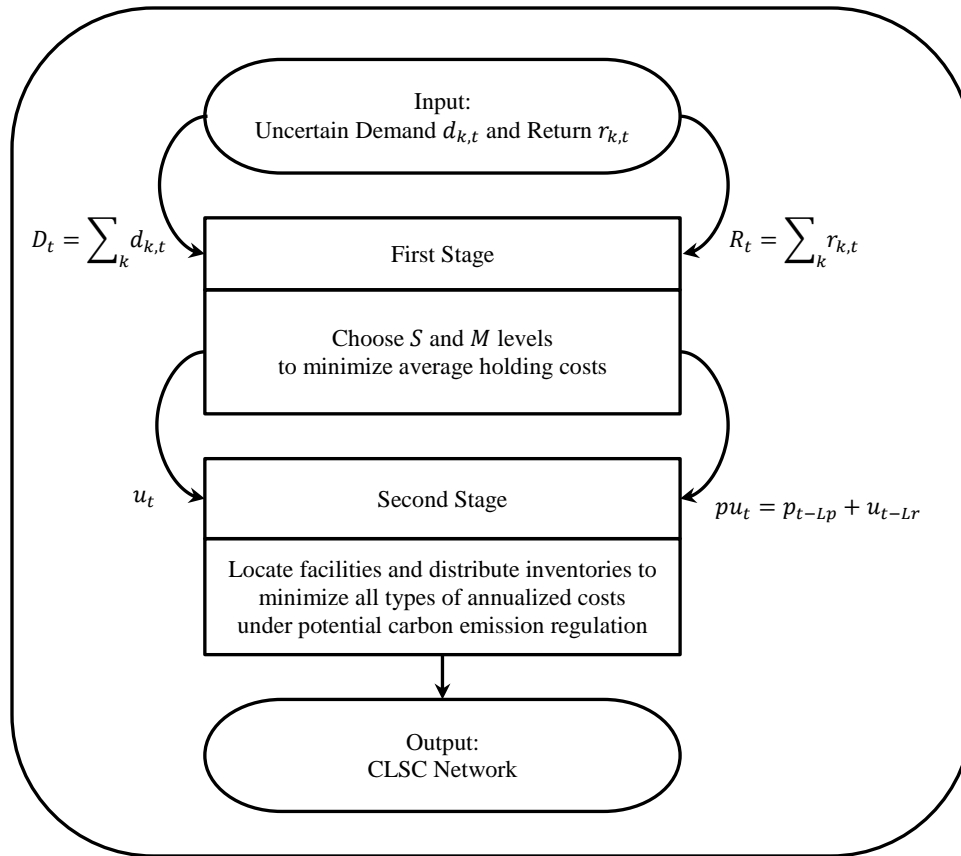
Input:
Uncertain Demand $d_{k,t}$ and Return $r_{k,t}$

$D_t = \sum_k d_{k,t}$

First Stage

$R_t = \sum_k r_{k,t}$

Choose S and M levels
to minimize average holding costs

u_t

Second Stage

$pu_t = p_{t-Lp} + u_{t-Lr}$

Locate facilities and distribute inventories to
minimize all types of annualized costs
under potential carbon emission regulation

Output:
CLSC Network

Figure 3.2   Two-stage optimization for a hybrid system with different lead-times

3.4   First-Stage: Inventory Management

This section reviews an inventory model [17] for the first stage which is applicable to a recovery system with different processing lead-times for production and remanufacturing. The first stage pays attention to the decisions on the levels of production p_t and remanufacturing u_t for each period, which leads to minimize the average costs of carrying the inventories over given periods based on total random demands $D_t = \sum_k d_{k,t}$ and returns $R_k = \sum_t r_{k,t}$ generated by all given retailer sites k.

However, the inventory model does not take other costs, such as the fixed costs to open each facility and the transportation cost, into account because it aims at anticipating the forward and reverse flows for each period in the network on the basis of designing the CLSC. Thus, the following objective function is suggested in the first stage.

$$Min \quad \zeta^1 = \frac{1}{|T|} \cdot \left\{ h^B \cdot \sum_{t=1}^{|T|} Ibf_t + h^S \cdot \sum_{t=1}^{|T|} Isf_t + h^R \cdot \sum_{t=1}^{|T|} Irf_t \right\} \tag{1}$$

Traditionally, ordering decision depends on a single inventory position which includes all information on how much has been ordered, but not received, and how much stock is in inventory. The first information is called the outstanding orders, and the other is the serviceable net inventory level IL_t at the beginning of the period, which is defined as follows.

$$IL_t = Isf_{t-1} - Ibf_{t-1} \tag{2}$$

The following represents the single inventory position in a recovery system where the remanufacturing process is integrated in regular production environment.

$$IP_t = IL_t + \sum_{i=1}^{Lp} p_{t-i} + \sum_{i=1}^{Lr} u_{t-i} \tag{3}$$

However, in a recovery system where the regular production lead-time is different from the remanufacturing lead-time, using a single inventory position causes large on-hand stocks in the serviceable inventory in accordance with unexpectedly large backorders. This is because if all outstanding orders are considered for the ordering decision with shorter lead-time, the inventory position is so large that the production

decision becomes too small to cover the uncertain demand at a certain period. It finally leads to make a large order occasionally and to increase the serviceable inventory levels.

The inventory model introduced in the first stage suggests two inventory positions for the production p_t and the remanufacturing u_t decisions for each period, respectively, based on a principle: *For the decision with longer lead-time include all outstanding orders in the inventory position and for the decision with shorter lead-time include only the orders which will arrive before the new released order comes in* [17]. This idea leads to remove unnecessary information in the inventory position for the decision with shorter lead-time so that it prevents the problems caused by using a single inventory position.

With this principle, in a system where the remanufacturing lead-time Lr is larger than the regular production lead-time Lp, the inventory position for the production decision only includes the outstanding orders which arrive at periods $t, t + 1, ..., t + Lp$ as follows.

$$IPP_t = IL_t + \sum_{i=1}^{Lp} p_{t-i} + \sum_{i=0}^{Lp} u_{t-Lr+Lp-i} \tag{4}$$

Also, since the remanufacturing decision with longer lead-time should be considered with all outstanding orders based on the principle, the second inventory position for the remanufacturing decision includes the production which is made from the first inventory position as follows.

$$IPU_t = IL_t + \sum_{i=0}^{Lp} p_{t-i} + \sum_{i=1}^{Lr} u_{t-i} \tag{5}$$

Similarly, when the production lead-time is greater than the remanufacturing lead-time, the production decision is first made. The first inventory position IPP_t for the production decision includes the recoverable on-hand stock Irf_t to avoid unnecessary production when the recoverable stocks are available for remanufacturing. It is defined as follows.

$$IPP_t = IL_t + Irf_t + \sum_{i=1}^{Lp} p_{t-i} + \sum_{i=1}^{Lr} u_{t-i} \tag{6}$$

For the second inventory position, the principle for the decision with shorter lead-time is applied again as follows.

$$IPU_t = IL_t + \sum_{i=0}^{Lr} p_{t-Lp+Lr-i} + \sum_{i=1}^{Lr} u_{t-i} \tag{7}$$

Starting with $i = 0$ in the outstanding orders in equations (3), (4), and (7), and adding Irf_t in equation (6) are also based on the echelon stock policy [2] and the assumption (iv) which describes that the production decision occurs only when there is not enough stock available in recoverable inventory. According to the echelon stock policy, *the echelon inventory position is obtained at the installation and all its downstream installation. The echelon stock at an installation is completely determined by the initial echelon stocks, the replenishments, and the final demands* [2]. Thus, with the definition of the echelon stock policy, if production lead-time Lp is equal to

remanufacturing lead-time Lr, the equations (4) to (7) become equal to (3) without each downstream installation in each inventory position as follows:

$$(4) \quad IPP_t = IL_t + \sum_{i=1}^{Lp=Lr} p_{t-i} + \sum_{i=0}^{Lp=Lr} u_{t-i} - u_t;$$

$$(5) \quad IPU_t = IL_t + \sum_{i=0}^{Lp=Lr} p_{t-i} + \sum_{i=1}^{Lp=Lr} u_{t-i} - p_t;$$

$$(6) \quad IPP_t = IL_t + Irf_t + \sum_{i=1}^{Lp=Lr} p_{t-i} + \sum_{i=1}^{Lp=Lr} u_{t-i} - Irf_t;$$

$$(7) \quad IPU_t = IL_t + \sum_{i=0}^{Lp=Lr} p_{t-i} + \sum_{i=1}^{Lp=Lr} u_{t-i} - p_t;$$

$$\therefore \quad IP_t = IPP_t = IPU_t = IL_t + \sum_{i=1}^{Lp=Lr} p_{t-i} + \sum_{i=1}^{Lp=Lr} u_{t-i} \qquad \text{if } Lr = Lp \qquad (8)$$

With these inventory positions defined by the difference between the production and the remanufacturing lead-time, the first stage determines the production and remanufacturing levels for each period based on a (S, M) policy proposed in the inventory model as follows:

$$p_t = \begin{cases} S - IPP_t & \text{if } IPP_t < S \\ 0 & \text{otherwise} \end{cases} \qquad (9)$$

$$u_t = \begin{cases} Irf_t & \text{if } IPU_t + Irf_t \le M, \ IPU_t < M \\ M - IPU_t & \text{if } IPU_t + Irf_t > M, \ IPU_t < M \\ 0 & \text{if } IPU_t \ge M \end{cases} \qquad (10)$$
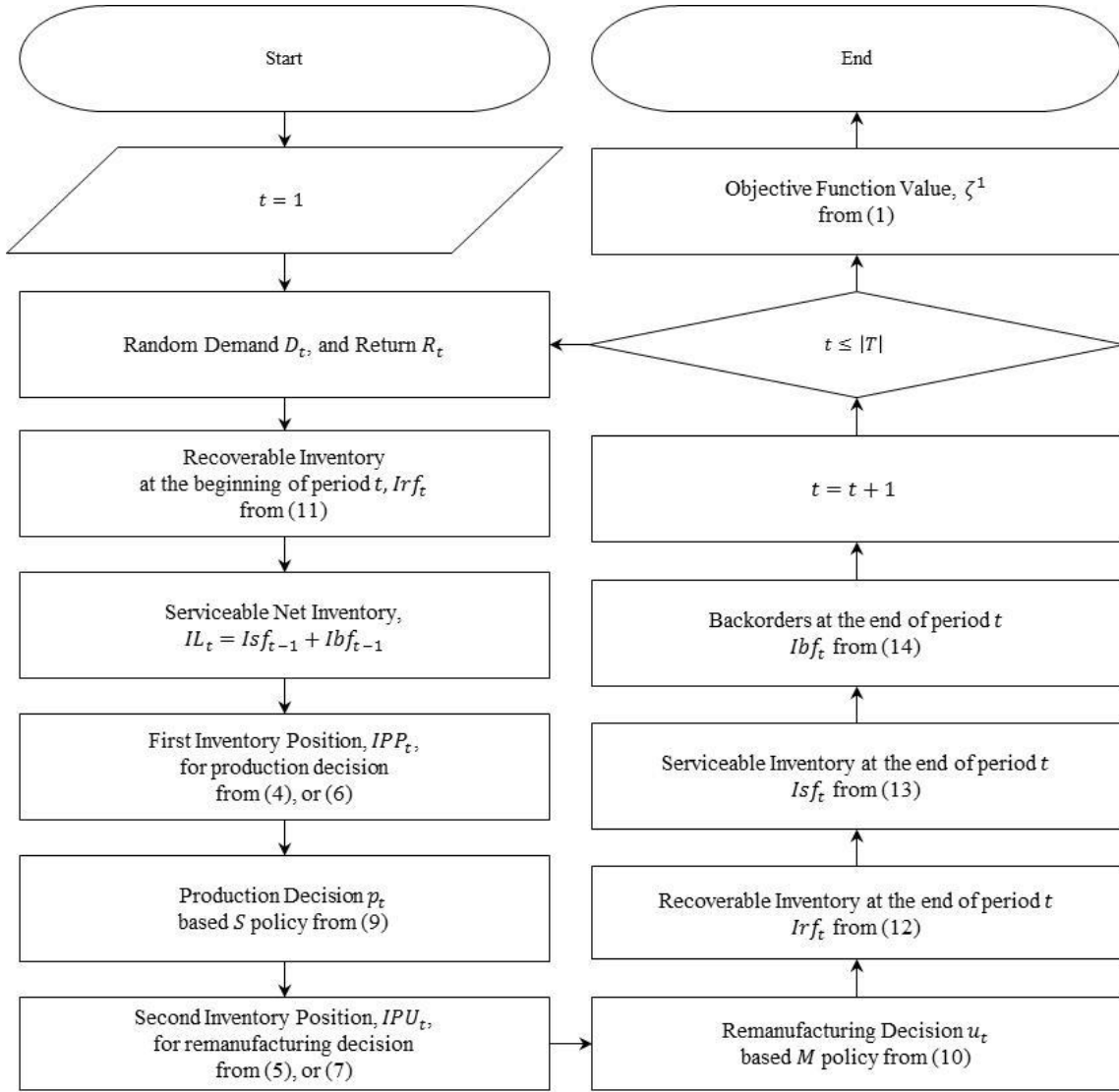
Figure 3.3   First Stage: Inventory Model

Note that equations (1) to (10) correspond to the same numbered equations in [17]. Finally, we can estimate each type of stock level as follows and Figure 3.3 illustrates a general event sequence of the first stage.

(i)   Recoverable inventory at the beginning of period t (before the decision u_t):

$$Irf_t = Irf_{t-1} + R_t - u_t \tag{11}$$

(ii)   Recoverable inventory at the end of period t (after the decision u_t):

$$Irf_t = Irf_t - u_t \tag{12}$$

(iii)   Serviceable inventory at the end of period t:

$$Isf_t = \begin{cases} Isf_{t-1} + p_{t-Lp} + u_{t-Lr} - D_t & \text{if } Isf_t \geq 0 \\ 0 & \text{otherwise} \end{cases} \tag{13}$$

(iv)   Backorders at the end of period t:

$$Ibf_t = \begin{cases} -Isf_t & \text{if } Isf_t < 0 \\ 0 & \text{otherwise} \end{cases} \tag{14}$$

The first stage makes an effort to decide the production p_t and the remanufacturing levels u_t which incur the average minimum backorder and holding costs throughout the system. However, to address the importance of the decisions p_t, and u_t made from two inventory positions IPP_t and IPU_t in each case of the different lead-times, we compare the results with the decisions from a single inventory position IP_t throughout this thesis. The decisions from two inventory positions are called the optimized decisions, and the other decisions from a single inventory position are called the sub-optimized decisions.

In the first stage, the average minimum holding costs always depend on the S and M levels, but it is hard to determine the optimal levels exactly. Thus, we approximate the final S and M levels by a heuristic approach to minimize the average costs. Before presenting it, we first define initial S and M levels as follows.

(i)   For the sub-optimized decisions from one inventory position

-     Larger remanufacturing lead-time ($Lr > Lp$)

$$S = M = (Lr - Lp - 1) \cdot \sum_k \mu(d_{k,t}) \tag{15}$$

where $\mu(d_{k,t})$ denotes a mean value to generate the random demand $d_{k,t}$

- Larger production lead-time $(Lp > Lr)$

$$S = M = (Lp - Lr - 1) \cdot \sum_k \mu(d_{k,t}) \tag{16}$$

(ii) For the optimized decisions from two inventory positions

- Larger remanufacturing lead-time $(Lr > Lp)$

$$S = (Lp + 1) \cdot \sum_k \mu(d_{k,t}) \tag{17}$$

$$M = (Lr - Lp - 1) \cdot \sum_k \mu(d_{k,t}) \tag{18}$$

- Larger production lead-time $(Lp > Lr)$

$$S = (Lp - Lr - 1) \cdot \sum_k \mu(d_{k,t}) \tag{19}$$

$$M = (Lr + 1) \cdot \sum_k \mu(d_{k,t}) \tag{20}$$

It is reasonable because the order-up-to levels play a role in the safety stocks for uncertain demand and they should consider each inventory position including the outstanding orders. Thus, for the sub-optimized decisions, the initial S and M levels are established to be equal because the inventory position IP_t is shared for each decision on production p_t and the remanufacturing level u_t. Also, the initial values count the half of the outstanding orders in the inventory position plus one more period safety stocks, respectively, which are anticipated according to a total mean values of the uncertain demand, $\sum_k \mu(d_{k,t})$. For the optimized decision from two inventory positions, one process with the shorter lead-time prepares one more period safety stocks than the total demands expected during the lead-time. On the other hand, the other process with the

longer lead-time only prepares the rest of the demands forecasted during the longer lead-time except for the amount prepared by the shorter lead-time process.

With the idea on the initial S and M levels, we build a heuristic search algorithm to find the final S and M levels which lead to minimize the average holding costs with the minimum levels of the production p_t remanufacturing u_t. Figure 3.4 illustrates the flow chart for the search algorithm for the final S and M.
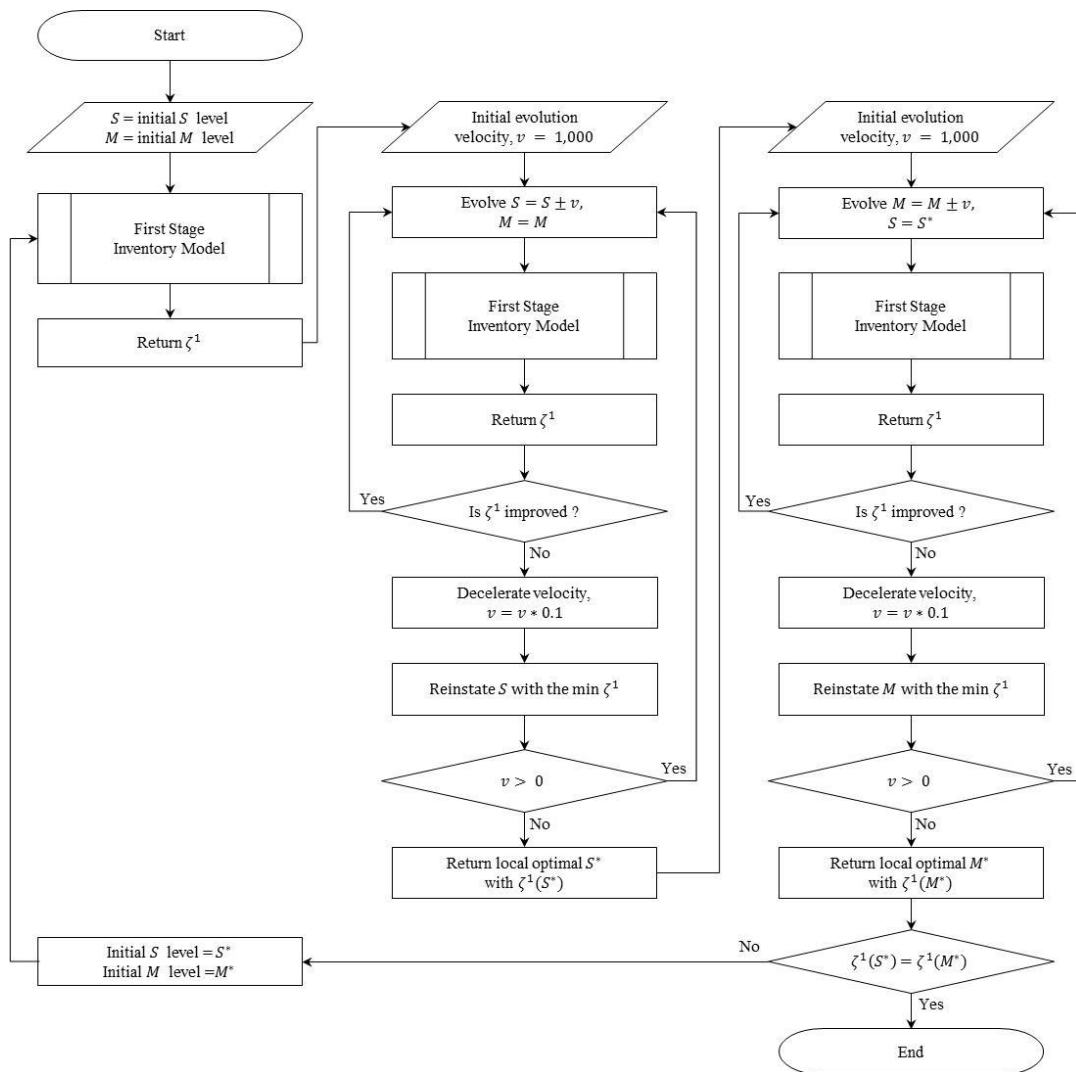

Figure 3.4   Search algorithm: the optimal S and M level

This algorithm is composed of a main iteration and two sub-iterations. In the main iteration, the algorithm first returns an objective function value for the initial S and M levels and enters the first sub-iteration for the S levels which plays role in searching for a local optimal value for the S level as the M level is fixed with the initial M value. Once the first sub-iteration returns a local optimal value for the S level, the next sub-iteration for the M level starts to look for a local optimal value for the M level as the local optimal value for the S level is fixed, and returns another local optimal value for the M level. If the objective function values found in each sub-iteration have the same value, the algorithm is terminated. Otherwise, the initial S and M levels are updated with the local optimal values found in each sub-iteration, and the algorithm repeats these procedures. For this algorithm, it is necessary to use the same values for the demand and the return in every iteration in order to minimize the random effect.

For the sub-iterations, we first define an evolution velocity v which has both positive and negative direction for each sub-iteration. Thus, in every iteration i of each sub-iteration, the S and M values of the previous iteration, $i-1$, are transmuted into $(S+v, S-v)$ or $(M+v, M-v)$, respectively. Once an objective function value is returned with the transmuted S or M value, the algorithm examine whether the objective function value is improved as comparing it with the current minimum value. If improved, then the evolution velocity is constantly maintained and the algorithm keeps looking for a better solution in each sub-iteration. However, if not, then the algorithm turns back to a point i where the minimum objective function value has been returned, and starts over to find a better solution with another transmuted values obtained from the

decelerated evolution velocity ($v = v * 0.1$). Each sub-iteration repeats these procedures until the velocity level falls below one ($v < 1$), and finally returns a local optimal value for S or M.

With the optimal S and M levels, the first stage aggregates the information on the minimum production and the remanufacturing levels which incurs the average minimum holding costs. Finally, we are ready to design the CLSC network for the hybrid manufacturing/remanufacturing system.

3.5   Second-Stage: CLSC Network Design

The second stage concentrates on building the CLSC network with the different processing lead-times under potential carbon emission regulations with the information on total products released from a factory in period t, pu_t ($= p_{t-Lp} + u_{t-Lr}$), and the needs to be remanufactured in period t, u_t, obtained from the first stage. This stage should use the same simulated values for the demands $d_{k,t}$ and the returns $r_{k,t}$ placed in retailer k for each period t as the first stage because the products pu_t are dependent on the random values generated in the first stage. Moreover, the demands in period t are satisfied not only with the products pu_t but also with serviceable on-hand stocks Isf_{t-1} in period $t-1$ so that the same initial serviceable on-hand stock Isf_0 should be established in this stage. Likewise, the same initial recoverable on-hand stock Irf_0 should be used as an input data in the second stage because the decision on the needs u_t is determined according to the return $r_{k,t}$ and the recoverable on-hand stock Irf_{t-1} in

period $t - 1$. Unless those are included in the second stage, the backorders generated in this stage could be greater than those of the first stage and we could not satisfy the needs to be remanufactured in period t. Also, it could lead total serviceable on-hand stocks $\sum_j Is_{j,t}$ and total recoverable on-hand stocks $\sum_j Ir_{j,t}$ at the end of period t to be different from those of the first stage. With this information, we can formulate the second stage model as a mixed integer program.

$$Min \quad \sum_{i \in L} ff_i \cdot x_i + \sum_{j \in L} fw_j \cdot y_j + \sum_{l \in L} fc_l \cdot z_l$$

$$+ \frac{1}{\rho} \left\{ h^S \cdot \sum_{t \in T} \sum_{j \in L} Is_{j,t} + h^B \cdot \sum_{t \in T} \sum_{k \in L} Ib_{k,t} + h^R \cdot \sum_{t \in T} \sum_{l \in L} Ir_{l,t} \right.$$

$$\left. + \sum_{t \in T} \sum_{(a,b) \in A} c_{a,b} \left(\alpha_{a,b,t} + \beta_{a,b,t} + \gamma_{a,b,t} + \delta_{a,b,t} \right) \right\} \tag{21}$$

subject to

$$\sum_{i \in L} \sum_{j \in L} \alpha_{ij,t} = pu_t, \ \forall \, t \in T \tag{22}$$

$$\sum_{j \in L} Is_{j,0} = Isf_0 \tag{23}$$

$$Is_{j,0} \le B \cdot y_j, \ \forall \, j \in L \tag{24}$$

$$Is_{j,t} = \sum_{i \in L} \alpha_{i,j,t} + Is_{j,t-1} - \sum_{k \in L} \beta_{j,k,t} \,, \ \forall \, j \in L, \ \forall \, t \in T \tag{25}$$

$$Ib_{k,t} = d_{k,t} - \sum_{j \in L} \beta_{j,k,t} \,, \ \forall \, k \in L, \ \forall \, t \in T \tag{26}$$

$$\sum_{l \in L} \gamma_{k,l,t} = r_{k,t}, \ \forall \, k \in L, \ \forall \, t \in T \tag{27}$$

$$\sum_{l \in L} Ir_{l,0} = Irf_0, \ \forall \, l \in L \tag{28}$$

$$Ir_{l,0} \le B \cdot z_l \tag{29}$$

$$\sum_{l \in L} \sum_{i \in L} \delta_{l,i,t} = u_t, \ \forall \, t \in T \tag{30}$$

$$Ir_{l,t} = \sum_{k \in L} \gamma_{k,l,t} + Ir_{l,t-1} - \sum_{i \in L} \delta_{l,i,t}, \ \forall \, l \in L, \forall \, t \in T \tag{31}$$

$$Is_{j,t} \le C \cdot y_l \quad \forall \, j \in L, \forall \, t \in T \tag{32}$$

$$Ir_{l,t} \le C \cdot z_l \quad \forall \, l \in L, \forall \, t \in T \tag{33}$$

$$\sum_{i \in L} \alpha_{i,j,t} \le B \cdot y_j, \ \forall \, j \in L, \forall \, t \in T \tag{34}$$

$$\sum_{k \in L} \gamma_{k,l,t} \le B \cdot z_l, \ \forall \, l \in L, \forall \, t \in T \tag{35}$$

$$\sum_{l \in L} \delta_{l,i,t} \le B \cdot x_i, \ \forall \, i \in L, \forall \, t \in T \tag{36}$$

$$\sum_{j \in L} \alpha_{i,j,t} \le B \cdot x_i, \ \forall \, i \in L, \forall \, t \in T \tag{37}$$

$$\sum_{k \in L} \beta_{j,k,t} \le B \cdot y_j, \ \forall \, j \in L, \forall \, t \in T \tag{38}$$

$$\sum_{i \in L} \delta_{l,i,t} \le B \cdot z_l, \ \forall \, l \in L, \forall \, t \in T \tag{39}$$

$$\sum_{i \in L} x_i = 1 \tag{40}$$

$$\sum_{j \in L} y_j \le |L| \tag{41}$$

$$\sum_{l \in L} z_l \le |L| \tag{42}$$

$$\alpha_{i,j,t}, \ \beta_{j,k,t}, \ \gamma_{k,l,t}, \ \delta_{l,i,t}, \ Is_{j,t}, \ Ib_{k,t}, \text{and } Ir_{l,t} \ge 0 \tag{43}$$

$$x_i, y_j, \text{and } z_l \in \{0, 1\} \tag{44}$$

The objective function minimizes three types of costs: 1) the annualized fixed costs to open each type of facility; 2) the average serviceable and recoverable holding cost and backorders which are annually accumulated; and 3) the average transportation cost between facility to facility which is annually accrued, where $\rho = |T|/52$ weeks. For the holding and backorder costs in the objective function of the second stage, although we have optimized those costs in the first stage, they should be included in the objective function of the second stage because the second stage are responsible for allocating the inventories found in the first stage to each different facility.

For an annualized investment in each facility, we assume that facility life span is finite and estimate those by a following equation for determining the value of the series of end-of-period payment A when the present sum P is known [25].

$$A = P \left[\frac{i(1+i)^\rho}{(1+i)^\rho - 1} \right] \tag{45}$$

where i is an interest rate.

The cost rates of carrying three types of inventory are the same as the cost rates defined in the first stage. The transportation cost $c_{a,b}$ between facilities a and b is defined as dollar per unit incurred by a cost ε per unit of distance travelled per unit of product and distance from location a to b as follows.

$$c_{a,b} = \varepsilon \cdot \tau_{a,b} \quad \text{where } (a,b) \in A \tag{46}$$

The cost ε composes of several components including the carbon emission cost under the potential government regulation in the following manner [6]:

$$\varepsilon = \frac{v + f(g + \theta \cdot e)}{q} \tag{47}$$

Constraint (22) ensures that total quantities to be distributed from a factory i to warehouse j in period t should correspond to total finished goods pu_t released from a factory in period t obtained from the first stage. Constraint (23) guarantees the serviceable on-hand stock initialized in the first stage should be the same as that of the second stage. Constraint (24) assures the initial stocks are allocated in warehouses j to be built, where B is a sufficiently large number. Constraint (25) calculates the serviceable on-hand stocks $Is_{j,t}$ at the end of period t after shipping out to satisfy the demand from warehouse j. Constraint (26) represents that non-satisfied demands generate the backorder $Ib_{k,t}$. Constraint (27) ensures that total returned items shipped out from a retailer site k should be the same as the returns $r_{k,t}$. Constraints (28) and (29) represent that the same initial recoverable on-hand stock should be allocated in collection center l to be built in the second stage, where B is a sufficiently large number in constraint (29). Constraint (30) assures the needs u_t to be remanufactured from the first stage should be satisfied with total quantities shipped out from collection center l. Constraint (31) estimates the recoverable on-hand stock $Ir_{l,t}$ at the end of period. Constraints (32) and (33) prevent each type of on-hand stock, $Is_{j,t}$ and $Ir_{l,t}$, at the end of the period t from exceeding the storage capacity C in two types of storage center. Constraints (34) to (39) guarantee all types of distributions are only shipped in or out from a facility to be built, where B is a sufficiently large number. Constraints (40) to (42) limit the possible number of facility not to exceed the total potential locations, but

since our model only consider one factory with each one production-up-to level S and remanufacturing-up-to level M, constraint (40) only looks for a location for one factory. Constraint (43) preserves non-negativities on the transportation and inventory decision variables while constraint (44) assures the binary nature of the facility location decision variables.

The second stage model is a mixed integer linear program (MILP) that designs the CLSC network with the number and location of the optimal facilities to minimize the annualized investment as well as the costs to transport products between facilities. In addition, this model guarantees total serviceable and recoverable on-hand stocks, and total backorders at the end of period t in the second stage correspond to those which minimize the average holding costs in the first stage. Therefore, our model can be implemented for a recovery system with different remanufacturing processing time from a regular production.

CHAPTER 4 NUMERICAL ANALYSIS

In this chapter, we conduct numerical analysis on the impact of the different processing lead-times on the configuration of the CLSC in the hybrid manufacturing/ remanufacturing system under the potential carbon emission regulation. Our two-stage optimization approach for the CLSC design suggests anticipating the forward and the reverse flows of the network in the first stage, and designing the CLSC network under the potential carbon emission regulation on the transportation in the second stage with the information on the production and the remanufacturing levels in each period obtained from the first stage.

To address the importance of the first stage optimization on the CLSC design of the recovery system with the different processing lead-times for the production and the remanufacturing, we conduct two types of experiments in this numerical analysis: One is an experiment for the sub-optimized decisions on the production p_t and the remanufacturing u_t levels in each period when one inventory position IP_t, which is defined in equation (3), is implemented for both decisions in the first stage; the other is for the optimized decisions when two inventory positions IPP_t and IPU_t, which are defined in equations (4) to (7) for each case of the different lead-times, is applied on each decision on the production p_t and the remanufacturing u_t in the first stage. In addition, each type of the experiment considers two cases for the different lead-times: One is a case of larger remanufacturing lead-time; the other is of larger production lead-time.

4.1   Assumptions

This section presents the assumptions used for the numerical analysis.

(i)   The model concentrates on the environment of an electronics original equipment manufacturer (OEM) which has a recovery system and produces an electronics component.

(ii)   Ten retailer regions are given and each retailer has weekly demand and return over 20 years of the facility life span considered.

(iii)   The longer lead-time is assumed to be 10 weeks and the shorter is 2 weeks in both cases of the different lead-times.

4.2   Parameter Estimation

For our numerical example, we choose a scenario for weekly random demand $d_{k,t}$ and return $r_{k,t}$ which are normally distributed on $[\mu = 10{,}000, \sigma = 1{,}000]$ and $[\mu = 2{,}500, \sigma = 1{,}000]$, respectively, where the return rate ρ is 0.5, defined as the quotient of the mean of return $\mu(r_{k,d})$ and the mean of demands $\mu(d_{k,t})$, and the coefficient of variation c_v, which is defined as the ratio of the standard deviation σ to the the mean μ, is 0.2 for both the demand and the return distribution [17].

The fixed cost (\$ million) of opening facilities is randomly generated once in each retailer zone according to a uniform distribution and calculated by equation (36) in section 3.5 with an interest rate of 10 percent and facility life span of 20 years. The cost for a factory ff_i ranges on $[100, 200]$ based on the data from Pecht [26], the cost for

each warehouse fw_j and collection center fc_l on $[10, 15]$ from Area Development Online News Desk [31]. We use the same values for these fixed costs when we conduct the sensitivity analysis under the different carbon emission costs to minimize the random effects. Figure 4.1 presents each type of the fixed cost rates in the 10 different retailer regions.
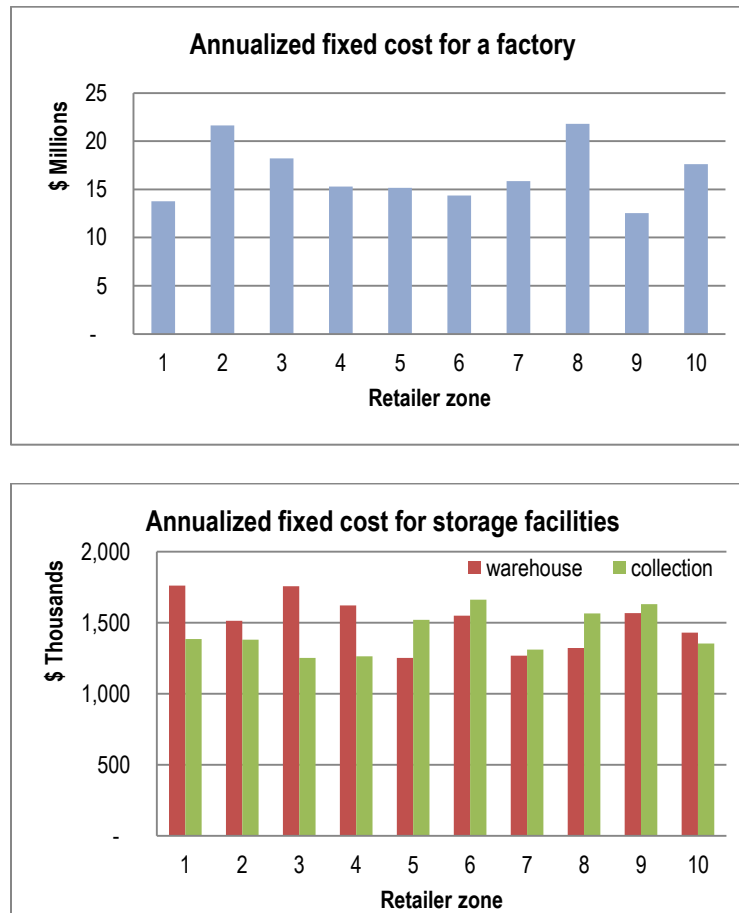
Figure 4.1   Randomly generated fixed costs for facilities

Based on data from Clottey *et al*. [7], we suppose the average unit purchase price of the returned product is \$450 including annual holding cost of 15% so that the recoverable holding cost h^R is estimated at \$1.3 per unit per week. The serviceable

holding cost h^S is valued at \$2.6 which is twice as much as the recoverable holding cost [17]. We also decide the backorder cost h^B at \$50 per unit per week [17]. In addition, we suppose that each warehouse and collection center can hold 50,000 units of the product or the return in each period based on Company Profile of Microtech Technology Company Limited [35]. In addition, we assume that a sufficiently large value of B for equations (24), (29), and (34) to (39) is 10 billion.

For the unit transportation cost ε defined by Cachon [6], we assume that a truck which achieves 6 miles per gallon of diesel fuel is the unique transportation mode and the fuel consumption f is at 0.392 liter per kilometer in accordance with \$0.479 per kilometer of the non-fuel variable cost v. The fuel price g per unit of fuel is estimated at \$1.086 per liter according to a report of U.S. Energy Information Administration (EIA) [37]. From a report of EIA [36], approximately 22.38 pounds of CO_2 are emitted by burning a gallon of diesel fuel so that the amount of emission θ released by the consumption of one unit of diesel fuel is estimated at 2.669 $kg\ CO_2$ per liter. For the total units of product q which can be carried by a truck, we assume that 10,000 units of the product are loaded. To model potential government regulation, we implement 5 different carbon emission costs. Table 4.1 summarizes the unit transportation cost according to the different carbon emission cost rates.

Table 4.1   Unit transportation cost for different carbon emission costs

$e\ (\$/kg)$	0	5	10	15	20
$\varepsilon\ (\$/km/unit)$	0.00009	0.00061	0.00113	0.00165	0.00218

Finally, to simplify our model, we consider a one dimensional network for the given retailer zones which act as the potential facility locations with the distance $\tau_{a,b}$ where $(a, b) \in A$ illustrated in the Figure 4.2. We assume that transportation cost within a zone is negligible.
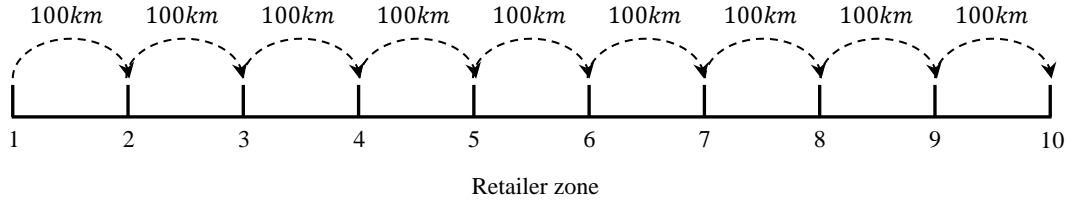
Figure 4.2   One dimensional network

4.3   First Stage Optimization

In this section, we describe how to determine the levels of the production p_t and the remanufacturing u_t in each period t which lead to the minimum average holding and backorder costs over 20 years based on the inventory model introduced in the section 3.4. We also demonstrate the significance of the first stage optimization achieved from two inventory positions for each decision on the production p_t and the remanufacturing u_t as comparing with the sub-optimized decisions obtained from one inventory position in two cases of the different processing lead-time.

First of all, based on the event sequence of the first stage defined in section 3.4, we initialize the order-up-to levels for the production S and the remanufacturing M. Table 4.2 represents the initial conditions on the S and M levels for each decision

obtained from the different inventory position types in two cases of the different lead-times.

Table 4.2   Initial levels for S and M

(i)   For the sub-optimized decisions from one inventory position

	$Lr > Lp$	$Lp > Lr$
S and M	700,000	700,000

(ii)   For the optimized decisions from two inventory positions

	$Lr > Lp$	$Lp > Lr$
S	300,000	700,000
M	700,000	300,000

With the initial conditions on the S and M levels, we approximates the final S and M levels by the heuristic search algorithm defined in section 3.4. However, prior to presenting the results from the algorithm, it is essential for the first stage to apply a statistical analysis for steady-state parameters [19], which eliminates the initial transient periods to ensure the steady-state mean over the entire periods for the objective function value in the first stage not to be biased. This is because we initialize serviceable and recoverable on-hand stocks as zero and there are no finished items until the period at least reaches the shorter processing lead-time in both cases. These initial conditions result in large backorders and cause the cost to be too big in the initial periods. Figure 4.3 illustrates the backorder and the total cost flows over the entire period including the

initial transient period, respectively, with the initial S and M levels for the optimized decisions from the two inventory positions.
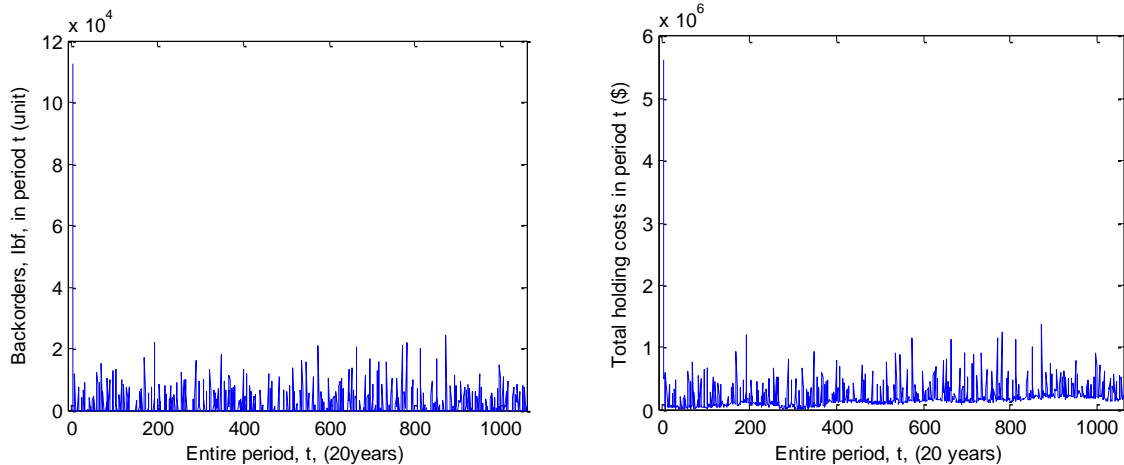
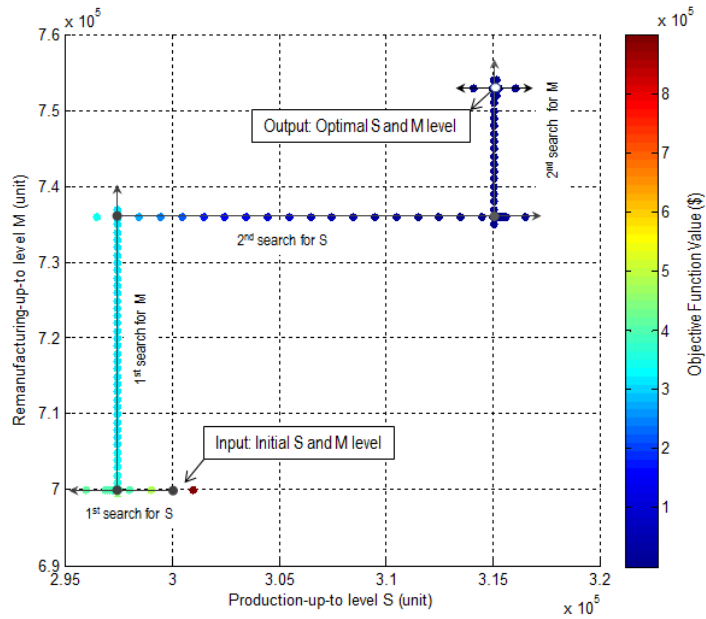(i)   Larger remanufacturing lead-time $Lr = 10, \; Lp = 2$
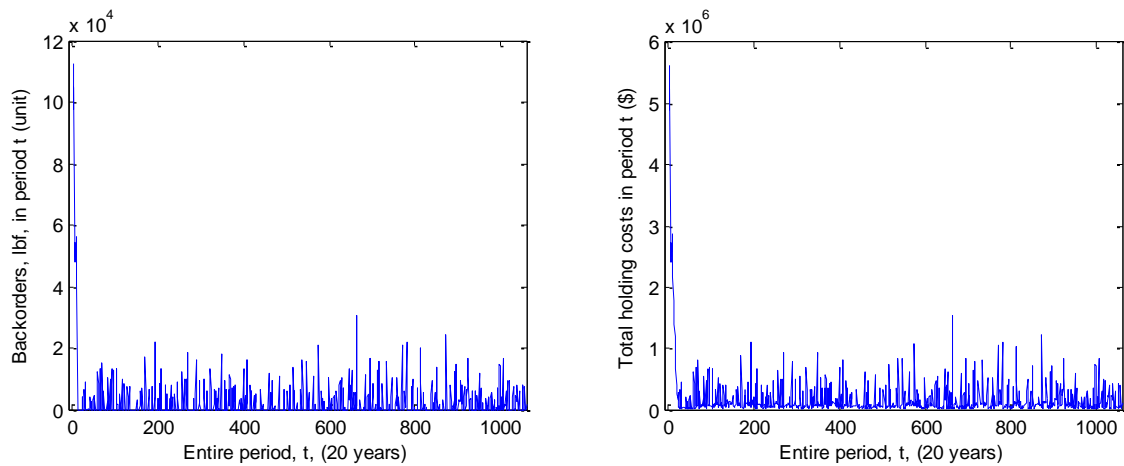
(ii)   Larger production lead-time $Lp = 10, \; Lr = 2$

Figure 4.3   Variable flows with the transient periods

We determine the initial transient periods to be $t \leq 20$ in the both cases of the different lead-times. It is reasonable because the initial condition on the serviceable and the recoverable condition cause a huge amount of the orders as much as the S and M levels at the very beginning of the period, and the orders arrive at the period after each

lead-time at once. Therefore, before the orders arrive, each inventory position IPP_t and IPU_t includes the information as the outstanding orders for them so that the stable decisions on the production and the remanufacturing cannot be made around the longer processing lead-time. Instead of the initial transient periods, we add extra 20 weeks at the end of the entire period to ensure that the simulation is conducted over the 20 year facility life span in the second stage.

With this idea, we find the final S and M levels by the search algorithm defined in section 3.4. Table 4.3 presents the final S and M levels, and the total iterations of the algorithm to find the final levels. Figures 4.4 and 4.5 illustrate the results of the algorithm to reach the optimal S and M level for the sub-optimized decision and the optimized decision, respectively.

Table 4.3   Final S and M levels

(i)   For the sub-optimized decision from one IP

	$Lr > Lp$	$Lp > Lr$
Number of Iterations	300	672
S	668,704	660,945
M	725,433	730,684

(ii)   For the optimized decision from two IP

	$Lr > Lp$	$Lp > Lr$
Number of Iterations	464	370
S	315,143	720,596
M	753,517	318,653
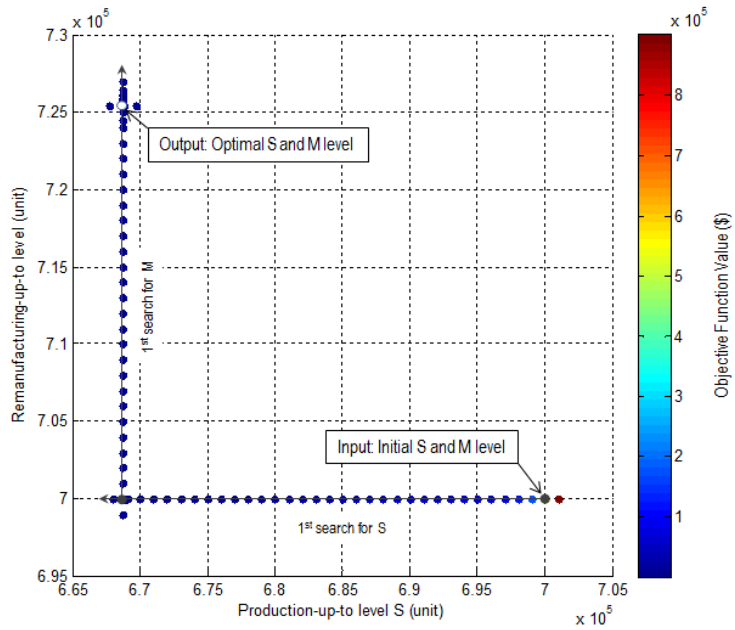
(i)   Larger remanufacturing lead-time $Lr = 10, \ Lp = 2$
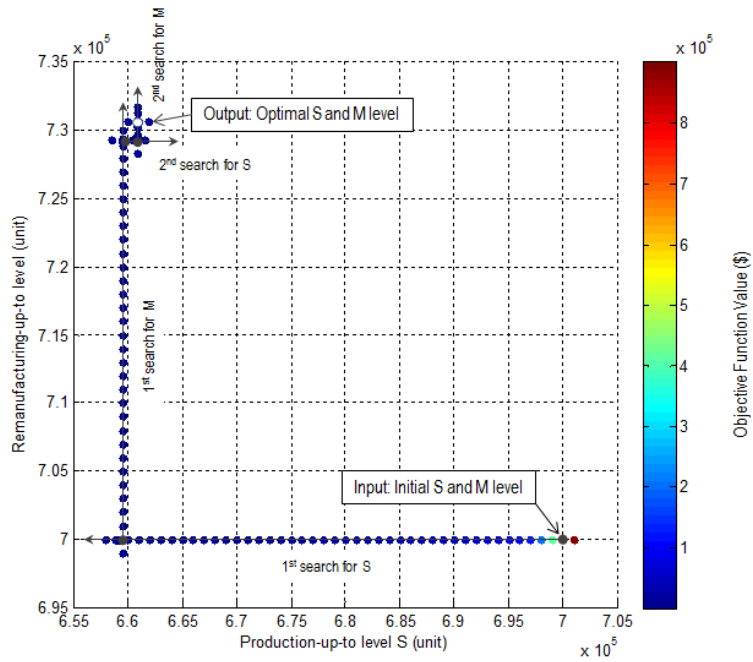
(ii)   Larger production lead-time $Lp = 10, \ Lr = 2$

Figure 4.4   Algorithm for the sub-optimized decision from one IP

(i)   Larger remanufacturing lead-time $Lr = 10, \ Lp = 2$
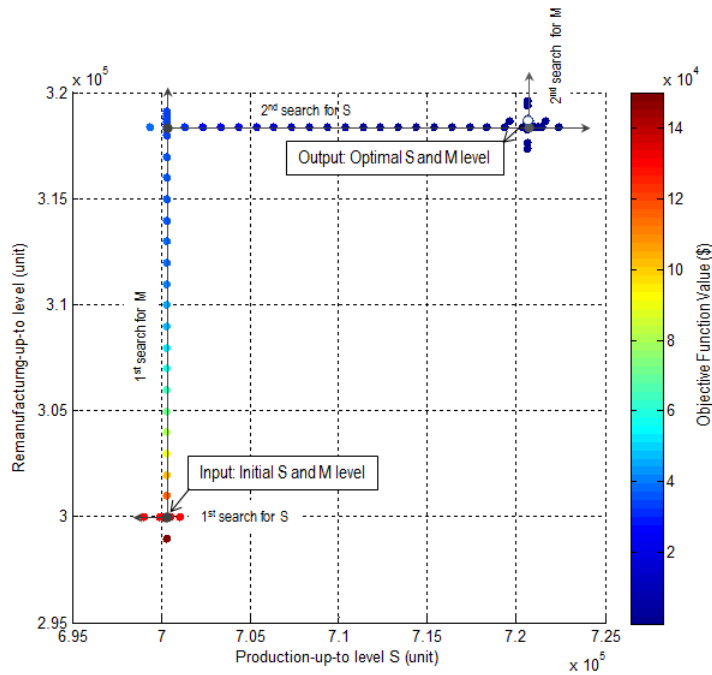
(ii)   Larger production lead-time $Lp = 10, \ Lr = 2$

Figure 4.5   Algorithm for the optimized decision from two IPs

With the final S and M levels for the sub-optimized decisions from the one inventory position and the optimized decisions from the two inventory positions, we compare the objective function values obtained from each different inventory position type as illustrated in Figure 4.6. Based on the batch means method [19], we divide each objective function value over 20 years into 20 batches so that each dot in the boxplots represents the average objective function value for a year.
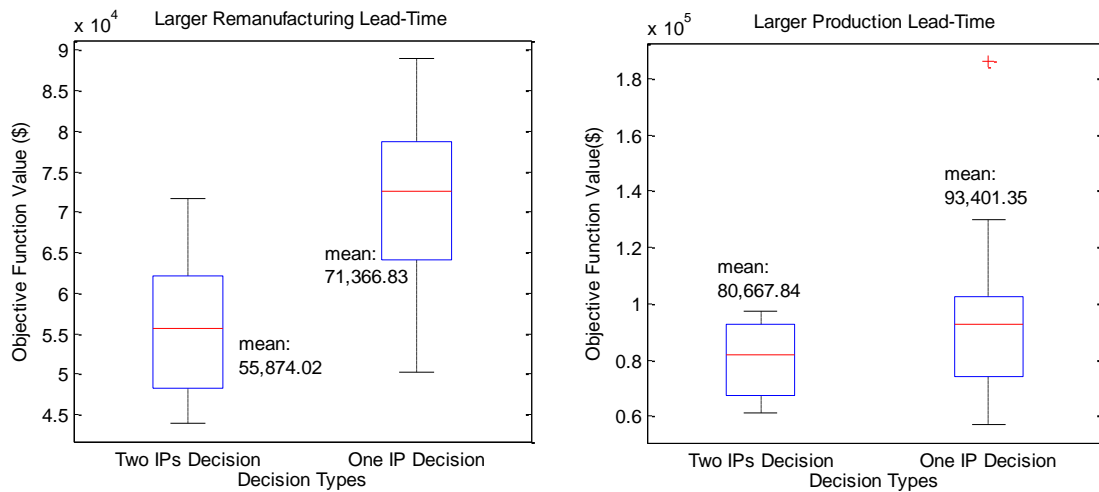
Figure 4.6   Optimal objective function value in the first stage

According to the results from a t test, the objective function value (μ_1) from the optimized decisions is significantly less than that (μ_2) of the sub-optimized decisions based on hypothesizes: $H_0: \mu_1 - \mu_2 = 0$; $H_A: \mu_1 - \mu_2 < 0$. For the case of the larger remanufacturing lead-time, $p - value$ $(< 0.0001^*)$ is smaller than a significance level of $.05$, and for the other case of the larger production lead-time, $p - value$ (0.0385) is also smaller than a significance level of $.05$.
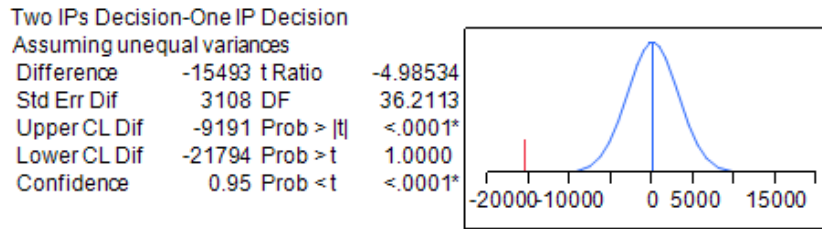
(i)   Larger remanufacturing lead-time
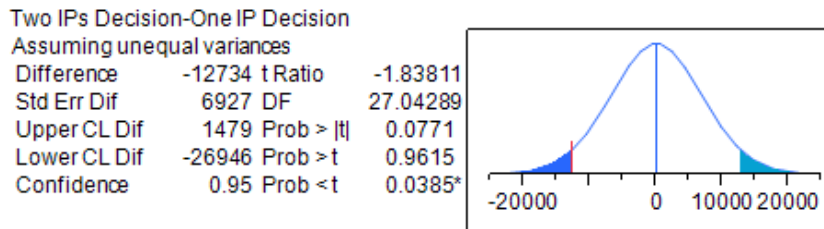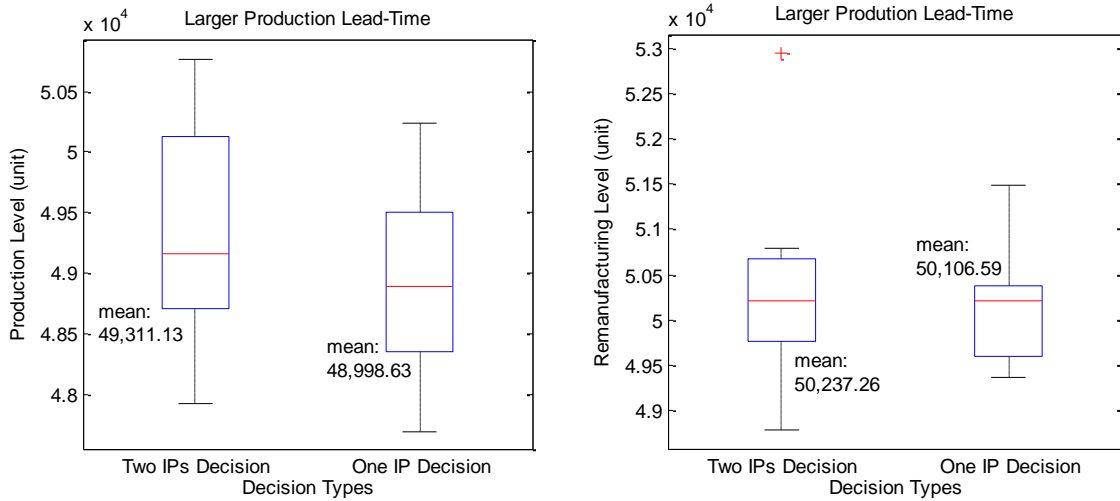

(ii)   Larger production lead-time

Figure 4.7 t Test for objective function value of each decision type

The difference of the optimal objective function values between the sub-optimized decision from the one inventory position and the optimized decision from the two inventory positions is caused by the different orders for the production p_t and the remanufacturing u_t as illustrated in Figure 4.8. This is because the inventory position for the shorter processing lead-time, as defined by Kiesmüller [17], only considers the outstanding orders which arrive in the next period after the shorter lead-time while the traditional inventory position IP_t counts all outstanding orders. Therefore, although the sub-optimized decision from one inventory position has higher ordering-up-to level for the shorter lead-time than that of the optimized decision, the one inventory position IP_t including all outstanding orders reduces the order levels, and it finally generates more frequent backorders.
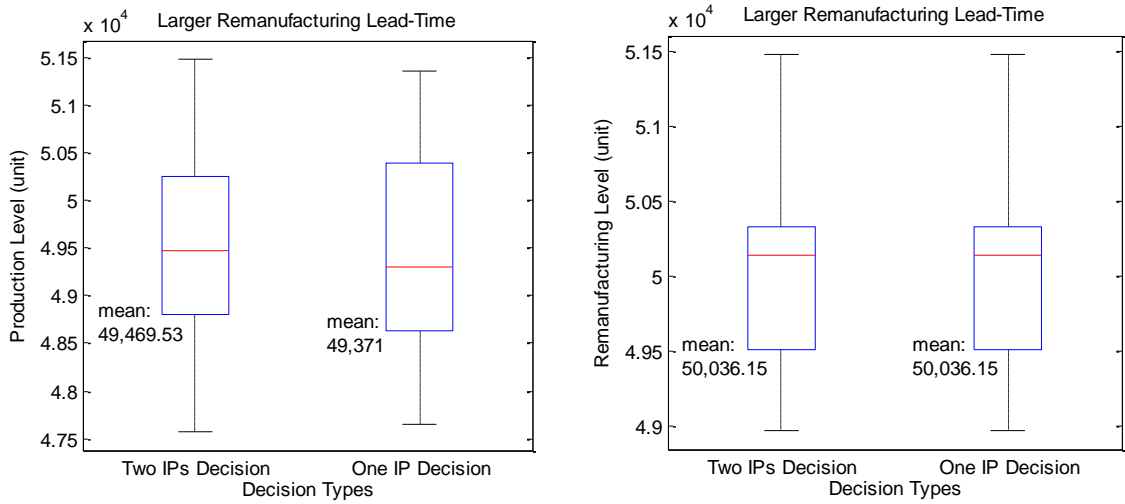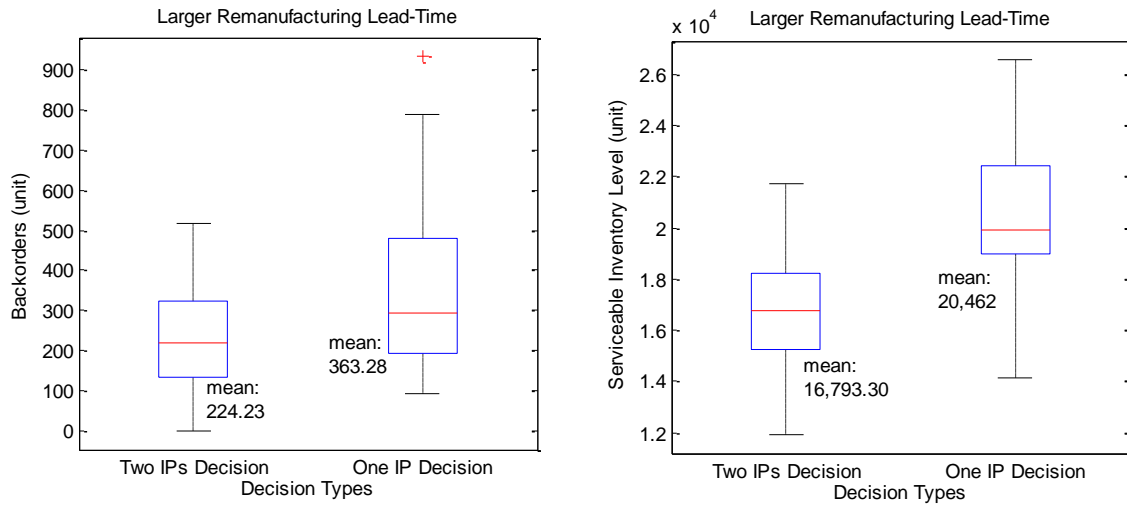
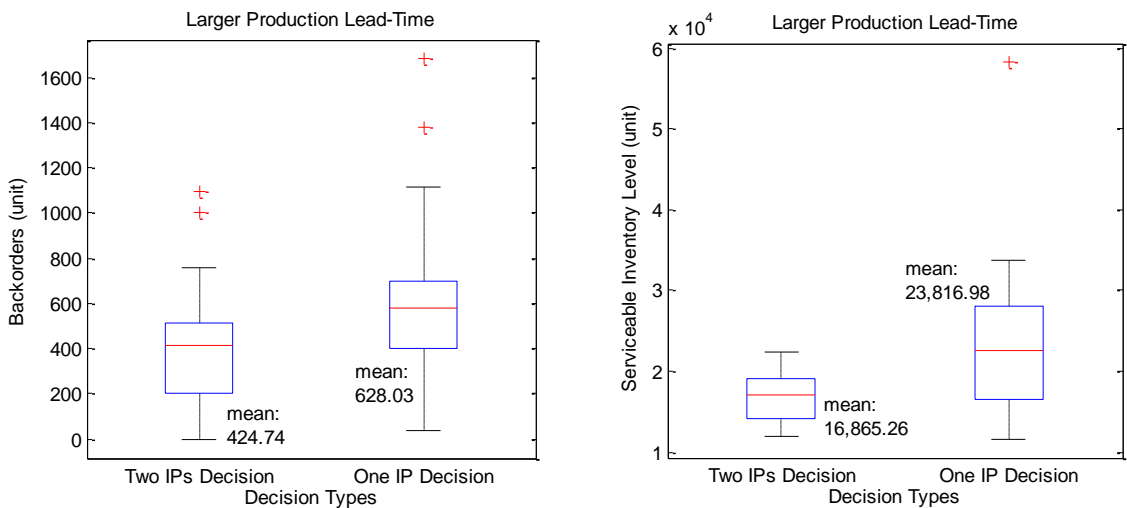(i)   Larger remanufacturing lead-time

(ii)   Larger production lead-time

Figure 4.8   Comparison for the production and remanufacturing levels

Moreover, once the backorders occur, temporarily a large amount of the ordering decision is made, and it causes the average serviceable on-hand stock at the end of the period to be higher, as illustrated in Figure 4.9.
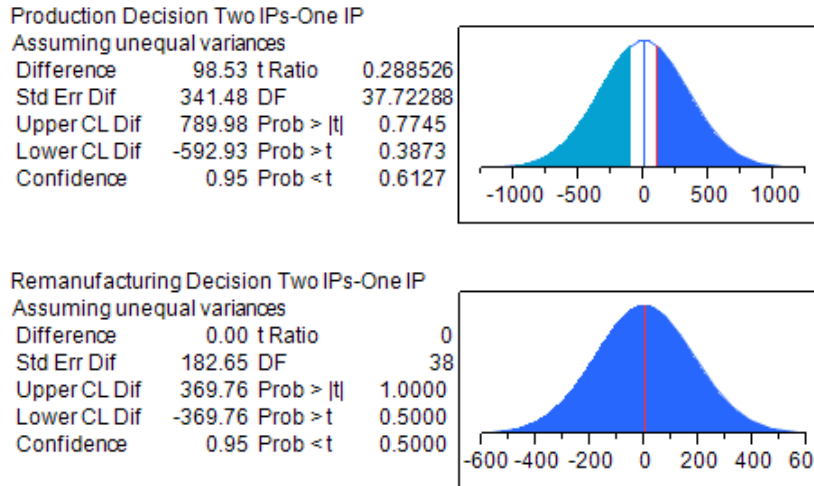
(i)   Larger remanufacturing lead-time
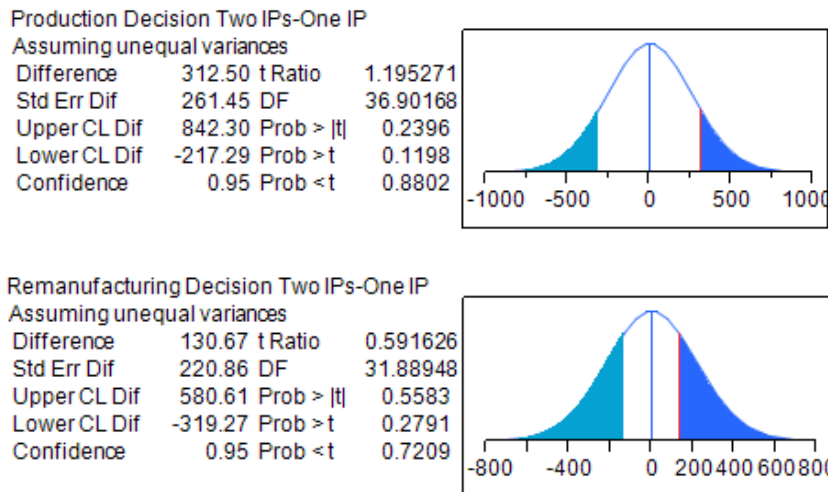

(ii)   Larger production lead-time

Figure 4.9   Backorders and serviceable on-hand stocks

According to t test for the production and the remanufacturing levels obtained from each decision type in both cases of the different lead-times, although there is no significant difference between the sub-optimized decision and the optimized decision on

the production and the remanufacturing levels as illustrated in Figure 4.10, such small

differences lead to the statistically significant difference for the backorders and the

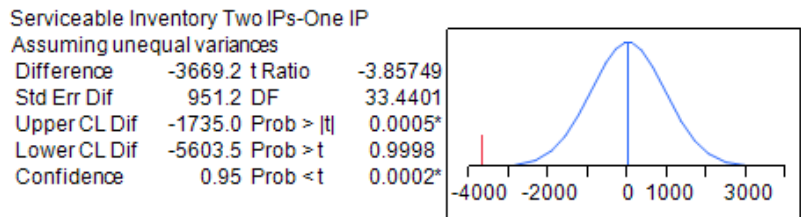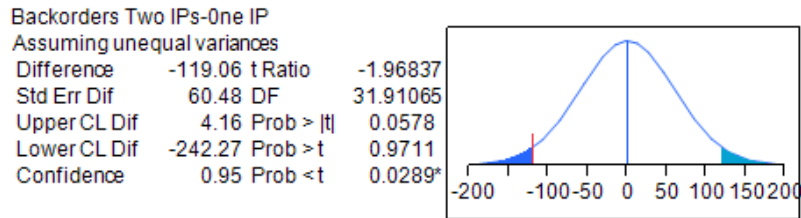serviceable inventory levels presented in Figure 4.11.
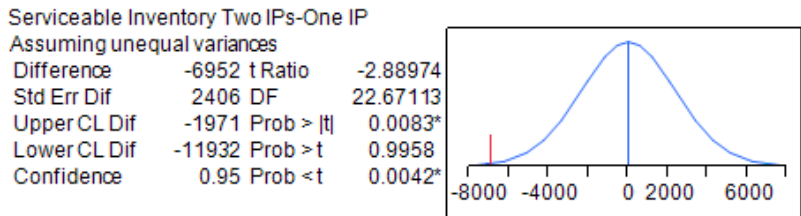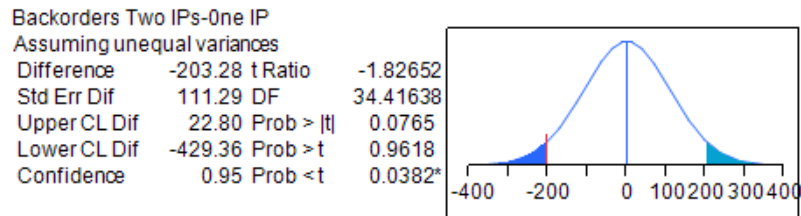

(i)   Larger remanufacturing lead-time

(ii)   Larger production lead-time

Figure 4.10   *t* Test for production and remanufacturing levels

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Backorders Two IPs-One IP
Assuming unequal variances
Difference   -119.06 t Ratio   -1.96837
Std Err Dif   60.48 DF   31.91065
Upper CL Dif   4.16 Prob > |t| 0.0578
Lower CL Dif   -242.27 Prob >t   0.9711
Confidence   0.95 Prob <t   0.0289*

Serviceable Inventory Two IPs-One IP
Assuming unequal variances
Difference   -3669.2 t Ratio   -3.85749
Std Err Dif   951.2 DF   33.4401
Upper CL Dif   -1735.0 Prob > |t| 0.0005*
Lower CL Dif   -5603.5 Prob >t   0.9998
Confidence   0.95 Prob <t   0.0002*

(i)   Larger remanufacturing lead-time

Backorders Two IPs-0ne IP
Assuming unequal variances
Difference   -203.28 t Ratio   -1.82652
Std Err Dif   111.29 DF   34.41638
Upper CL Dif   22.80 Prob > |t| 0.0765
Lower CL Dif   -429.36 Prob >t   0.9618
Confidence   0.95 Prob <t   0.0382*

Serviceable Inventory Two IPs-One IP
Assuming unequal variances
Difference   -6952 t Ratio   -2.88974
Std Err Dif   2406 DF   22.67113
Upper CL Dif   -1971 Prob > |t| 0.0083*
Lower CL Dif   -11932 Prob >t   0.9958
Confidence   0.95 Prob <t   0.0042*

(ii)   Larger production lead-time

Figure 4.11   *t* Test for backorders and serviceable inventory

For the recoverable on-hand stocks at the end of the period, in the case of a larger remanufacturing lead-time, there is no on-hand stock in every period in the both decision types because the inventory position, as defined by Kiesmüller, only affects the shorter lead-time decision [17] and all returned items are remanufactured at once based on the

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remanufacturing-up-to level M. However, in the other case of the larger production lead-time, the optimized decision from the two inventory positions leads the average recoverable on-hand stocks to be higher than that of the sub-optimized decision from the one inventory position. This is because the optimal remanufacturing-up-to level M for the sub-optimized decision is not affected by the remanufacturing lead-time, but is similar to the level in the case of the larger remanufacturing lead-time. On the other hand, for the optimized decision from the two inventory positions, the recoverable holding cost forces the M level to be as small as possible because it is lower than the serviceable holding cost. Therefore, the system keeps the returned items in the recoverable inventory instead of pushing them to be remanufactured [17].
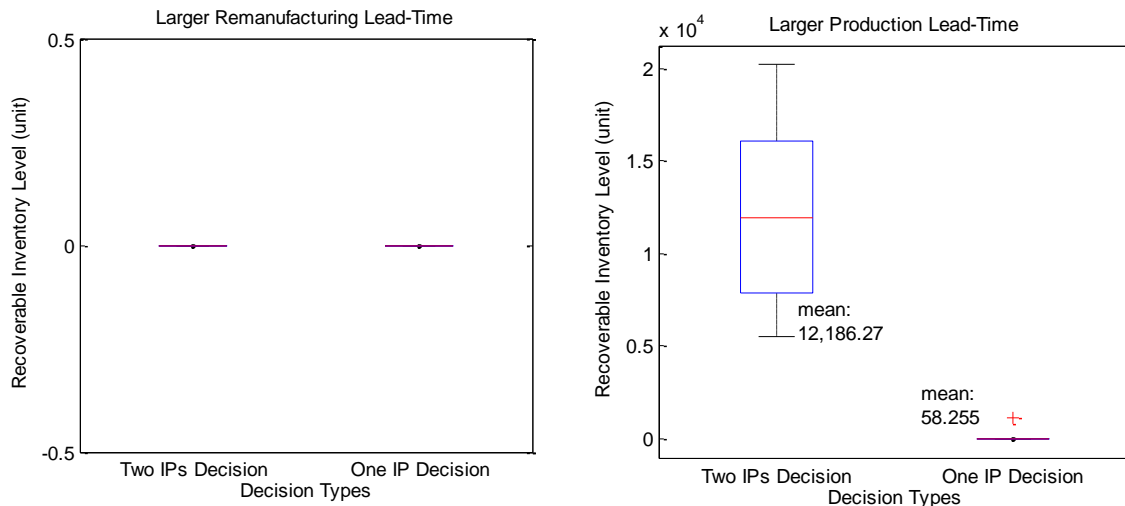
Figure 4.12   Recoverable on-hand stock

In this section, we optimized the forward and reverse flows and studied the different results caused by the sub-optimized decisions and the optimized decisions. Therefore, with the fundamental information from the first stage, we are finally ready to design the CLSC network in the second stage.

4.4   Second Stage Optimization

In the second stage, we design the CLSC network under the potential carbon emission regulation for two cases of the different processing lead-times. We also study the different configurations of the network with the fundamental information from the sub-optimized decisions and the optimized decisions obtained from the first stage.

In the first stage, since we exclude the initial transient period to ensure the average minimum holding costs to be less biased, we import pu_t and u_t except for their values during the transient period and assume that the first period of the second stage is the week ($21st$ week) after the transient periods (first 20 weeks), and that the last week is $1,060th$ week of the first stage. Based on the input parameters obtained from the first stage, and the cost parameters defined in the section 4.2, the second stage is solved by the CPLEX 12.1.0 MIP solver implemented in GAMS.

The second stage implements 4 types of the information from the first stage to build the CLSC network: 1) the total products released from a factory in period t, pu_t, 2) the needs to be remanufactured in period t, u_t, 3) the initial serviceable on-hand stocks Isf_0, and 4) the initial recoverable on-hand stock Irf_0. The initial period $t = 0$ represents the end of the $20th$ week of the first stage before eliminating the transient period because we assume that the first week of the second stage is the $21st$ week of the first stage. The information from the first stage is very important to the second stage because these provide the understanding of the forward and reverse flows for the CLSC design. Thus, it is necessary for the second stage to verify whether each type of the total inventory levels, which are stored in every storage facility, at the end of each period in

the second stage is exactly the same as those of the first stage because if not, the results of the second stage cannot guarantee the reliability. Thus, we conduct the equivalence test on the serviceable on-hand stocks, the recoverable on-hand stocks, and the backorders obtained from each stage in the case of larger remanufacturing lead-time as illustrated in Figure 4.13. The results of the each equivalence test shows that each type of the inventory in the second stage has the same level of the first stage.
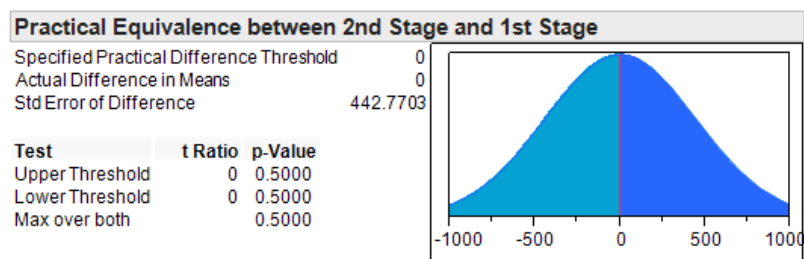
(i)   Serviceable on-hand stocks
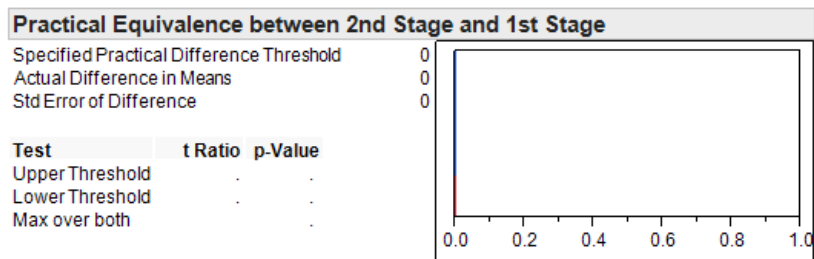
(ii)   Recoverable on-hand stocks
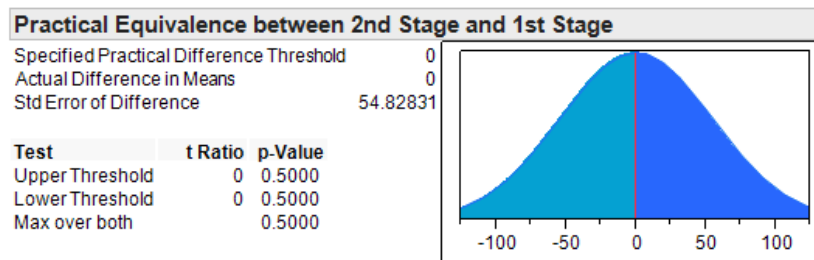
(iii)   Backorders

**Figure 4.13   Equivalence test for the reliability of the second stage**

With the equivalence test result, we could assure our second stage model to be connected with the first stage so that we design the CLSC network in the hybrid remanufacturing/manufacturing system with the different processing lead-time. We generate two types of the network configurations for each potential value of carbon price based on the sub-optimized results and the optimized results of the first stage in order to show the advantage of using the two inventory positions to minimize the total costs incurred by building the CLSC network.

We first construct the CLSC network without the carbon emission cost to investigate the impact of the potential carbon emission regulation on the network.

(1)   Without the potential carbon emission regulation, $e = \$ 0/kg$

In the case of the larger remanufacturing lead-time, the optimized decision of the first stage from the two inventory positions establishes a factory in the retailer zone 9 with the lowest fixed cost, a warehouse in the zone 7 with the second lowest fixed cost, and a collection center in the zone 7 with the third lowest fixed cost as illustrated in Figure 4.14 (i). On the other hand, the sub-optimized decision of the first stage from the one inventory position also locates one factory and one collection center in the same zones, but builds another warehouse in the zone 5 with the lowest fixed cost.

For the larger production lead-time, the optimized decision of the first stage draws the same results for the factory and the warehouse locations compared with
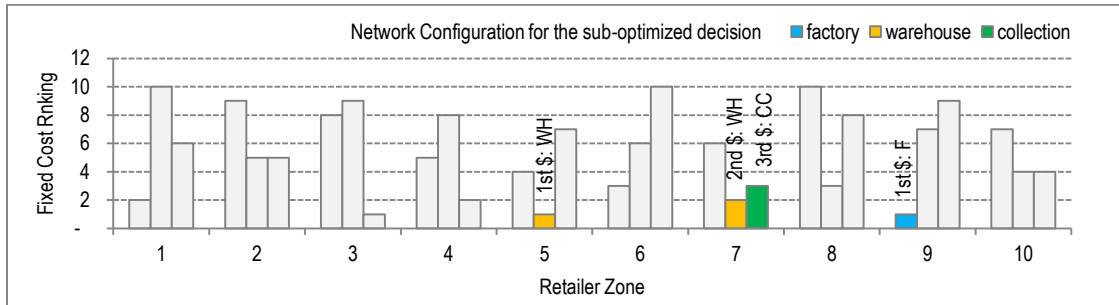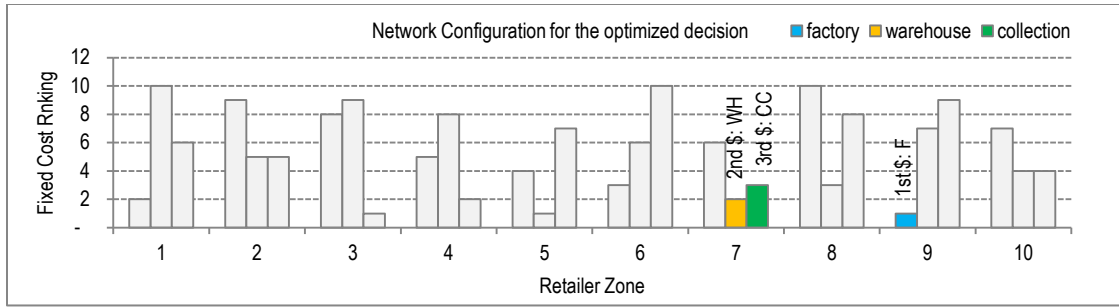
(i)   Larger remanufacturing lead-time, $Lr > Lp$
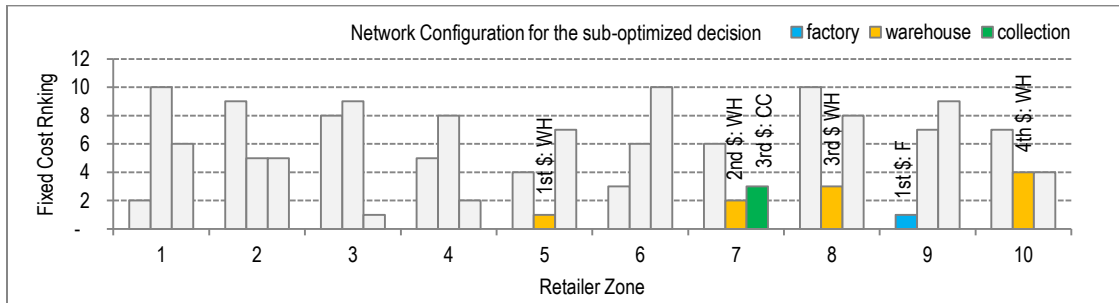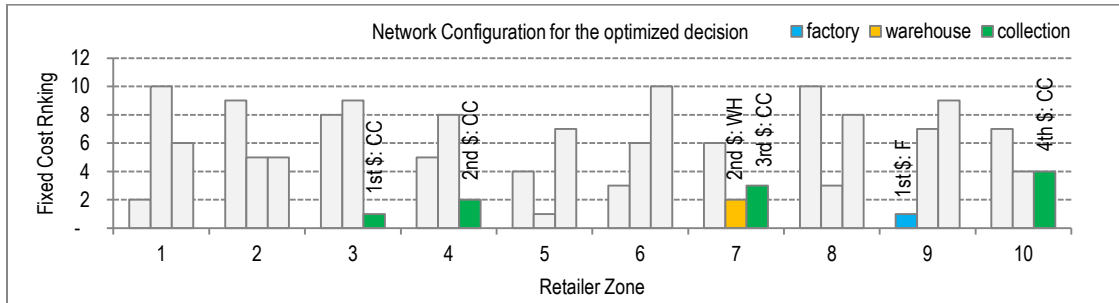
(ii)   Larger production lead-time, $Lp > Lr$

Figure 4.14   Network configurations without carbon emission cost

the case of the larger remanufacturing lead-time. However, it makes different decisions on the collection center. As described in Figure 4.14 (ii), the collection centers are located in the zones 3, 4, 5, and 6 which incur the four lowest fixed costs. On the other hand, in the case of the sub-optimized decision, the factory and the collection center are located in the same zone as in the case of the larger remanufacturing lead-time, but two more warehouses are located in zones 8 and 10 with the third and fourth lowest fixed costs, respectively.

In the two cases of the different processing lead-times, we can find that the sub-optimized decision of the first stage from the one inventory position causes the construction of more warehouses than the network configuration drawn from the optimized decision of the first stage. As mentioned in section 4.3, the sub-optimized decision generates higher average serviceable inventory levels due to the occasional large ordering decision caused by the backorders. Therefore, in the second stage, the warehouse storage constraints, defined in the equation (25), force investment in more facilities.

For the collection center in the case of the larger production lead-time, the optimal remanufacturing-up-to level M for the optimized decision is not high enough to remanufacture the returned items at once due to less expensive recoverable holding cost than the serviceable holding cost. Therefore, it leads the average recoverable on-hand stocks to be high and finally results in more collection centers according to another storage constraint of the equation (26). On the contrary, the M level for the sub-optimized decision is not affected by the short remanufacturing

lead-time so that it leads to building one collection center in the region that balances the transportation cost and the fixed cost of opening the collection center.

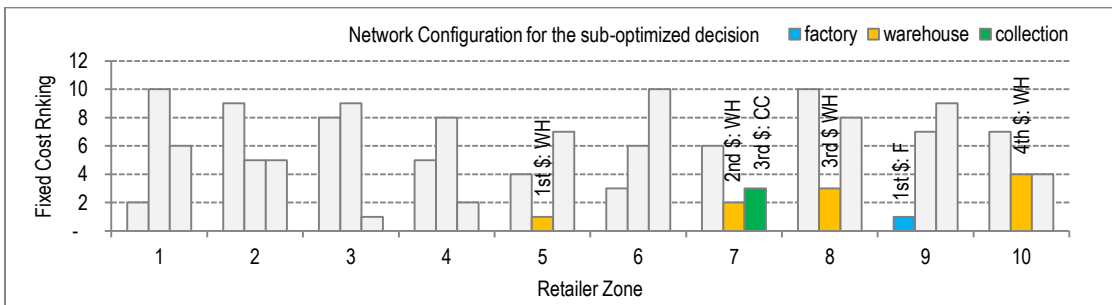### (2) With the carbon emission costs, $e = \$5/kg$ or $\$10/kg$
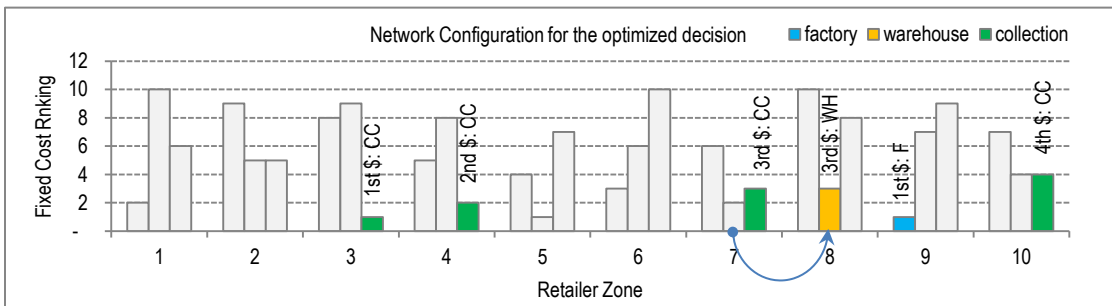
When the carbon emission cost e is anticipated at $\$5/kg$ or $\$10/kg$, the factory and the collection center locations are not affected from the increased transportation costs in all cases, but the location of warehouse changes region 7, with the second lowest fixed cost, to region 8, with the third lowest fixed cost, which is the nearest region to the factory as illustrated in Figure 4.15.

This is because the increased transportation cost generated from the factory to the warehouse dominates the cost difference incurred when the warehouse location is changed to region 8 from region 7, but the increased transportation cost from collection center to the factory is not enough to relocate the collection center to the region close to the factory.

For the sub-optimized decision of the larger production lead-time, however, the increased transportation cost has not affected any one of four warehouses, which are necessary to be built due to the storage constraint. This is because two warehouses have been already located in region 7 and 8, and the cost differences that would occur if two other warehouses were also in region 9, where the factory is located, dominate the increased transportation costs.
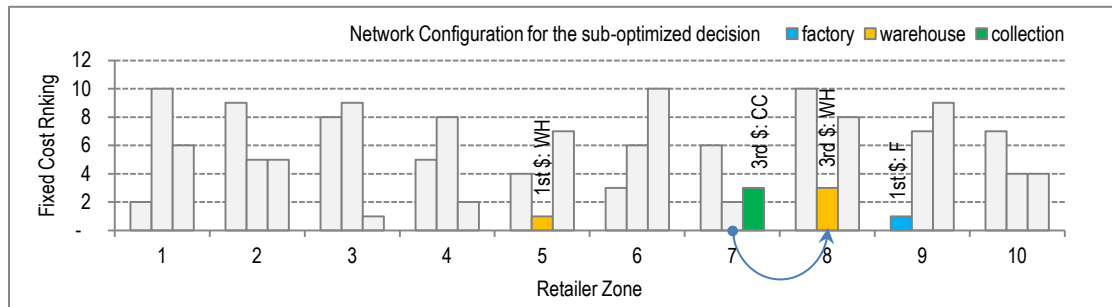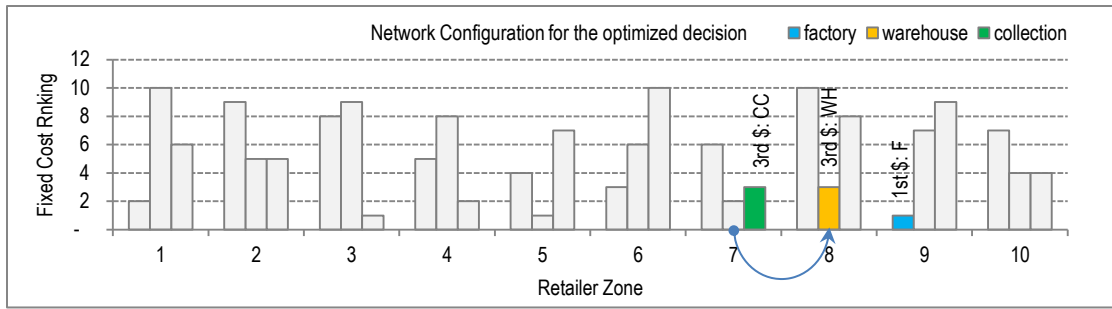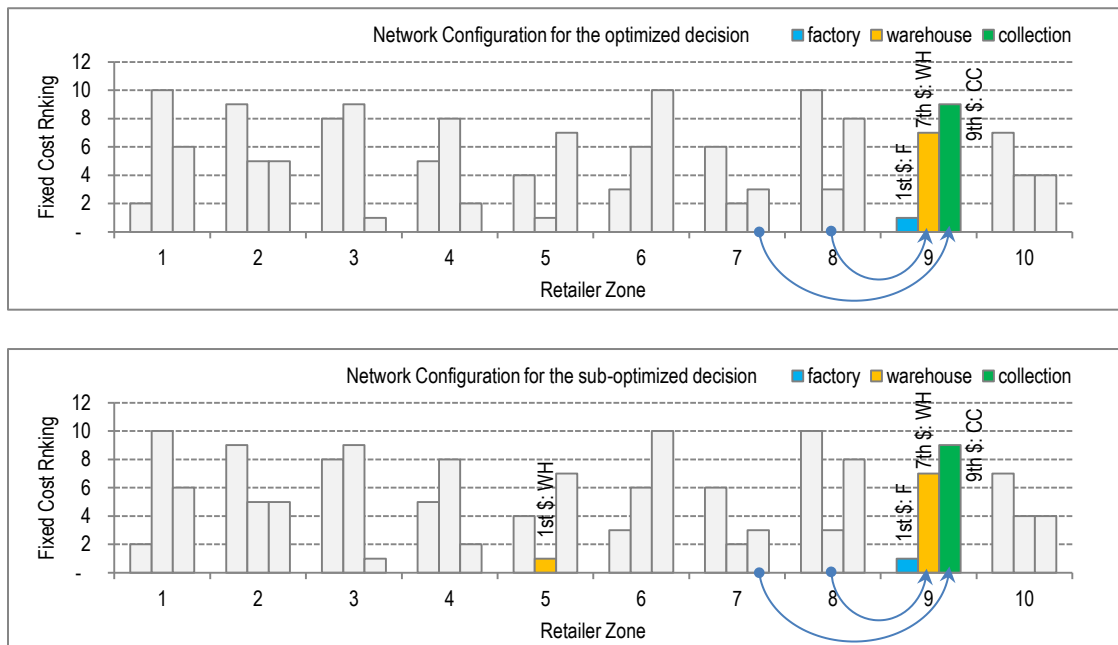
(i) Larger remanufacturing lead-time, $Lr > Lp$
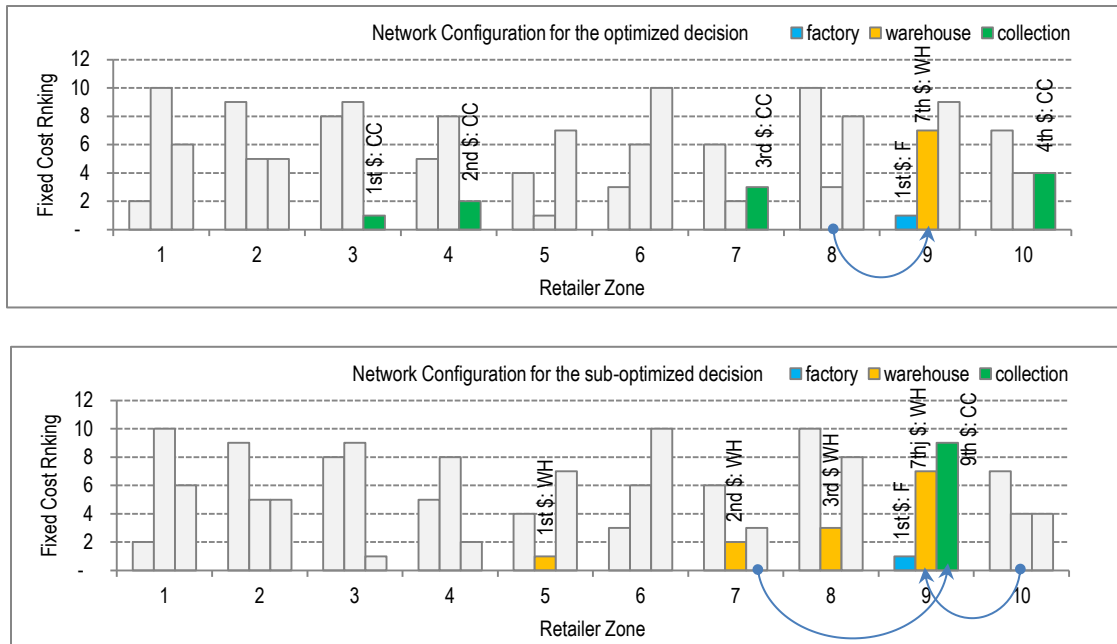

(ii) Larger production lead-time, $Lp > Lr$

Figure 4.15 Network configuration with emission cost, $e = \$\,5/kg\ or\ \$10/kg$

(3)   With the carbon emission cost, $e = \$15/kg$

When the carbon emission cost reaches to $\$15/kg$, all facilities tend to be gathered in the region where the factory is built at the lowest cost in order to reduce the transportation costs incurred from or to the factory as shown in Figure 4.16. Even, in the case of the sub-optimized decision for the larger production lead-time, the transportation cost placed from the factory to the warehouse located in the region 10 overwhelms the cost difference for the warehouse between the region 9 and the region 10, and it leads the warehouse to be located in region 9 rather than 10.
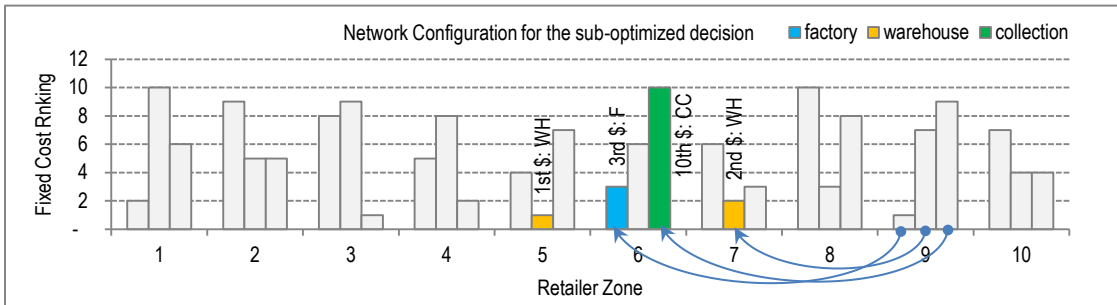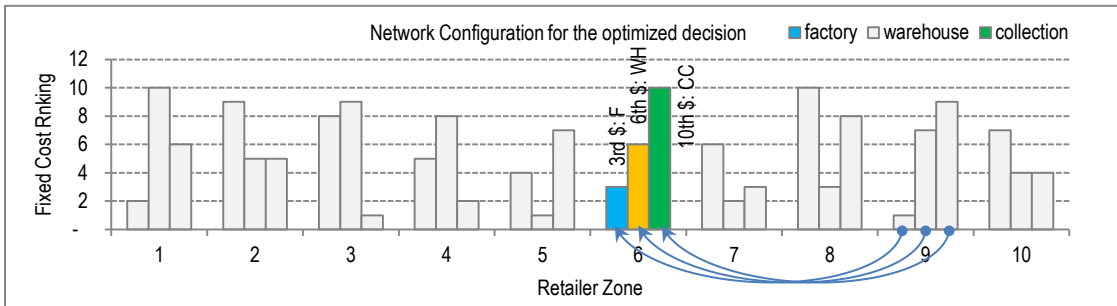

(i)   Larger remanufacturing lead-time, $Lr > Lp$
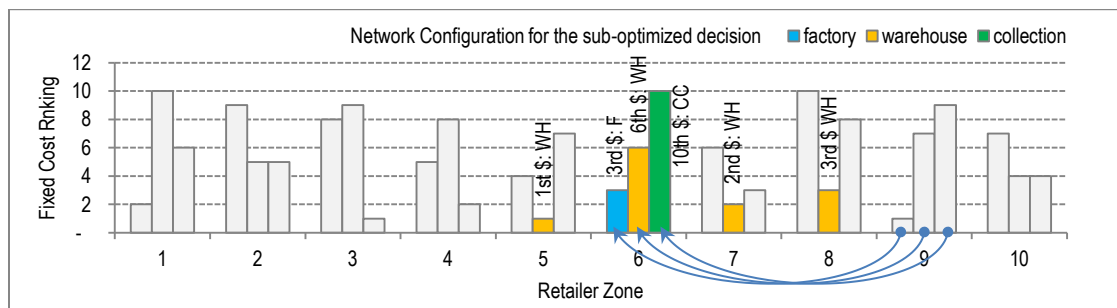
(ii) Larger production lead-time, $Lp > Lr$

Figure 4.16 Network configuration with emission cost, $e = \$ 15/kg$

(4)   With the carbon emission cost, $e = \$20/kg$

In the extremely highest case of the carbon emission cost, all facilities show a tendency toward being centralized in the network as illustrated in Figure 4.17. In the previous cases, the lowest fixed cost for the factory has dominated the transportation cost, but the cost is finally overwhelmed by the transportation cost as the effective transportation cost increases by the addition of high carbon emission cost. Therefore, the factory is located in the region which minimizes the transportation cost as illustrated in Figure 4.18. In addition, the factory location has an effect on the other types of facilities so that they are also placed in the region where the factory is located.

(i)   Larger remanufacturing lead-time, $Lr > Lp$
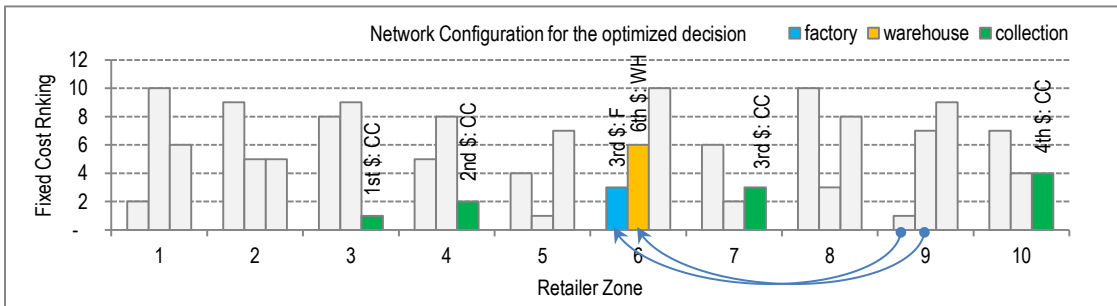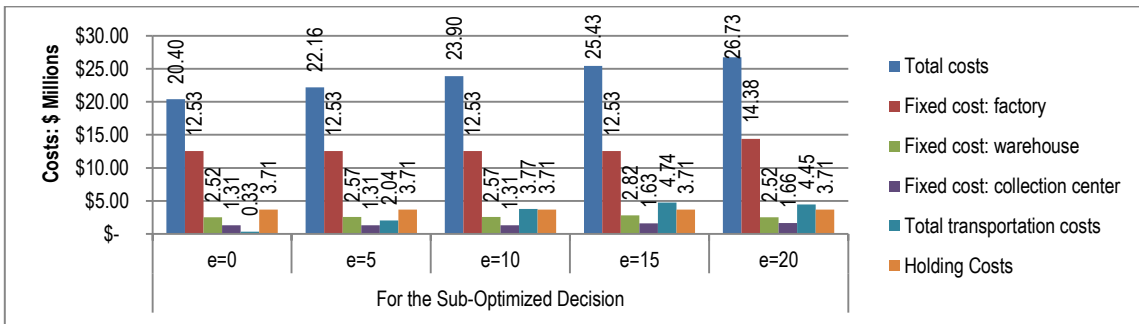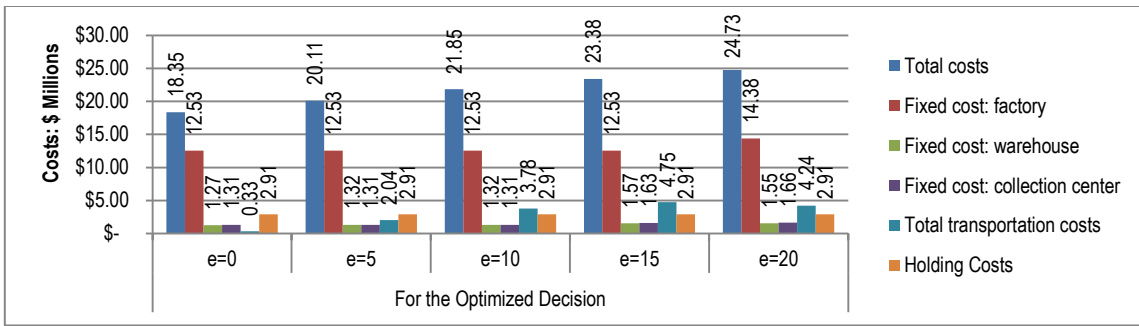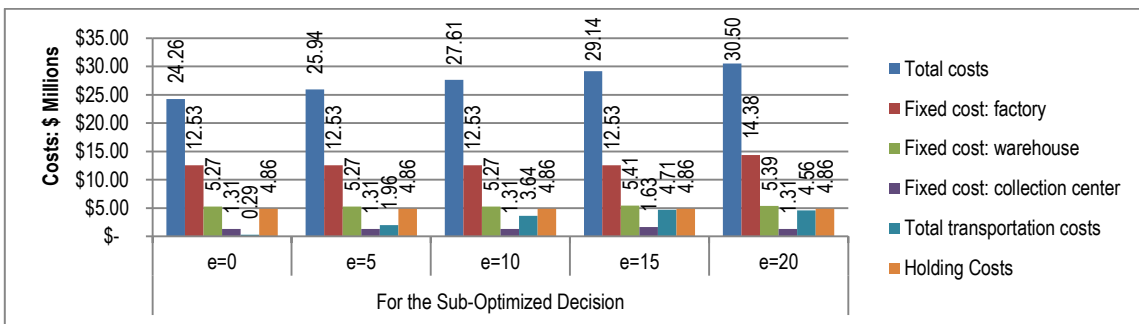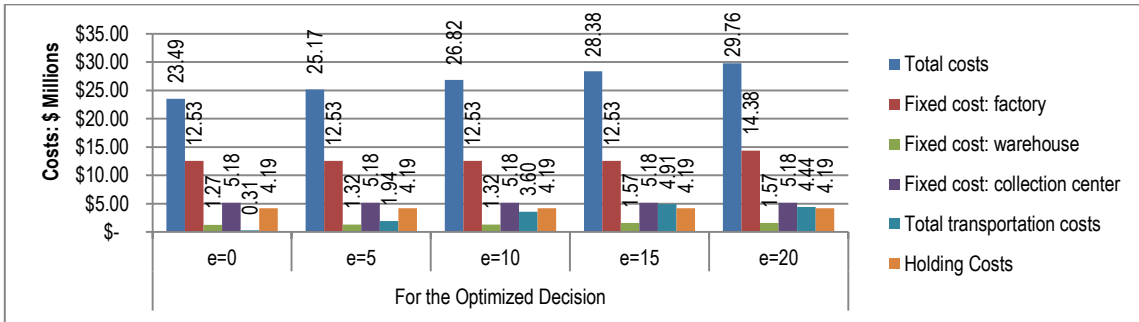

(ii)   Larger production lead-time, $Lp > Lr$

Figure 4.17   Network configuration with emission cost, $e = \$ 20/kg$

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(i)   Larger remanufacturing lead-time

(ii)   Larger production lead-time

Figure 4.18   Cost trend due to the different carbon emission costs

In this section, we studied the impact of the potential carbon emission regulation on the CLSC network design in the hybrid manufacturing/remanufacturing system with different processing lead-times for production and remanufacturing. We observed that the optimal solution for the configuration of the CLSC network reflected the trade-off between the transportation cost and the fixed cost as the potential carbon emission cost was incorporated in the transportation cost. We also found that the optimized decision of the first stage from the two inventory positions always designed the CLSC network with lower cost rather than the sub-optimized decision form the one inventory position represented in the Figure 4.18. Therefore, in order to design the CLSC network for the hybrid manufacturing/remanufacturing system with the different processing lead-times as minimizing the total costs, it is necessary to understand the flows of the network.

CHAPTER 5 CONCLUSION

5.1   Thesis Summary

This thesis addresses the network design for a hybrid manufacturing/ remanufacturing system where production lead-time is different from remanufacturing lead-time, accounting for inventory and backorders. In addition, we examine the impact of potential government regulation on the carbon emission generated by the transportation.

To deal with the different time sensitivity for the remanufacturing, two-stage optimization is proposed. In the first stage, we anticipate the flows in the network based on the Kiesmüller inventory management model [17], and configure the CLSC network design in the second stage. A numerical analysis illustrates how the decisions of the first stage influence the optimal network configuration in the second stage. In both cases for the different processing lead-time, the sub-optimized decision of the first stage always causes more costs to build unnecessary facilities due to the storage constraint in the second stage. It implies that forecasting the forward and reverse flows in the network is a very important procedure to build the CLSC network for a recovery system with different processing lead-times.

For the impact of the uncertain regulation on the carbon emission by the transportation, we found that the optimal network configuration in all cases is balanced between the facility investment and the increased transportation cost by the carbon

emission cost. Without the carbon emission cost, each facility tends to be located in the region which incurs the lowest possible fixed cost, but when the carbon emission cost is incorporated into the transportation cost, it is optimal to locate storage facilities in the region where the factory is located. In a case of considering extremely high cost for the carbon emission, the fixed cost for the factory is so dominated that its optimal location is in the center of the network and the other facilities are also centrally located.

We believe that this thesis helps decision makers who consider the CLSC network design to make a right decision with respect to the potential for carbon costs when their recovery system is characterized by different processing lead-times.

5.2   Limitations

This thesis aims at designing the CLSC for a recovery system with different processing lead-times, but has several limitations.

First, we suggested a two-stage optimization to construct the CLSC because it was hard to estimate the forward and the reverse flows in a recovery system with different processing lead-time based on a mathematical optimization approach [17]. However, the problem with a two-stage optimization could cause the second stage to yield the limited results according to the first stage.

In addition, we optimized the inventory management in the first stage to find the flows in the network. However, inventory management is usually considered as a tactical planning problem, while the investments in facilities are strategic decisions. Therefore, it

may be more appropriate to consider the strategic decisions for the investments in the first stage and then the inventory management could occur in the second stage. This modification would require the development of a more sophisticated inventory model with multiple facility locations.

Next, we developed our own heuristic search procedure shown in figure 3.4 to find the production and remanufacturing-up-to levels, which minimize the average holding costs. However, it would be worth considering whether other approaches, such as Particle Swarm Optimization or Genetic Algorithm, would be more efficient and effective.

Lastly, a generally accepted practice in simulation-based optimization is to test the solutions on different realizations of the same random variable. However, the first stage of our model aimed at optimizing the flows with a single stream of random values for the demands and the returns, and the second stage configured the network with the simulated values from the first stage. The robustness of the CLSC design for other demand and return streams should be investigated.

5.3   Future Study

With the limitations discussed in section 5.2, our study could be extended in several ways.

First, for limitations of using a single stream of random values for the demands and the returns in the first stage, a scenario-based stochastic program in the first stage

with several behaviors of uncertain demands and returns could help our results to be robust to uncertain demands and returns. Moreover, based on the scenario-based analysis, the heuristic search algorithm for inventory management parameters could be extended to find more reasonable ordering-up-to levels for production and remanufacturing for each stream of random values based on each scenario.

In addition, based on other assumptions, this study could be extended in several ways. We assume that our model considers a single product produced in a single factory. This assumption is derived from the characteristic of (S and M) policy of the first stage because each order-up-to level is limited to a single product. However, it can be further extended to consider multiple products produced in multiple plants. In this case, we imagine that the first stage optimization problem perform consider a production planning under uncertain demands and returns for each product type. Another limitation of this thesis is that our model assumes each processing lead-time as a constant. However, in practice, the remanufacturing lead-time varies considerably according to types of returns classified by commercial returns, end-of-use returns, and end-of-life returns [11]. According to different reasons of the returns, therefore, one interesting extension of our study is to determine the remanufacturing level with a scenario-based stochastic programming for the remanufacturing lead-time, and to observe the impact on the CLSC network design. Finally, in conjunction with the lead-time flexibility, the assumption of identical costs for manufacturing and remanufacturing could be relaxed.

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