MULTI-CRITERIA DECISION MAKING
OPTIMIZATION FOR REVERSE SUPPLY CHAINS

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DEDICATION

To my wife Sally,

my parents (Abdulrahman and Jawaher),

and my children Abdulrahman and Nora.

For their unconditional love, enthusiasm, support, understanding, and
courage to make all my dreams come true!
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Chapter 5

\( c_i \)  
Unit purchasing cost of used product at collection center \( i \)

\( c_{di} \)  
Disposal cost of used product \( i \)

\( t_i \)  
Cost of transporting one used product from collection center \( i \) to remanufacturing facility \( j \)

\( d_j \)  
Demand for used product \( j \)

\( i \)  
Collection center index, \( i = 1, 2, \ldots, s \)

\( k_i \)  
Capacity of collection center \( i \)

\( p_i \)  
Probability of breakage of used products purchased from collection center \( i \)

\( p_{\text{max}} \)  
Maximum allowable probability of breakage

\( Q_i \)  
Decision variable representing the quantity to be purchased from collection center \( i \)

\( s \)  
Number of candidate collection centers

\( w_i \)  
Performance index of collection center \( i \) obtained by carrying out ANP

Chapter 6

\( R_T \)  
Total revenue.

\( C_D \)  
Total disposal cost.

\( C_P \)  
Total preparation cost.

\( C_H \)  
Total holding cost.

\( C_A \)  
Total disassembly cost.

\( C_Q \)  
Total acquisition cost.

\( C_S \)  
Total sorting cost.
\( P_N \)  
Net profit.

\( n_r \)  
Number of unique reusable components in a discarded product.

\( n'_r \)  
Number of unique recyclable components in a discarded product.

\( n_d \)  
Number of unique disposable components in a discarded product.

\( m_{ri} \)  
Multiplicity of reusable component \( i \).

\( n'_{ri} \)  
Multiplicity of recyclable component \( i \).

\( m_{di} \)  
Multiplicity of disposable component \( i \).

\( w_{ri} \)  
Weight of reusable component \( i \).

\( w'_{ri} \)  
Weight of recyclable component \( i \).

\( w_{di} \)  
Weight of disposable component \( i \).

\( w_p \)  
Weight of discarded product.

\( p_{ri} \)  
Selling price of remanufactured component \( i \) ($/unit).

\( p'_{ri} \)  
Selling price of high quality recyclable component \( i \) ($/lb).

\( p_{ai} \)  
Selling price of high grade as-is reusable component \( i \) ($/unit).

\( p_{si} \)  
Price of scrap grade reusable component \( i \) ($/lb).

\( p'si \)  
Price of scrap quality recyclable component \( i \) ($/lb).

\( p_p \)  
Price of discarded product ($/lb).

\( \lambda_{ri} \)  
Demand for remanufactured component \( i \).

\( \lambda'_{ri} \)  
Demand for high quality recyclable component \( i \).

\( \lambda_{ai} \)  
Demand for high grade as-is reusable component \( i \).

\( \lambda_{si} \)  
Demand for scrap grade reusable component \( i \).

\( \lambda'si \)  
Demand for scrap quality recyclable component \( i \).

\( \lambda_p \)  
Demand for damaged discarded products.
β  Yield of sorting process.
γ_{ri}  Yield of high grade reusable component \( i \).
γ'_{ri}  Yield of high quality recyclable component \( i \).
θ_{ri}  Yield of remanufacturable quality reusable component \( i \).
\( R_q \)  Quantity of proactively acquired returns.
\( R_p \)  Quantity of passively accepted returns.
\( C_s \)  Cost to sort a discarded product.
\( C_r \)  Cost to disassemble a product.
\( C_q \)  Cost to acquire a discarded product (acquisition price) ($/unit).
\( C_{pi} \)  Cost to remanufacture high grade reusable component \( i \).
\( C'_{pi} \)  Cost to prepare (such as crushing) high quality recyclable component \( i \).
\( C_{ai} \)  Cost to prepare high grade reusable component \( i \) for as-is sale.
\( C_{hi} \)  Holding cost for high grade reusable component \( i \).
\( C'_{hi} \)  Holding cost for high quality recyclable component \( i \).
\( C_{di} \)  Cost to dispose reusable component \( i \).
\( C'_{di} \)  Cost to dispose recyclable component \( i \).
\( C_{ddi} \)  Cost to dispose the disposable component \( i \).
\( C_{dp} \)  Cost to dispose the discarded product.
\( C_{oi} \)  Penalty cost to dispose reusable component \( i \).
\( C'_{oi} \)  Penalty cost to dispose recyclable component \( i \).
\( C_{odi} \)  Penalty cost to dispose the disposable component \( i \).
\( C_{op} \)  Penalty cost to dispose the discarded product.
\( D_{ri} \)  Disposal limit for reusable component \( i \).
\( D'_{ri} \) Disposal limit for recyclable component \( i \).

\( D_{di} \) Disposal limit for disposable component \( i \).

\( D_p \) Disposal limit for damaged discarded products.

**Chapter 7**

\( C_{1v} \) Storage capacity at remanufacturing facility \( v \) per remanufactured unit;

\( C_{2v} \) Storage capacity at remanufacturing facility \( v \) per used unit;

\( C_u \) Storage capacity at collection center \( u \) per unit;

\( C_w \) Storage capacity at reselling center \( w \) per unit;

\( D_u \) Demand of products at collection center \( u \);

\( D_w \) Demand of products at reselling center \( w \);

\( d_{uu} \) Distance from collection center \( u \) to remanufacturing facility \( v \), per mile;

\( d_{wv} \) Distance from remanufacturing facility \( v \) to reselling center \( w \), per mile;

\( EX_u \) Energy cost at collection center \( u \) per unit;

\( EX_v \) Energy cost at remanufacturing facility \( v \) per unit;

\( EX_w \) Energy cost at reselling center \( w \) per unit;

\( GH \) GHG emissions per ton-mile;

\( GH_u \) GHG emissions in collection center \( u \), per unit;

\( GH_v \) GHG emissions in remanufacturing facility \( v \), per unit;

\( GH_w \) GHG emissions in reselling center \( w \), per unit;

\( H_u \) Holding cost per unit at collection center \( u \);

\( L_u \) Labor cost at collection center \( u \) per unit;

\( L_v \) Labor cost at remanufacturing facility \( v \) per unit;

\( L_w \) Labor cost at reselling center \( w \) per unit;
\(O_1\) Occupied space by remanufacturing unit;

\(O_2\) Occupied space by used-product unit;

\(Kg\) Weight of each unit;

\(P\) Reprocessing cost per unit;

\(R\) Retrival cost per unit;

\(RCAP_v\) Remanufacturing facility \(v\) capacity;

\(RC_u\) Rent cost at collection center \(u\) per unit;

\(RC_v\) Rent cost at remanufacturing facility \(v\) per unit;

\(RC_w\) Rent cost at reselling center \(w\) per unit;

\(SH_u\) Shortage cost per unit at collection center \(u\);

\(SUP_u\) Supply at collection center \(u\);

\(T_{uv}\) Transportation cost from collection center \(u\) to remanufacturing facility \(v\), per unit;

\(T_{vw}\) Transportation cost from remanufacturing facility \(v\) to reselling facility \(w\), per unit;

\(u\) Collection center;

\(v\) Remanufacturing facility;

\(w\) Reselling center;

\(X_{uv}\) Decision variable for the number of units transferring from collection center \(u\) to remanufacturing facility \(v\);

\(Y_{vw}\) Decision variable for the number of units transferring from remanufacturing facility \(v\) to reselling center \(w\);

\(Z_v\) Binary variable (0/1) for selection of remanufacturing facility \(v\);
$Z_w$ Binary variable (0/1) for selection of reselling center $w$.

**CHAPTER 8**

$C_{1v}$ Storage capacity at remanufacturing facility $v$ per remanufactured unit;

$C_{2v}$ Storage capacity at remanufacturing facility $v$ per used unit;

$C_u$ Storage capacity at collection center $u$ per unit;

$C_w$ Storage capacity at reselling center $w$ per unit;

$D_u$ Demand of products at collection center $u$;

$D_w$ Demand of products at reselling center $w$;

$d_{uu}$ Distance from collection center $u$ to remanufacturing facility $v$, per mile;

$d_{uvv}$ Distance from remanufacturing facility $v$ to reselling center $w$, per mile;

$EX_u$ Energy cost at collection center $u$ per unit;

$EX_v$ Energy cost at remanufacturing facility $v$ per unit;

$EX_w$ Energy cost at reselling center $w$ per unit;

$GH$ GHG emissions per ton-mile;

$GH_u$ GHG emissions in collection center $u$, per unit;

$GH_v$ GHG emissions in remanufacturing facility $v$, per unit;

$GH_w$ GHG emissions in reselling center $w$, per unit;

$H_u$ Holding cost per unit at collection center $u$;

$L_u$ Labor cost at collection center $u$ per unit;

$L_v$ Labor cost at remanufacturing facility $v$ per unit;

$L_w$ Labor cost at reselling center $w$ per unit;

$O_1$ Occupied space by remanufacturing unit;
$O_2$ Occupied space by used-product unit;

$Kg$ Weight of each unit;

$P$ Reprocessing cost per unit;

$R$ Retrival cost per unit;

$RCAP_v$ Remanufacturing facility $v$ capacity;

$RC_u$ Rent cost at collection center $u$ per unit;

$RC_v$ Rent cost at remanufacturing facility $v$ per unit;

$RC_w$ Rent cost at reselling center $w$ per unit;

$SH_u$ Shortage cost per unit at collection center $u$;

$SUP_u$ Supply at collection center $u$;

$T_{uv}$ Transportation cost from collection center $u$ to remanufacturing facility $v$, per unit;

$T_{vw}$ Transportation cost from remanufacturing facility $v$ to reselling facility $w$, per unit;

$u$ Collection center;

$v$ Remanufacturing facility;

$w$ Reselling center;

$X_{uv}$ Decision variable for the number of units transferring from collection center $u$ to remanufacturing facility $v$;

$Y_{vw}$ Decision variable for the number of units transferring from remanufacturing facility $v$ to reselling center $w$;

$Z_v$ Binary variable (0/1) for selection of remanufacturing facility $v$;

$Z_w$ Binary variable (0/1) for selection of reselling center $w$. 
ABBREVIATION

AHP: Analytic Hierarchy Process

ANP: Analytic Network Process

CBECS: Commercial Buildings Energy Consumption Survey

CE: Circular Economy

CLSC: Closed-loop Supply Chain

COP21: the 21st Conference of the Parties

DM: Decision Maker

EIO-LCA: Economic Input-Output Life Cycle Assessment

EOL: End of Life

EPR: Extended Producer Responsibility

GHG: Greenhouse Gas Emissions

IPCC: The Intergovernmental Panel on Climate Change

LCA: Life-Cycle Assessment

LPP: Linear Physical Programming

MCDM: Multi-Criteria Decision Making

MECS: Manufacturing Energy Consumption Survey
MILP: Mixed Integer Linear Programming

NPP: Nonlinear Physical Programming

OA: Orthogonal Arrays

OEM: Original Equipment Manufacturers

PP: Physical Programming

PRF: Product Recovery Facilities

RL: Reverse Logistics

RSC: Reverse Supply Chain

SCC: Social Cost of Carbon

tCO2e: ton CO₂ equivalent

UNFCCC: United Nations Framework Convention on Climate Change

USEPA: United States Environmental Protection Agency

USITC: United States International Trade Commission
ABSTRACT

Modern supply chains are typically linear, transforming virgin raw materials into products for end consumers, who then discard them after use to landfills or incinerators. Nowadays, there are major efforts underway to create a circular economy to reduce non-renewable resource use and waste. One important aspect of these efforts is the development of Reverse Supply Chain (RSC) systems to enable a reverse flow of used products from consumers back to manufacturers, where they can be refurbished or remanufactured, to both economic and environmental benefit. This dissertation develops novel multi-objective optimization models to inform RSC system design at multiple levels: (1) strategic planning of facility location and transportation logistics; (2) tactical planning of optimal pricing; and (3) policy planning to account for potential valuation of RSC emissions. First, physical linear programming was applied to evaluate RSC facility placement by determining the quantities of end-of-life products for transport from candidate collection centers to remanufacturing facilities while satisfying cost and capacity criteria. Second, disassembly and remanufacturing processes have received little attention in industrial engineering and process cost modeling literature. The increasing scale of remanufacturing operations, worth nearly $50 billion annually in the United States alone, have made RSC pricing an important subject of research. A non-linear physical programming model for optimization of a pricing policy for remanufactured products that maximizes total profit and minimizes product recovery costs, was examined and solved. Finally, a deterministic equilibrium model was used to determine the effects of internalizing a cost of RSC greenhouse gas (GHG) emissions into optimization models. Changes in optimal facility use, transportation logistics, and pricing/profit margins were all investigated against a variable cost of carbon,
using case study system created based on actual data from sites in the Boston area. As carbon costs increase, the optimal RSC system undergoes several distinct shifts in topology as it seeks new cost-minimal configurations. A comprehensive study for quantitative evaluation and performance of the model has been done using Orthogonal Arrays. Results were compared to top-down estimates from economic input-output life cycle assessment (EIO-LCA) models, to contrast remanufacturing GHG emission quantities with those from original equipment manufacturing operations. Introducing a carbon cost of $40/t CO2e increases modeled remanufacturing costs by 2.7%, but also increases original equipment costs by 2.3%. The assembled work advances the theoretical modeling of optimal RSC systems and presents a rare case study of remanufactured appliances.
Chapter 1  INTRODUCTION

This chapter provides an introduction to the dissertation. In Section 1.1, current issues in reverse supply chain are discussed. Section 1.2 explains the motivation of the study. The research scope and contribution are presented in Section 1.3. Finally, Section 1.4 presents the outline of the dissertation.

1.1 Background and Motivation

Most modern supply chains are linear, that is, they are designed to maintain a flow of products from new raw material to end customers, who discard products to waste disposal facilities. Today there is also increasing reverse flow of products across a range of industries. Product recovery in which, reprocessing (either recycling or remanufacturing) of used products is very important in a world that supports a growing population with finite resources and disposal capacities (Gungor and Gupta, 1999). Remanufacturing is the process of transforming used, non-functional product or components to “like-new” conditions and recapturing value added to products during the manufacturing stage; it is distinct from "recycling" or "repairing" (Remanufacturing Industries Council, 2016). On the other hand, recycling processes “retrieve the material content of used product without retaining the identity of their component” (Pochampally et al., 2008), thus losing the value added during product manufacturing and assembly and requiring additional energy and resources to create products anew. Consumers can find remanufactured products significantly more attractive, due to lower price for comparable quality (Abbey et al., 2015).
Corporations across multiple industries are increasingly exploring ways to improve supply chain systems and efficiently and profitably meet consumer demands (Vadde et al., 2006). Some of the most commonly remanufactured product categories are, aircraft components, automotive parts, electrical and electronic equipment, engines and components, medical equipment, office furniture, and printing equipment.

There are many methods for and examples of successful remanufacturing operations. Original equipment manufacturers (OEMs) that engage in remanufacturing may incorporate remanufactured components into new products, as in Fuji Xerox’s photocopier and Fuji Film’s single-use camera (Matsumoto and Umeda, 2011), which both have used components incorporated in all new products, with no distinction made between remanufactured and new products (Matsumoto and Umeda, 2011). According to Ricoh, one of the major photocopy machine manufacturers that started selling remanufactured machines in the 2000s, approximately 93% by weight of a typical remanufactured photocopy machine is composed of reused parts, with costs anywhere of 50% to 60% less than new products, which makes the profits from remanufactured machines higher than those from newly produced machines (Matsumoto and Umeda, 2011). In Apple’s annual environmental report of 2016 (Apple, 2016), the company states that it is planning to disassemble 1.2 million phones a year and sort all their various components, for incorporation into new units if possible. Remanufactured auto parts is the largest remanufacturing sector in the world. Up to two-thirds of remanufacturing businesses worldwide include ‘aftermarket’ auto parts, (Parker, 1997), which are commonly incorporated into existing vehicles, both by dealerships that represent the OEMs but also by independent mechanics.
Another example is of remanufactured (refilled) printer ink cartridges and toner cartridges. In Japan, where there are 200 million ink cartridges sold annually, primarily for use in personal printers, Japan’s largest ink cartridge remanufacturer Ecorica ships around 10 million remanufactured products annually. Remanufactured cartridges account for $15 million in sales, while the company sells remanufactured ink cartridges at 20% to 30% less than new products (Matsumoto and Umeda, 2011).

Another motivation for remanufacturing is to be able to resell returned items. In the United States, returned items have a value of nearly $100 billion annually, especially for the products that are returned by customers for any reason within 90 days of sale (Guide et al, 2003b; Guide et al, 2006). Just in the electronics sector, around $13.8 billion was spent in 2007 to repackage, restock, and resell returned products (Lawton, 2008).

The U.S. market for remanufactured goods, according to United States International Trade Commission (USITC), has increased by 15% from $36.0 billion in 2009 to $41.5 billion in 2011, and the value of U.S. remanufactured production during that same period increased by 15% to at least $43.0 billion, hence this would create 180,000 full-time U.S. jobs and exported a total of $11.7 billion of remanufactured goods (USITC, 2012). In another estimate for the United States, the remanufacturing industry is at least a $50 billion industry distributed in 73,000 firms with direct employment of 480,000 (Gutowski et al., 2011).

In 2015, the U.S. alone have returned products worth of $261 billion, out of a total of $3.3 trillion sold. This makes a vast returned products market with sales that over $486 billion in 2014 (The Economist, 2016). Moreover, the sales for the secondary market rose by 31% from 2010 to 2014, and due to growth of e-commerce, this rise is set to be much
With online purchases, the return goods are getting higher due to the fact that customers buy without seeing them. By 2020, the U.S. e-commerce sales are expected to be 50% higher than they were in 2015, offering enormous opportunity (The Economist, 2016). The secondary market has both an environmental benefit resulting from extended product life, and a social benefit to increase buyer and seller access.

Leased or rented items are also commonly remanufactured after the lease expires. As an example, the total U.S. market of remanufactured office furniture (commonly leased or rented) in 2015 is estimated to be 15% of the total market of office furniture, with $2.2 billion in sales (Davies, 2016).

In this work, a Reverse Supply Chain (RSC) is described as an initiative that plays an important role in the global supply chain for those who seek environmentally responsible solutions for their end-of-life (EOL) products (Gupta, 2013). A generic reverse supply chain is shown in Figure 1-1. RSC has gained significant attention in both corporate and academic institutions during recent years (Wang et al., 2016). For years, the quantity of consumer-discarded products has been rising, and as a result there has been increased legislative action in countries that hold OEMs responsible for end-of-life processing of products, often called extended producer responsibility (Vadde et al., 2006; Lindhqvist & Lidgren, 1990). The relative economic and environmental benefits of RSC are influenced by costs and emissions during collection, transportation, recovery facilities, disassembly, recycling, remanufacturing, and disposal of unrecoverable components (Ilgin & Gupta, 2010).
Figure 1-1: Generic reverse supply chain

Supply chains in general involve different levels of design and decision making: strategic planning, tactical planning, and operational levels (Pochampally et al., 2008). Strategic planning involves long-term decisions that cannot be changed easily, such as the location and capacity of different facilities, transport links, and the type of product to be manufactured. This level is expensive to change on short notice; therefore, companies usually take into consideration the uncertainty in anticipated market conditions for the next few years. Tactical planning includes all medium-term activities, such as which markets will be supplied from which locations, planned inventories, inventory policies, subcontracting, and timing and size of market promotions. Lastly, the operational level consists of day-to-day decisions, such as individual customer orders, inventory control, production planning to specific order, and delivery schedules over a short-term period. This level has less uncertainty in demand information (Pochampally et al., 2008).

The dramatic increase in world consumption of household and industrial products has created a call to reduce the depletion of mineral resources, the amount of waste generated and the quantity of end-of-life products sent to disposal facilities without material recovery (Agrawal et al., 2016).

Environmental concerns and changes in policy drive to redesign the RSC considering environmental policy, and for this addressing the gaps in RSC research by using a multi-criteria decision-making technique for the issues at the strategic and tactical levels of RSC with multiple stages to achieve effective and profitable operation.
This dissertation applies strategic and tactical level planning tools to help design a reverse supply chain with simultaneous consideration of economic, environmental, and social factors. The applied design approach is formulated as a multi-criteria optimization problem and explored using several available multi-criteria optimization techniques. The literature includes many forward supply chain developed studies and analysis, where the customer is the end of the process. However, the returns processes enabled by RSC covers many areas, including collecting, cleaning, disassembly, recovering, transportation, remanufacturing, reselling, and disposed or shredded products that cannot be reprocessed or are hazardous all over the reverse supply chain activities still need analytical development, as reviewed in the following chapter.

1.2 Research Scope and Contribution

This dissertation is comprised of an empirical analysis and compilation of five research papers that in concert develop novel and effective approaches to build upon the extant literature on reverse supply chain systems. As previously explored, this study is structured around three primary research questions. These questions are explored through the five studies incorporated herein, with the first two research papers providing the foundation for Chapters 5 and 6, presented below. Through a consideration of Alkhayyal and Gupta (2015a; 2015b) both quantitative and qualitative factors that are taken into account within the assembly of a RSC strategy, exhibiting the profitability involved in the process, in addition to the qualitative factors that may influence the purchasing decisions of remanufacturers, and thereby the viability of the industry at large. Chapters 7 and 8 expand upon this and delve further through a consideration of Alkhayyal et al. (2016a; 2016b), and
Alkhayyal et al. (2017), moving further into the later elements of the RSC spectrum and related process.

To support the consideration undertaken herein, an exhaustive review of extant literature on RSC has been conducted to guide the analysis and structure of the study. RSC is an increasingly prevalent subject in modern research, and comprises many fields, including the handling of EOL products and their processing through collection, transport, recovery, disassembly, recycling, and remanufacturing, as well as the disposal of those materials and products that cannot be reprocessed and may be hazardous (Gungor & Gupta, 1999; Ilgin & Gupta, 2010; Kumar & Kumar, 2013). These and other related issues are explored within this dissertation, with a specific focus on the strategic planning and tactical planning levels of RSC management.

Planners of RSC face several decision-making problems, beginning with the significant choices related to collection center placement and capacity. The first stage begins with the determination of the most profitable collection center, a multi-criteria process employing various tools such as Goal Programming and Analytic Network Process. The tactical element of the problem is then encountered in the second stage, that of the pricing of product containing remanufactured materials. This particular facet of the issue has been under-studied in extant literature, and the in-depth consideration thereof is a key part of the empirical contribution of this dissertation. Transforming used and recycled products into “like-new” condition for resale is complicated by scale and various unique processes, with the profitability thereof mitigated by the recapturing of missing value that is added to the products during the remanufacturing process. Whatever the cost, pricing is the ultimate determinant of profitability within the context of the product recovery process.
Pricing is a key element of RSC-related research, and is a multi-criteria issue and complicated process wherein product recovery facilities (PRFs) serve as an intermediary. PRFs passively accept discarded products, and proactively acquire particular objects to optimize profitability by managing recovery costs. An effective pricing model proposed herein that addresses the challenges faced by PRFs is: (a) competition between OEMs and other PRFs; (b) requirement of costly, skilled workers for product recovery operations; (c) valuation of environmental considerations for inclusion into economic optimization tools; (d) uncertainty of the arrival time and the quantity for the discarded products; (e) inventory levels of recovered components; and (f) promotional, markdowns, sales, and clearance price discounts to clear inventory. The third stage of the RSC process is that of the optimization of EOL products’ costs, factoring associated fuel and carbon costs across the RSC.

Through the application of a multi-criteria decision-making approach, this dissertation explores the following research questions and develops general models through which they are studied:

1. What qualitative and quantitative factors determine the strategic planning employed in collection centers and how are they evaluated?

2. Through the application of a Physical Programming approach, how are the prices of reusable and recyclable components, and the acquisition price of discarded products determined in a multi-criteria environment?

3. What is the effect of a social cost of carbon (SCC) on the optimal configuration of RSC, and how does increasing the SCC affect the unit price of remanufactured equipment, relative to OEM?
Research Question #1. What qualitative and quantitative factors determine the strategic planning employed in collection centers and how are they evaluated?

This particular research question is explored through a consideration of a given fixed supply-and-demand scenario, through which the optimal number of EOL products to be processed are identified, and how their transportation may be effectively managed to optimized profits. Figure 1-3 shows the current stage of the RSC for this study.

As studied by Alkhayyal and Gupta (2015a), this is a question of strategic planning that is employed to identify ideal quantities of EOL products to be transported from the candidate collection centers to the contracted remanufacturing facility. This number is identified through the consideration of remanufacturing facility criteria including the maximization of the total purchase value, minimizing the total purchase cost, as well as transportation and disposal. The process applies an analytical network process (ANP) application, a multi-criteria analysis tool developed to present a simplification of the analytic hierarchy process (AHP) (Saaty, 1996). ANP may be structured as either hierarchical or nonhierarchical, and like AHP, allows interdependencies, outer-dependencies, and feedback within the various facets of the decision-making process (Ravi et al., 2005). ANP is of particular value to RSC.

ANP is of value in that it effectively acknowledges the complex interrelationships between decision levels and attributes, particularly due to the fact that many decision problems may be structured hierarchically insofar as they involve interaction between and dependence on
elements in a hierarchical structure of varying levels (Gorener, 2012; Saaty, 1996). Through the application of ANP, the decision maker (DM) is able to make parallel judgments of independent criteria and alternative decisions, and is then capable of converting preferences into numeric scale priorities or weights. The prioritization enables the DM to rank alternatives on a scale of 1 to 9, with 1 demarcating equal importance while 9 indicates extreme importance, as exhibited in Table 1.1 (Saaty, 1980).

Table 1-1: Saaty’s Scale Ranges in Pair-wise Comparison

<table>
<thead>
<tr>
<th>Importance indicator</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>equal importance</td>
</tr>
<tr>
<td>3</td>
<td>moderate importance</td>
</tr>
<tr>
<td>5</td>
<td>strong importance</td>
</tr>
<tr>
<td>7</td>
<td>very strong importance</td>
</tr>
<tr>
<td>9</td>
<td>extreme importance</td>
</tr>
<tr>
<td>2, 4, 6, 8</td>
<td>intermediate importance values</td>
</tr>
</tbody>
</table>

See Figure 1.2 for an exhibit of the ANP hierarchical structure, evaluating collection center candidates. Within ANP criteria, sub-criteria and alternative are perceived equally as facets within a network. Each facet may be contrasted with another, insofar as there is a relationship between them. Ranking alternatives may depend not only the weighting of criteria, but also the alternatives that are present, thereby influencing the application of weight upon the criteria. ANP is presented herein as a matrix that is comprised of a list of all facets listed horizontally and vertically. This particular method is
of value when key elements of a decision are difficult to quantify and contrast, and thus the identification of important facets and their incorporation into a linear programming environment is of value. Within this chapter, a unique approach will be presented based on Linear Physical Programming (LPP) in order to produce a priority vector through an ANP framework.

![ANP hierarchical structure for RCS](image)

**Figure 1-3: ANP hierarchical structure for RCS**

Decision-makers benefit from LPP in that it is a multi-criteria decision-making tool that facilitates the expression of ideas in a realistic manner through a consideration of all available information and facets concerning the decision. This is an issue of optimizing outcomes, and in general, optimization problems are classified as one of two problems, blind or physical. Blind optimization is realized when the desire to optimize a function, whether through minimization or maximization, is subject to constraints in terms of
available information related to the physical meaning of the objective function, decision variable, or constraints. Physical optimization is realized within the context of decision making that results in the most satisfactory possible outcome (Alkayyal & Gupta, 2015a; Messac et al., 1996). There are two classes of criteria within LPP, hard and soft, in reference to the sharpness of the preference. DM preferences may be expressed through the following four soft classes: smaller is better (1S), larger is better (2S), value is better (3S), and range is better (4S). The most substantial benefit of employing LPP is the lack of having to specify weights in order to achieve evaluation. It is only necessary that the DM specify a preference structure for each criterion given that they have a more tangible meaning to the DM than a randomly assigned weight to the criterion (Alkhayyal and Gupta, 2015a; Ilgin and Gupta, 2012; Messac et al., 1996). Within this study, the differing ranges of desirability for the classes are defined as follows (in decreasing order):

- Ideal Range: \( gp \leq t+p1 \)
- Desirable Range: \( t+p1 \leq gp \leq t+p2 \)
- Tolerable Range: \( t+p2 \leq gp \leq t+p3 \)
- Undesirable Range: \( t+p3 \leq gp \leq t+p4 \)
- Highly Undesirable Range: \( t+p4 \leq gp \leq t+p5 \)
- Unacceptable Range: \( gp \geq t+p5 \)

For example, let’s consider the operation of low-price clothes factory. Assume that the DM wishes to:

a) minimize clothes unit price (P),

b) minimize capital investment (C),

c) minimize workforce (W),
d) maximize clothes durability (S), and

e) minimize risk (R).

These criteria can be expressed in terms of a decision variable vector $\mathbf{x}$, under these conditions, the aggregate objective function is:

$$
\text{Min } J(x) = w_1 P(x) + w_2 C(x) + w_3 W(x) - w_4 S(x) + w_5 R(x)
$$

(1)

Where $w_i$ is a generic weight and the key difficulty with the above approach is, indeed determining the correct weights.

Consider for example the unit price above. The DM knows that a price of $20 or less is ideal; $28 desirable; $35 acceptable but undesirable, $40 is highly undesirable, and $45 or more, unacceptable. Thus, instead of attempting to find correct weights, the DM expresses their preference regarding the unit price as follows, using the LPP lexicon:

- Ideal <$20
- Desirable $20-$28
- Tolerable $28-$35
- Undesirable $35-$40
- Highly Undesirable $40-$45
- Unacceptable >$45

LPP employs this data systematically and explicitly to form the core of the problem formulation. Through the application of LPP, no weights need be specified for the evaluation criteria. It is only necessary that the DM specify a preference structure for each criterion, each with more tangible meaning to the DM than would randomly assigned weights to the criteria. Within the context of Chapter 5 herein, an ANP application and an LPP tool are employed that integrate a multi-objective optimization technique with multi-
criterion analysis. An ANP was employed to performance indices of the candidate collection centers, measured through qualitative criteria provided by the relevant remanufacturing facility in terms of purchasing used products. The collection centers’ evaluation criteria are comprised of a four-level hierarchy, as exhibited in Figure 1-2. The LPP approach was employed to determine the quantity of EOL products for transport from the candidate collection centers to remanufacturing facilities while satisfying the four criteria within the hierarchy. The criteria incorporate the maximization of the total value of purchase, and the minimization of disposal and transportation costs in addition to the minimization of the total cost of purchase. Following the application of this approach, a numerical example is explored through three candidate collection results. The results were realized through the LPP model, through which the selection of candidate collection centers was determined.

**Research Question #2.** Through the application of a Physical Programming approach, how are the prices of reusable and recyclable components, and the acquisition price of discarded products determined in a multi-criteria environment?

The second research question, as explored in Chapter 6, is concerned with when product recovery facilities (PRFs) passively accept discarded products and proactively acquire others as needed with the goal of maximizing revenue while minimizing product recovery costs. Through a consideration of Alkhayyal and Gupta (2015b) the second research question, a tactical planning level question, will be explored. The purpose of this question is to determine the optimal pricing policy of reusable and recyclable products to optimize the entirety of the process from profit maximization to product recovery cost minimization, comprised of disposal cost, preparation cost, holding cost, disassembly cost,
acquisition cost, and sorting cost. Figure 1-4 shows the current stage of the RSC for this study.

Figure 1-4: Current stage of the RSC in Research Question #2

In general, there are two primary systems through which used products are obtained from end users:

1. The market-driven system, which relies on financial incentives to motivate end-users.
2. The waste stream system relying upon diverting discarded products while passively accepting all product returns.

Generally, there are four practical acquisition options for used products, in which the Product Recovery Facility (PRF) passively accepts discarded products while acquiring others, as necessary:

1. Drop-off collection
2. Curbside collection
3. Point of Sale Collection
4. Mail-in Collection

Often, pricing policies are non-linear problems as a result of their operating environment, and even when boundaries are limited to smaller ranges, nevertheless may become linear. Despite this, when all linear smaller problems are viewed in concert, because of the environmental effect, the problem may be non-linear. Herein, a non-linear physical programming model seeking to optimize pricing policy for remanufactured
products while maximizing total profit and minimizing product recovery costs is explored, solved, and examined, thereby adding further empirical value to this study as derived from the literature.

**Research Question #3.** What is the effect of a social cost of carbon (SCC) on the optimal configuration of RSC, and how does increasing the SCC affect the unit price of remanufactured equipment, relative to OEM?

Climate change concerns is continuing to increase along with the acceleration of global warming. The Intergovernmental Panel on Climate Change (IPCC) reports that globally GHG emissions have increased by more than 80% from 1970 to 2010, resulting a threat to the global ecosystem (IPCC, 2014). Recently, the 21st Conference of the Parties under the United Nations Framework Convention on Climate Change (UNFCCC) in Paris (COP21, 2015) reached a new global agreement in which all agreed parties were committed to achieve the goal of having zero net GHG emissions by the second half of this century. Figure 1-5 shows the current stage of the RSC for this study.

![Figure 1-5: Current stage of the RSC in Research Question #3](image)

Alkhayyal et al. (2016a; 2016b) are explored in Chapter 7 while Alkhayyal et al. (2017) are explored in Chapter 8, through which the SCC was employed to ranges of $40-120 per ton of CO₂ equivalent. These are the levels proposed at the 21st Conference of the Parties under the UNFCCC in Paris (COP21, 2015), the U.S. Interagency Working Group (2013), the U.S. Environmental Protection Agency (2015), and the recent updated report of the SCC by the National Academies of Sciences, Engineering, and Medicine (National
Academies of Sciences et al., 2017) to determine how proposed ranges influence remanufacturing costs and profit margins associated with remanufactured goods. To elaborate upon the contents of the third research question, a case study was undertaken, based upon actual sites in the Boston area, to compare the environmental and economic impacts of remanufactured air conditions through an RSC model, while also testing the influence of GHG emissions pricing on various configurations of an RSC. Air conditioners were selected for the case study due to the large and expanding market associated with them in addition to their identification as a remanufacturing target due to the presence of refrigerants with mandated handling rules within them. Figure 1-5 shows the current stage of the RSC for this study.

1.3 Outline of Dissertation

This dissertation is organized in a linear fashion that builds upon itself to clarify and expand upon the subject considered, with this first chapter identifying the research questions and providing the structure and objective of the study. Chapter 2 presents a literature review on circular economy, the three different planning levels (strategic, tactical, and operational) in reverse supply chain and GHG emissions, the multi-criteria optimization techniques in reverse supply chain, and economic input-output life cycle assessment (EIO-LCA) studies in remanufacturing. The problem statement and dissertation objectives are presented in Chapter 3, and multi-criteria techniques are introduced in Chapter 4.

Chapter 5 presents a linear physical programming approach to evaluate collection centers for end-of-life products by determining the quantities of end-of-life products for transport from candidate collection centers to remanufacturing facility, in order to determine the optimal collection center from amongst the available candidates. Following
the development of the model, the pricing of returned products is considered given its importance, underlined by the competition between OEMs and other PRFs, compounded by the uncertainty of arrival and demand. Additional challenges faced by PRFs include sales. Chapter 6 recognizes these challenges, and proposes an improved model through which a pricing policy for remanufactured products may be achieved through the use of nonlinear physical programming.

Within Chapter 7 the model is further improved and developed to the next step of transporting the returned products while accounting for the GHG emissions realized throughout the RSC. The model is further developed and applied to the market for GHG emissions within Chapter 8. These refinements of the model allow for the examination of the performance of the proposed policy and how it would impact the profitability of remanufactured goods. The model has been studied through quantitative evaluation of performance through the application of Orthogonal Arrays. A case study structured around actual data from sites in the Boston area is presented to compare the outcome using input-output life cycle assessment (EIO-LCA) model, and to exhibit the difference between remanufacturing emission quantities and new manufacturing production per unit. To conclude this dissertation, Chapter 9 presents a summary and conclusion of the results, with recommendations for future research.
Chapter 2 LITERATURE REVIEW

2.1 Introduction

This chapter provides a brief review of literature surveyed on circular economy, the three planning levels for reverse supply chain and greenhouse gas emissions, multi-criteria optimization techniques for reverse supply chain systems, and economic input-output life cycle assessment (EIO-LCA) studies in remanufacturing.

2.2 Circular Economy

The circular economy concept was developed as a substitution for treating the environment as a waste reservoir, and was first raised forty years ago in a report to the European Commission (Stahel & Reday-Mulvey, 1981). A generic circular economy is shown in Figure 2-1.

A circular economy (CE) is described as turning end-of-life goods into resources for others and minimizing waste, applying the concept of closing loops in industrial ecosystems. This could slowly replace the economic logic of production by being more efficient through reusing, recycling, and remanufacturing. A study was done by a number of European nations on CE, and it was found that greenhouse gas emissions would be...
reduced by each nation up to 70%, and at the same time the workforce would increase by about 4% (Stahel, 2016). A circular economy encourages the use of remanufacturing over other waste management strategies such as reusing, recycling, recovery, and disposal. A critical review of existing studies on remanufactured products in reverse logistics was done by Peters (2016). Recent research by Derigent and Thomas (2016) concerned product and material recyclable in the framework of a circular economy, including a review of the existing literature and highlighting potential research directions. Remanufacturing first defined by Lund (1984) as “the restoration of used products to a like-new condition, providing them with performance characteristics and durability at least as good as those of the original product”. Lund (1996) conducted a survey and established a database of 9,903 remanufacturing industries in the United States, and found that it’s a $53 billion annual product sales in 73,000 firms with a least 80 different product sectors and direct employment of about 480,000. In many cases, remanufacturing offers higher material recovery due to more reused resources (Smith and Keoleian, 2004).

An effective RSC can help enterprises better utilize their resources and maintain a more sustainable balance between the environment and the economy (Xiangru, 2008). RSC practices are also helpful for ‘greening’ the whole supply chain by reintroducing end-of-life and used products into the production system (Efendigil et al., 2008). RSC operations are widely considered a central component of a circular economy (Prakash & Barua, 2015).

2.3 Environmentally Conscious Manufacturing

2.3.1 Operational Planning of Reverse Supply Chains

The first crucial step of reprocessing (also called product recovery) is disassembly. Disassembly can be defined as the automated process of removing desirable components
from the original product without damaging any useful components. Due to its role in reprocessing, disassembly has been receiving attention in the literature. Barker and Zabinsky (2011), Imtanavanich and Gupta (2006a), Massoud and Gupta (2010), and Pochampally et al. (2004), presented a comprehensive list of issues associated with planning and scheduling a disassembly line. Gungor and Gupta (1999) addressed the issues of environmentally conscious manufacturing and product recovery with an extensive review of the literature, with regard to environmentally conscious design, environmentally conscious production, recycling, and remanufacturing, and production planning and inventory control. Ilgin and Gupta (2010) further extended this literature review through 2010. There are several other authors who reported on product recovery designs under specific legislation and regulations (Das, 2002; Bellmann & Khare, 2000; Dekker & Fleischmann, 2004; Guide et al., 1999; Guide, 2000; Henshaw, 1994).

In Lambert and Gupta’s (2005) book on disassembly modeling they presented disassembly in the context of the entire product life cycle. They studied disassembly on the intermediate level, including design for disassembly, concurrent design, and reverse logistics. The book provides real-world examples that explore the three main areas of the disassembly theory: assembly optimization, maintenance and repair, and end-of-life processing.

Haapala et al. (2013) classified the environmental impacts of energy, gaseous wastes, liquid, materials, solid, and water use in manufacturing sector, as well as the sustainable manufacturing concepts, methods, and tools were explored. It concluded that while efforts have considered in all three sustainability domains, environmental and social
aspects need more research attention, in addition to sustainable manufacturing process and system levels have many challenges.

In the same vein, Imtanavanich and Gupta (2006a, 2006b), Kongar and Gupta (2002), and Lambert and Gupta (2005) developed several multi-criteria decision-making methodologies for disassembly-to-order problems under different conditions to determine the product amount to be taken back from end-of-life and disassembled products. Boon et al. (2000, 2003) used a multi-criteria decision-making method to evaluate the economic impact of several different aluminum-intensive vehicles (AIV) and the sensitivity of disassemblers and recyclers on U.S. end-of-life vehicles. Lambert (2010) presented a survey of the available literature on disassembly sequencing, and a search involving all possible disassembly sequences with selection of the optimal sequence. Gupta and Taleb (1996) and Taleb and Gupta (1997) proposed a heuristic methodology of disassembly for multiple product structures with multiple parts. The model used core and allocation algorithms to determine total disassembly requirements of root items and to provide the schedule for disassembling the roots and the subassemblies. Rubio et al. (2008) provided a list of articles published from 1995 to 2005 on reverse logistics, creating a database of the topics, methodologies, techniques, and featured research. Similarly, Meade et al. (2007) presented a comprehensive review of literature on reverse logistics with definitions and research opportunities.

2.3.1.1 Inventory Control

Most inventory control and production planning methods are well structured for a traditional forward supply chain. Not all traditional forward supply chain techniques are
transferable to reverse supply chains. Guide and Srivastava (1997) listed the reasons behind the complexities in inventory control and production planning in a reverse supply chain:

- Uncertainty of recovery rate of parts from used products.
- Uncertainty in inventory of used products.
- Uncertainty about condition of used products.
- Uncertainty in correlation between inventory of used products and demand rates.

Reverse supply chains cannot apply the same techniques as traditional forward supply chains due to the uncertainty of quantity, quality, and timing of products returned, in addition to lack of control over the reverse flow of products. Therefore, inventory control plays an important role in the reverse logistics field. An effective inventory control helps minimize the total costs associated with holding inventories. It controls the return flow of end-of-life (EOL) products, which is essential to the overall performance of the disassembly facility.

For this reason, Fleischmann et al. (2002) employed a model for controlling inventories with stochastic item returns. This provides a step toward systematic analysis of inventory control in the context of reuse. Poisson demand and return were assumed in the model. Korugan and Gupta (1998) studied a two-echelon inventory system with independent demand and return rates; the model used an open queueing network with finite buffer. Van der Laan et al. (1999) presented a comparison study of PUSH and PULL policies in inventory systems, considering both remanufactured and new products. Similarly, fifteen years later, Korugan and Gupta (2014) considered a CONWIP (constant work in progress) problem of hybrid production systems with two different production
lines (remanufacturing and manufacturing). It showed that adaptive Kanban control policy performed better than static Kanban control policy. Vadde et al. (2006) studied the pricing effect on the inventory level of end-of-life (EOL) products with some inventory constraints, such as disposal limits.

2.3.1.2 Production Planning

The use of traditional forward supply chain production planning methods may be possible when there is certainty about reuse of returned products. This takes into account the complexities of production planning for reverse supply chains that are mentioned in section 2.2.1.

A number of papers use material requirements planning (MRP) approaches to remanufacturing with respect to their behavior under uncertainty (Gupta & Taleb, 1994; Krupp, 1993; Muckstadt & Isaac; 1981). A study was conducted by Guide and Srivastava (1997) to calculate safety stock for material recovery under uncertainty. Guide and Jayaraman (2000a) studied the acquisition of end-of-life (EOL) products and its difficulties. They proposed a formal framework for product acquisitions management (PrAM) to coordinate, provide, and monitor an interface between reverse logistics and production planning. They concluded that there is no single method that addresses all the closed-loop supply chain critical issues on its own. Guide et al. (2003a) examined three cases: remanufacture-to-stock (RMTS), reassemble-to-order (RATO), and remanufacture-to-order (RMTO). These cases proposed intermediate and end points for closed-loop supply operations. Aksoy and Gupta (1999, 2001) developed an open queueing network (OQN) model for remanufacturing systems, then studied the reusable rate effect on the performance of each remanufacturing system.
At the operational level, we can conclude that production planning and inventory control are related processes in disassembly and remanufacturing operations.

### 2.3.1.3 Greenhouse Gas Emissions

Concerning carbon-constrained economy matters, replacing the original manufactured product with a remanufactured product generates large revenue in terms of carbon-saving returns (Fatimah & Biswas, 2016). Usually, original equipment manufacturer (OEM) refers to the company that originally manufactured the product and/or used virgin materials. Many studies have confirmed, however, that remanufacturing is more profitable than OEM (Hammond et al., 1998; Guide, 2000).

In Japan, at least 80% of air conditioner materials are recycled under the home appliance recycling law. In 2014 alone, Japan recovered about 230,000 products, totaling 10,783 tons, with an 89% recycling ratio (Daikin, 2015).

Recent literature reviews considering different aspects of supply chain sustainability include: energy use (Dotoli, 2005) GHG emissions reduction (Guillen-Gosalbez & Grossmann, 2009), green design (Hugo & Pistikopoulos, 2005), production planning and control for remanufacturing (Hugo et al., 2005), product recovery (Jayaraman, 2006), reverse logistics (Sheu, 2008), and waste management (Guillen-Gosalbez & Grossmann, 2009).

Reducing emissions generated by a supply chain has become an important goal. The "trade-offs in the supply chain are no longer just about cost, service and quality, but also about cost, service, quality and carbon," (Chaabane et al., 2012). A "closed-loop supply chain" considered by Paksoy et al. (2011) focused on transportation costs and GHG emissions, to explore the trade-off between operational and environmental performance...
measures. Abdallah et al. (2012), meanwhile, investigated greenhouse gas emissions as a consequence of supply chain network design and supplier selection using a life cycle assessment (LCA) approach.

A mixed-integer programming model was formulated by Diabat and Simichi-Levi (2010) to find an optimal strategy for companies to meet their carbon cap while minimizing costs. Similarly, a mixed-integer linear programming model was formulated by Alkhayyal et al. (2016a, 2016b) to find the optimal flow of parts among multiple remanufacturing centers under a specific carbon tax while minimizing costs. Chaabane et al. (2012) created a model that targeted processes with an aluminum firm and examined the impact of greenhouse gas emissions on designing a sustainable CLSC network based on LCA principles; it also evaluated the trade-offs between economic and environmental dimensions under various costs and strategies. The issues surrounding facility location with a trading price of GHG Emissions and cost of procurement were considered in Diabat et al.’s (2013) work; Fahimnia et al. (2013) evaluated the forward and reverse supply chain influences on carbon footprint using a mixed-integer linear programming (MILP) model, with GHG Emissions evaluated in terms of carbon cost dollar. Benjaafar et al. (2013) measured the impact of GHG Emissions when a series of lot-sizing models were integrated into operations decisions, and how significant emissions reductions without cost increases can be achieved by operational adjustments alone. A supply chain and transportation mode selection study for a major retailer, based on carbon policies, was reported by Jin et al. (2014).

Importantly, a few studies have examined the impact of integrating international, national, and corporate policies and legislation on a sustainable supply chain. For example,
Nagurney et al. (2006) addressed carbon taxes in electric power supply chains, and Subramanian et al. (2010) proposed adding and integrating environmental considerations within the overall agenda. Biswas et al. (2013) compared the environmental impacts among repaired, remanufactured, and new air compressors. The results showed that a remanufactured air compressor led to a 96% reduction in GHG Emissions more than the others. Likewise, Zanghelini et al. (2014) showed that the remanufacturing process saved 46% more than the others in GHG Emissions when compared to newly manufactured air compressor production systems. Seuring and Muller (2008) defined sustainable supply chain management as “the management of materials, information, and capital flows, as well as cooperation among companies along the supply chain while taking goals from all three dimensions of sustainable development, viz., economic, environmental and social, into account which are derived from customer and stakeholder requirements.”

### 2.4 Strategic and Tactical Planning of Reverse Supply Chains

The literature studies of reverse supply chains combine tactical planning and strategic planning. Strategic planning (designing) of reverse and closed-loop supply chains with application of quantitative models has not been studied sufficiently. There is a need for more case studies. Academia and industry have yet to answer all strategic planning questions (Guide et al., 2003b). Difficult decisions need to be made at the strategic level, because they are difficult to change and may later become fixed. Every new decision relies on the impact of previous decisions. For instance, recovery decisions can be made during the design stage, by including a design for recovery. Design for recovery should be at the top of current supply network design. This also applies to network design issues that focus
on location, such as where to locate warehouses and re-distribution plants, as well as management of future capacity limits. These issues may use different techniques to support strategic decisions.

At the tactical level, transportation, handling, and warehousing of returns products affect decisions about the best forecasting techniques to use. Many studies have reported on product recovery designs under certain legislation and regulations (Fleischmann et al., 2001; Das, 2002). There is sufficient literature on product recovery designs (remanufacturing and recycling), as reported by Bellmann and Khare (2000), Dekker and Fleischmann (2004), Fleischmann (2001), Guide et al. (1999, 2000b), Gungor and Gupta (1999), Henshaw (1994), and Ilgin and Gupta (2010). Guide and Van Wassenhove (2001) discussed in detail decision models for used product acquisition with uncertain quality in the return flows. De Brito et al. (2004) provided an extensive number of case studies in reverse logistics, published in the last decade. Integrating product recovery design, product return, and supply chain incentives was discussed by Guide and van Wassenhove (2001, 2002); integrating reprocessing (remanufacturing or recycling) and reverse logistics with supply chain design was addressed by Chouinard et al. (2005), Fleischmann et al. (2001), Goggin and Browne (2000), and Savaskan et al. (2004).

The Pochampally et al. (2008) book appears to be the first complete work published on strategic planning of reverse and closed-loop supply chains and addresses complex issues of reverse and closed-loop supply chain management, planning, and design by using eighteen quantitative modeling techniques from operations research for different decision-making situations. They provided an extensive literature review in the areas of strategic planning, tactical planning, and operational planning. For more details see McGovern
Jayant et al. (2011, 2012) studied, reviewed, and identified gaps in the existing literature on design, planning, control issues, and product recovery in a reverse supply chain. Savaskan et al. (2004) investigated the problem of reverse channel choice between three decentralized reverse supply chain channels: manufacturer, retailer, and third party. Each of these channels collected the used products; the model then compared the total profit, taking into account return rate and unit sale price. Similarly, Savaskan and Wassenhove (2006), extended the findings of this model to study the competitive retailing environment, focusing on the interaction between reverse channel choice for collection of used products and strategic product pricing decisions in the forward channel when retailing is competitive. The extended model has two product collection systems (direct and indirect) from the consumers. This showed that the repurchase payments transferred to retailers for used products provided flexibility in unit sale price that could be used to price distinguish between retailers. Lu and Bostel (2007) employed a strategic design model for a closed-loop supply chain remanufacturing network. The model assumed that demand was deterministic and considered three types of facilities centers: intermediate, producer, and remanufacturing. A Lagrangian heuristic approach was using to solve the 0-1 mixed-integer programming problem.

Pochampally et al. (2004a), Pochampally et al. (2004b), and Pochampally and Gupta (2008) evaluated collection centers and recovery facilities for profit, consumer preference, and government preference (with respect to environmental consciousness). They calculated criteria weights using the Eigen vector method, and then employed the TOPSIS (technique for order preference by similarity to ideal solution) to find the success potential of each alternative evaluated. Lastly, Borda’s choice rule was applied to each
alternative, combining individual success potentials into group success potential. Pochampally et al. (2009b) and Nukala and Gupta (2007a) evaluated the metrics performance of a reverse and closed-loop supply chain with a mathematical model that used quality function deployment (QFD) and linear physical programming (LPP) to measure the "satisfaction level" of the supply chain with respect to each of the given metrics. They concluded that “developing the metrics for performance measurement of a supply chain is a difficult problem.” Pochampally and Gupta (2012), addressed the issues of selecting collection centers and evaluating the status of end-of-use products in recovery facilities with a multi-criteria decision making approach, employing fuzzy logic and Bayesian updating.

Gautam and Kumar (2005) proposed a multi-objective programming approach for strategic planning of recycling options with a geographical information system (GIS) platform. This approach evaluated four criteria: the trade-off between numbers of and sizes of drop-off stations, service network population coverage, average population walking distance to drop-off stations, and collection vehicle distance traveled by collection vehicles. Blackburn et al. (2004) designed a return network for rapid response and found that product value typically drops if it takes long to retrieve, decreasing the financial attraction of a reuse option. Krikke et al. (2004) supported the idea by studying organizations that have put significant effort into optimizing return networks, with the belief that what makes product returns profitable is the design of a good product return network.
2.5 Multi-Criteria Optimization Technique in Reverse Supply Chains

The ultimate goal of a multi-criteria technique is to achieve the optimal or aspired goal by considering several iterations within constraints (Ilgin et al., 2015). Banasik et al. (2016) developed a framework review to find relevant papers that used multi-criteria decision making (MCDM) techniques and classified them with respect to decision problems, indicators, and MCDM approaches under the area of designing green supply chain. This included over 188 scientific articles published between 2000 and 2015.

Pishvaee and Razmi (2012) proposed a multi-objective fuzzy mathematical programming model for designing an environmental supply chain under uncertainty with two objectives (that is, minimizing the total cost and the total environmental impact). Wang et al. (2011) employed a multi-objective mixed-integer programming model to study a supply chain network design with environmental concerns by considering the trade-off between total cost and environment influence. Ramezani et al. (2013) presented a stochastic multi-objective model for forward/reverse logistic network design in an uncertain environment with three goals (that is, maximizing profit and responsiveness and minimizing defective parts from suppliers). A set of Pareto optimal supply chain configurations is determined using the ε-constraint method. Özkır and Başligil (2013) use a fuzzy multi-objective optimization model with three recovery options (that is, material, component, and product recovery) to design a closed-loop supply chain network. The model considers three objectives: maximizing trade, customer satisfaction, and total closed-loop supply chain profit.
2.5.1 Mixed-Integer Linear Programming

In Ozceylan and Paksoy (2013), a mixed-integer mathematical model for a closed-loop supply chain network (including both forward and reverse) with N-period and multiple parts was proposed. The model considered purchasing (new raw material) and refurbishing (used parts/products) costs to determine optimal transportation quantities, location of plants, and retailers. Kongar and Gupta (2000) employed a preemptive integer goal-programming approach to the disassembly-to-order (DTO) process to satisfy several economical, physical, and environmental goals. Kongar and Gupta (2002) developed a multi-criteria decision-making approach for disassembly-to-order systems using goal programming to achieve the preemptive goals of maximum total profit and sales from materials, minimum number of disposed items, and minimum number of stored items, cost of disposal, and cost of preparation. This model determined the numbers of each product type to be taken back from the end-of-life and disassembled products. Kongar et al. (2002) and Kongar and Gupta (2006) solved the disassembly-to-order (DTO) problem by using a fuzzy goal-programming approach. Imtanavanich and Gupta (2006c) solved a multi-criteria DTO problem with stochastic yields using a preemptive goal-programming approach. Massoud and Gupta (2010) extended the work of Imtanavanich and Gupta (2006d) to solve a similar problem but under limited supply and quantity discount by using preemptive goal-programming (PGP). Imtanavanich and Gupta (2005) solved an N-period DTO problem by using a weighted fuzzy goal-programming method. Imtanavanich and Gupta (2006c) solved a similar DTO problem by integrating a genetic algorithm with weighted fuzzy goal programming. Rickli and Camelio (2013) proposed a multi-objective partial disassembly optimization by using a genetic algorithm (GA) heuristic to optimize
the sequences based on disassembly operation costs, recovery reprocessing costs, revenues, and environmental impacts.

In McGovern and Gupta (2008), lexicographic goal programming was proposed to compare search algorithm techniques used to solve disassembly line balancing problems. This model determined the sequence of parts to be removed from end-of-life (EOL) products so as to minimize the resources for disassembly, maximize the quality of parts recovered, and maximize automation of the process. Similarly, Xanthopoulos and Iakovou (2009) employed lexicographic goal programming to determine the desired nondestructive disassembly of an EOL product. Ondemir and Gupta (2014) proposed a multi-objective advanced remanufacturing-to-order and disassembly-to-order (ARTODTO) system using a lexicographic mixed-integer goal-programming approach employing collected life cycle data, stored and delivered by the Internet of Things. Battaia and Dolgui (2013) and Delorme et al. (2014) presented a state of the art of multi-objective method for the design of assembly and disassembly line balancing problems.

In Gupta and Isaacs (1997), goal programming was used to analyze the trade-off between technological, economic, and environmental factors in U.S. vehicle recycling infrastructure with lightweighting and dismantler and shredder profitabilities. The model compared two specific vehicles (steel unibody and polymer intensive). Isaacs and Gupta (1997) proposed a goal-programming method to explore changes to the current U.S. vehicle recycling infrastructure and effects on dismantler and shredder profitabilities. Likewise, Boon et al. (2000 and 2003), used goal programming to evaluate the economic impact of several different aluminum-intensive vehicles (AIV) on the U.S. vehicle recycling infrastructure. Harraz and Galal (2011) proposed a lexicographic mixed-integer
goal-programming approach to designing a recovery network for end-of-life vehicles (ELVs) in Egypt with determination of facility locations and allocation costs for different EOL options. In Gupta and Evans (2009), a model for operational planning of closed-loop supply chains was developed using non-preemptive goal programming, for multiple products as well as operations associated with product, subassembly, part, and material levels.

Chaabane et al. (2011) developed a multi-objective mixed-integer linear programming model to determine the trade-off between economic and environmental considerations when designing a supply chain. The model considered carbon emissions, supplier and subcontractor selection, transportation mode, total logistics costs, and technology acquisition. Mehrbod et al. (2012) developed a multi-objective mixed-integer nonlinear programming formulation for a closed-loop supply chain and solved it using interactive fuzzy goal programming (IFGP). The paper concluded that this had a better capability of addressing the decision-makers’ objective goals. Ghorbani et al. (2014) designed a reverse logistics network using a fuzzy goal-programming method. Gupta and Taleb (1996) and Taleb and Gupta (1997) proposed a heuristic methodology for disassembly of multiple products with multiple parts. Two companion algorithms were applied, a core algorithm to determine total disassembly requirements of the root items over the planning horizon, and an allocation algorithm to provide the schedule for disassembling the roots and the subassemblies. Later, Langella (2007) extended this method in several ways to deal with holding costs and external procurement of parts. Liu and Huang (2014) solved two scheduling problems related to economic and environment
criteria by using a multi-objective genetic algorithm. Wang et al. (2014) employed a genetic algorithm approach to multi-objective application in closed-loop supply chain network design.

Ilgin et al. (2015) reported on all papers that discussed multi-criteria decision-making techniques for environmentally conscious manufacturing and product recovery, including over 190 scientific articles published between 1996 and 2014.

2.5.2 Physical Programming

Physical programming (PP) is a multi-criteria decision-making tool that allows the decision maker (DM) to express ideas in a more realistic fashion for each criteria of interest (Alkhayyal & Gupta, 2015a; Ilgin & Gupta, 2012; Messac, 2006, 2015; Messac et al., 1996). In PP, four different soft classes are used to help express DM preferences: smaller is better (1S), larger is better (2S), value is better (3S), and range is better (4S). The most significant advantage of using PP is that no weights need to be specified for evaluation. The DM only needs to specify a preference structure for each criterion, which has a more physical meaning to the DM than weight that is randomly assigned to the criterion (Alkhayyal and Gupta, 2015a; Ilgin and Gupta, 2012; Messac et al., 1996). For more explanation of how physical programming works, refer to section 4.4.

The literature reported that the physical programming technique is used principally for network design of reverse and closed-loop supply chains and for disassembly system problems. Pochampally et al. (2003) used linear physical programming (LPP) to identify potential recovery facilities for a reverse supply chain network by considering multiple criteria (customer service rating of the recovery facility, ratio of throughput to supply of used products, multiplication of throughput by disassembly time, and quality of products
Pochampally and Gupta (2004b) developed a linear physical programming model to design a reverse supply chain in three stages. In stage I, cost-effective end-of-life (EOL) products for recycling or remanufacturing were selected from three candidate centers. Stage II involved selecting the best recovery facilities using the criteria defined, and stage III optimized the transportation of EOL products with the right transport quantities for the reverse supply chain. A single-phase LPP model was used by Nukala and Gupta (2006a) to explore the strategic and tactical planning stages of a closed-loop supply chain network, which was an extension of the work of Pochampally and Gupta (2004b) and focused on strategic and tactical planning with the same three stages. Further similar LPP models were presented by Ilgin and Gupta (2012), Pochampally et al. (2009a), and Pochampally et al., (2008).

Pochampally et al. (2009b) used metrics to measure the “satisfaction level” of a reverse and closed-loop supply chain by integrating quality function deployment (QFD) and LPP with respect to each of the metrics. A similar model was presented in Pochampally et al. (2009a). Pochampally and Gupta (2012) presented an LPP-based approach for collection center selection by defining eight criteria (sigma level, per capital income of people in residential area, utilization of incentives from local government, distance from residential area, distance from highways, incentives from local government, space cost, and labor cost).

Alkhayyal and Gupta (2015a) used a linear physical programming approach to multi-criteria decision making to determine the quantity of end-of-life products for transport from candidate collection centers to remanufacturing facility while satisfying four important criteria. Alqahtani and Gupta (2014) developed a linear physical programming model to
deliver the optimal quantities of remanufactured products for N-periods within the reverse supply chain. Alqahtani and Gupta (2015) proposed a similar model for multi-period for a remanufacturing system. Alkhayyal and Gupta (2015b) addressed issues in product recovery facilities (PRFs) using nonlinear physical programming (NPP) for pricing to satisfy multiple criteria. This work was probably the first of its kind to provide a pricing model using NPP.

For disassembly system problems, Kongar and Gupta (2002) developed an LPP model for disassembly to determine of the number of items to be disassembled for re-processing (remanufacturing, recycling), storing, and disposal. Their model considered nine criteria: average customer satisfaction, average quality achievement, average environmental damage, average environmental benefit, number of disposed items, resale and recycle revenue, number of recycled items, and total profit. Lambert and Gupta (2005) presented a similar model. Kongar and Gupta (2009) modeled a disassembly-to-order (DTO) system using LPP, considering five ultimate aims, number of recycled, disposed, and environmental damage, customer satisfaction, and total profit. Imtanavanich and Gupta (2006b) used LPP to solve an N-period DTO problem. Massoud and Gupta (2010) developed an LPP approach for an N-period DTO problem with four objectives (maximization of profit, minimization of procurement cost, minimization of purchase cost, and minimization of disposal cost). Ondemir and Gupta (2011) used an LPP model for a remanufacture-to-order system with a demand-driven environment using the life cycle data collected, stored, and delivered by developing information technologies (sensors and RFID tags). Alqahtani and Gupta (2015b) presented a similar model for different products.

2.6 Multi-Criteria Analysis Techniques in Reverse Supply Chains

Physical programming technique is a multi-criteria decision-making tool that allows decision makers to express ideas in a more realistic fashion and look for new solutions. On the other hand, multi-criteria analysis techniques consider a limited number of prearranged alternatives and preference ratings (Tzeng and Huang, 2011). Multi-objective optimization techniques and multi-criteria analysis techniques can work together with integrated multi-objective optimization technique and multi-criteria analysis. In this section, some general closed-loop supply chain and RSC studies done using multi-criteria analysis techniques, with subsections for analytical hierarchy process and analytical network process, were presented.

Kumar and Jain (2010) developed a data envelopment analysis (DEA) model to evaluate green supplier selection by considering carbon footprints. Similarly, Mirhedayatian et al. (2014) use a DEA model to evaluate the performance of green supply chains with undesirable outputs and fuzzy data. Gupta and Pochampally (2004c) proposed a fuzzy-TOPSIS method to evaluate recycling programs with respect to drivers of public participation. Shaik and Abdul-Kader (2011) proposed a multi-attribute utility theory (MAUT) with both quantitative and qualitative attributes to evaluate green supplier selection by considering the environmental, green, and organizational factors required for the selection process. Zeid et al. (1997) presented a case-based reasoning (CBR) method to solve planning for disassembly (PFD) for a single product. Extending Zeid et al.'s (1997)
work, Gupta and Veerakamolmal (2000) and Veerakamolmal and Gupta (2002) developed CBR approaches to automating disassembly process planning for N-product.

Ilgin et al. (2015) reported on papers that used multi-criteria analysis techniques for environmentally conscious manufacturing and product recovery. This included over 190 scientific articles published between 1996 and 2014.

### 2.6.1 Analytic Hierarchy Process

Analytic hierarchy process (AHP) is a multi-criteria decision-making technique developed by Saaty (1980) that helps organize and analyze complex decision problems. AHP is based on simple mathematics; it has been widely studied and amplified since then. For more explanation of how AHP works, refer to section 4.2.

remanufacturing portfolio selection. Ziout et al. (2013) developed an AHP method for sustainability assessment of manufacturing systems. This AHP method was similar to work of Sarmiento and Thomas (2010) determining improvements in implementation of sustainability initiatives. Subramoniam et al. (2013) used AHP to validate the remanufacturing decision-making framework (RDMF) modeled by Subramoniam et al. (2010).

### 2.6.2 Analytic Network Process

Analytical network process (ANP) is a multi-criteria analysis tool developed by Saaty (1996) as a simplification of AHP. It can be structured as hierarchical or nonhierarchical. As AHP, ANP allows interdependencies, outer-dependencies, and feedback among decision elements (Ravi et al., 2005). For further explanation of how ANP works, refer to section 4.3.

Cheng and Lee (2010) used ANP to select appropriate outsourcing reverse logistics for a high-tech manufacturing system by studying the importance of service requirements. Meade and Sarkis (2002) used ANP to evaluate and select third party reverse logistics suppliers. Govindan et al. (2013) modeled a multistep process to select a third-party reverse logistic provider (3PRLP). First, AHP was used to define priority factors, then ANP was used to select reverse logistic suppliers. Hsu and Hu (2007) and Hsu and Hu (2009) integrated provider selection and hazardous substance management using ANP. Chen et al. (2012) used ANP to solve complex green supply chain management (GSCM) strategy selection problems and evaluate the most important activity in each business function. A case study of the Taiwanese Electronics Company was proposed. Sarkis (1998) evaluated environmentally conscious business practices using ANP. Vinodh et al. (2012) used the
Sarkis (1998) ANP model to evaluate environmentally conscious business practices in an Indian manufacturing organization. Chen et al. (2009) used ANP with pair-wise comparison to evaluate green supply chain management strategies, (i.e., design, purchasing, manufacturing, and marketing).

In Büyüközkan and Çiftçi (2012), a fuzzy ANP approach was used for green supply chain management evaluation and applied to automotive companies. Büyüközkan and Çiftçi (2011) modeled a novel fuzzy multi-criteria decision, ANP based, for sustainable supplier selection under incomplete preference relations and analyzed the sustainable number of suppliers in a real-life problem to validate the model. Ravi et al. (2005) use ANP and a balanced scorecard approach (BSC) to determine the selection of reverse logistics operation alternatives for EOL computers. Bhattacharya et al. (2014) integrated a fuzzy ANP-based and balanced score card to help managers decide whether provider performance met industry and environment standards. This was implemented by a UK-based company. Tuzkaya and Gulsun (2008) evaluated the centralized return center location problem in a reverse logistics network using integrated ANP with a fuzzy multi-criteria decision approach (TOPSIS). For a disassembly model, Gungor (2006) used ANP method to evaluate connection types in design-for-disassembly (DFD).

2.7 Integration of Multi-Objective Optimization Technique with Multi-Criteria Analysis

This section provides a brief review of works integrating multi-objective optimization techniques with multi-criteria analysis. Govindan et al. (2015) developed a large body of literature review for the area of green supplier evaluation and selection that used multi-criteria decision making (MCDM) approaches. They found that analytical hierarchy
process (AHP) with fuzzy based model is the most widely used in MCDM, and “environmental management system” is the most widely considered criteria for green supplier evaluation and selection. This included articles published between 1997 and 2011.

Nukala and Gupta (2006b) integrated ANP-GP methodology for supplier selection problems in a closed-loop supply chain network. First, they evaluated supplier criteria (reliability, responsiveness, financial issues, cultural and strategic issues, and others). Then, preemptive goal programming (PGP) was applied to determine optimal quantities to order from suppliers. Ravi et al. (2008) employed an integrated ANP–zero one goal programing (ZOGP) methodology to select reverse logistics projects for EOL computers. First, ANP was used to determine the level of interdependence between selected criteria and candidates, and then resource limitations and several other selection constraints were considered; ZOGP determined resource distribution among the reverse logistics projects. In Buyukozkan and Berkol (2011), analytic network process integrated quality function deployment (QFD) and zero-one goal programming to determine design requirements for a sustainable supply chain (SSC). ANP was used to measure levels of importance in a house of quality (HOQ), which then translated customer requirements into product design requirements. Based on the results, zero-one goal programming was applied to determine the most appropriate design requirements.

Dehghanian and Mansour (2009) integrated an analytical hierarchy process (AHP) and multi-objective genetic algorithm (MOGA) to design a sustainable recovery network for end-of-life products. First, AHP was used to determine social impact. Then, MOGA was used to find the Pareto-optimal solutions. Vadde et al. (2011) presented a multi-criteria decision model to determine a pricing policy for product recovery facilities by integrating
AHP, multi-objective mathematical programming, and genetic algorithms. First, AHP was used to weight decision maker preferences, then those weights were applied to the genetic algorithm model objective function. Lastly, the multi-objective mathematical programming problem was solved. Ge (2009) employed an integrated GA-AHP methodology to evaluate green suppliers.

Nukala and Gupta (2007b), integrated two multi-criteria analysis techniques, Taguchi loss functions and AHP with fuzzy programming, to evaluate supplier selection in a closed-loop supply chain network. First, Taguchi loss functions were used to calculate supplier attributes to quality loss. Second, AHP was used to convert the quality loss into a variable for use as the objective function of the fuzzy programming model. Finally, fuzzy programming determined the optimal quantities to be ordered from the suppliers. In Paksoy et al. (2012), three multi-criteria analysis techniques compared (AHP, fuzzy AHP, and fuzzy TOPSIS) when evaluating different criteria and guiding decision makers designing a closed-loop supply chain (CLSC) network.

Kannan et al. (2013) integrated the fuzzy multi-criteria decision-making method and multi-objective programming approach for supplier selection and order allocation in a green supply chain management (GSCM) system. First, fuzzy AHP was used to weight supplier selection criteria; suppliers were then ranked based on the selected criteria using fuzzy TOPSIS. Walther et al. (2006) use the preference ranking organization method for enrichment of evaluations (PROMETHEE) to compare various treatment alternatives and to evaluate these alternative systems. Results were then used to determine short-term decisions by weighted goal programming (WGP). Finally, multi-objective linear programming (MOLP) was applied to determine optimal order quantities for each supplier.
Ilgin et al. (2015) reported on papers that used multi-criteria analysis techniques for environmentally conscious manufacturing and product recovery. This included over 190 scientific articles published between 1996 and 2014.

2.8 Economic Input-Output Life Cycle Assessment (EIO-LCA) Studies in Remanufacturing

Latham (2016) used the EIO-LCA method to study the economic and environmental impact of manufactured traditional vehicles and remanufactured new vehicles. The results showed that in every EIO-LCA category remanufactured vehicles were a better alternative than manufactured vehicles both economically and environmentally.

EIO-LCA was used to study statistical data on U.S. cellular phone shipments and average bills of material from 2003 and 2004 with respect to the environmental impact of upstream cellular phone production chains, such as, air pollutants, energy use, and greenhouse emissions (Zhou and Schoenung, 2006). They concluded that reusing, recycling, refurbishing, and remanufacturing cellular phones and their components were better alternatives for environmental risk reduction. Mihelcic et al. (2003) studied the life cycle stages of products. In most cases, reusing and remanufacturing were preferred since they required fewer natural resources, less energy and time, and lower costs. Kerr and Ryan (2001) have one of the most detailed LCA remanufacturing study, which was based on a case study for photocopiers remanufacturing at Fuji Xerox Australia. The study found that over the life cycle of a photocopier remanufacturing production can reduce resource consumption and waste generation by up to a factor of 3.1, however, more reductions will happen if a photocopier is designed for disassembly and remanufacturing. Besides lowering the environmental burdens, photocopier remanufacturing results in better service
for the consumer and higher profit for the producer. A life-cycle assessment (LCA) model was developed by Smith and Keoleian (2004) to examine the energy savings and pollution prevention over remanufactured midsized automotive gasoline engine compared to manufacturing a new one. The study found that the remanufactured engine has 75% less energy and 80% less CO₂ emissions during production process.

2.9 Conclusion

This chapter provided a brief review of the literature on circular economy, distribution planning, inventory control, and production planning and control in reverse supply chains, greenhouse gas emissions, multi-criteria optimization techniques for reverse supply chains, and economic input-output life cycle assessment (EIO-LCA) studies in remanufacturing.
Chapter 3 STATEMENT OF THE PROBLEM AND RESEARCH OBJECTIVES

3.1 Problem Statements

Currently, there are international, national, and corporate policies intended to reduce pollution in a flexible and economical manner (Carmona et al., 2009). Therefore, today there is increasing reverse flow of products across a range of industries. Corporations across multiple industries are increasingly exploring ways to improve supply chain systems and efficiently and profitably meet consumer demands and government regulations (Vadde et al., 2006). As a result, remanufacturing has been found to be the most environmentally friendly option for end-of-life products, both because of avoiding waste and substituting for primary materials but also because of upgrading product performance, which saves energy (and associated emissions) during product use. Therefore, and by looking at the literature review, there have been few works done for designing reverse supply chain and satisfied environmental consciousness issues (refer to Chapter 2 for a brief review).

This dissertation examines these issues with focus on strategic planning and tactical planning levels of reverse supply chain. The decision-making problems that are faced by strategic planners of reverse supply chains include first (1) collection center placement and capacity. Evaluation of the collection centers is the first stage in choosing the most profitable collection center. Next, (2) optimization of transport of EOL products while considering fuel and potential carbon costs, which has the focus of achieving transporting (used and remanufactured) products across a reverse supply chain while satisfying certain
constraints that all fall under optimization of costs. Lastly, (3) pricing of remanufactured products, to determine a pricing policy for reusable and recyclable products in a multi-criteria environment, to maximize the revenue and minimize the product recovery costs.

3.2 Research Objectives

The objectives of this dissertation is to address the issues related to strategic “designing” and planning “tactical” levels of RSC. Within the modern environment, there are 5 primary efforts being undertaken to establish a circular economy to reduce non-renewable resource utilization, and waste. A key facet of such efforts is the development of RSC systems capable of facilitating a reverse flow of used products from consumers back to manufacturers, at which point they may be refurbished or remanufactured to realize both environmental and economic benefits. The applied design approach is formulated as a multi-criteria optimization problem and explored using several available multi-criteria optimization techniques. The literature includes many forward supply chain developed studies and analysis, where the customer is the end of the process. However, the returns processes enabled by RSC covers many areas, including collecting, cleaning, disassembly, recovering, transportation, remanufacturing, reselling, and disposed or shredded products that cannot be reprocessed or are hazardous all over the reverse supply chain activities still need analytical development, as reviewed in the Chapter 2.

Through the application of a multi-criteria decision-making approach, this dissertation explores the following research questions and develops general models through which they are studied:

1. What qualitative and quantitative factors determine the strategic planning employed in collection centers and how are they evaluated?
2. Through the application of a Physical Programming approach, how are the prices of reusable and recyclable components, and the acquisition price of discarded products determined in a multi-criteria environment?

3. What is the effect of a social cost of carbon (SCC) on the optimal configuration of RSC, and how does increasing the SCC affect the unit price of remanufactured equipment, relative to OEM?

These and other related issues are explored within this dissertation, with a specific focus on the strategic planning and tactical planning levels of RSC management have never been addressed in the literature before and will form a guide to future research.
Chapter 4  TECHNIQUES USED

4.1 Introduction

In this chapter, we introduce the multi-criteria techniques used to solve the various issues in strategic planning of a reverse supply chain.

4.2 Analytic Hierarchy Process

Analytic hierarchy process (AHP) is a multi-criteria decision-making technique developed by Saaty (1980) that helps organize and analyze complex decision problems. AHP is based on simple mathematics; it has been widely studied and amplified since then. AHP has been used in almost all applications related to decision-making analysis, such as optimization, planning, resource allocation, and resolving conflict. Forman and Gass (20010, Vargas (1990), and Vaidya and Kumar (2006) reviewed more than 150 papers describing successful applications of AHP. More AHP applications to closed-loop supply chains are presented in section 2.6.1.

AHP allows the decision maker (DM) to make parallel judgments of independent criteria and decision alternatives, and then converts preferences into numeric scale priorities or weights that are used to rank the alternatives on a scale of 1 to 9, with 1 signifying equal importance and 9 extreme importance, as shown in Table 4.1 (Saaty, 1980). This numeric scale is derived from Eigen vectors and the consistency index is derived from Eigen value. AHP involves six steps (Cheng and Li, 2001):

1. Identify the criteria;
2. construct an AHP hierarchy;
3. collect paired judgments,
4. apply the Eigen vector method, as follows:
   a. Eigen value ($\lambda_{\text{max}}$),
   b. mean transformation,
   c. or geometric mean;

5. calculate the consistency index (CI) for the matrix with size n (the matrix number of rows or columns) using the CI formula, $\text{CI} = (\lambda_{\text{max}} - n)/(n -1)$,

6. and calculate the consistency rate (CR) using the formula of $\text{CR} = \text{CI}/\text{RI}$, where RI is the random index for each n value in the matrix that is greater than or equal to 1, ranging from 1 to 10.

Table 4-1: Saaty’s Scale Ranges in Pair-wise Comparison

<table>
<thead>
<tr>
<th>Importance indicator</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>equal importance</td>
</tr>
<tr>
<td>3</td>
<td>moderate importance</td>
</tr>
<tr>
<td>5</td>
<td>strong importance</td>
</tr>
<tr>
<td>7</td>
<td>very strong importance</td>
</tr>
<tr>
<td>9</td>
<td>extreme importance</td>
</tr>
<tr>
<td>2, 4, 6, 8</td>
<td>intermediate importance values</td>
</tr>
</tbody>
</table>

Table 4-2: Saaty (1980) shows the random indices for a matrix with $n = 500$

<table>
<thead>
<tr>
<th>n</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td>RI</td>
<td>0.00</td>
<td>0.00</td>
<td>0.58</td>
<td>0.90</td>
<td>1.12</td>
<td>1.24</td>
<td>1.32</td>
<td>1.41</td>
<td>1.45</td>
<td>1.49</td>
</tr>
</tbody>
</table>
4.3 Analytic Network Process

Analytical network process (ANP) is a multi-criteria analysis tool developed by Saaty (1996) as a simplification of AHP. It can be structured as hierarchical or nonhierarchical. As AHP, ANP allows interdependencies, outer-dependencies, and feedback among decision elements (Ravi et al., 2005). ANP allows for complex interrelationships between decision levels and attributes, since not many decision problems can be structured hierarchically if they involve interaction between and dependence upon higher or lower level elements in a hierarchical structure (Görener, 2012; Saaty, 1996).

Görener (2012) presented a comparison application study of AHP and ANP in a manufacturing company. Cheng and Lee (2010) used ANP to select the appropriate outsourcing reverse supply chain for a high-tech manufacturing firm by studying the importance of service requirements. Gencer and Gürpinar (2007) presented a case study of an electronic company, evaluating the supplier and supplier selection criteria in a feedback manner, using ANP. In addition, Jharkharia and Shankar (2007) used the ANP approach to evaluate selection of a logistic service provider. More ANP applications to decision making along with benefits, opportunities, costs, and risks in closed-loop supply chains are presented in section 2.6.2.

The ANP approach involve four steps (Saaty, 1996, 2005):

1. Develop the model and formulate the problem;

2. make paired comparisons: in addition to AHP, main criteria and sub-criteria are also compared to address interdependencies among sub-criteria. The relative importance values are determined with regard to Saaty’s scale in Table 4.1;
3. formation of super-matrix: it is actually a partitioned matrix, with global and local priorities entered in the appropriate columns of the matrix designed by the decision makers;

4. and selection of best alternatives, depending on the values of many desirability indices that indicate alternative importance values in supporting a determinant.

4.4 Integer Linear Programming

4.4.1 Mixed-Integer Linear Programming

This approach optimizes a linear objective function, subject to linear constraints. For example, the expression of a linear programming problem such as:

- Maximize \( Z \) \( X \) (objective function)
- Subject to \( AX \leq B \) and \( X \geq 0 \) (constraints)

Where \( X \) represents the vector of variable, \( Z \) and \( B \) represent the vectors of coefficients, and \( A \) is the matrix of coefficients. When the variables of this linear problem are restricted to integers, the model is called a linear integer problem. Mixed-integer linear programming (MILP) is a special case, in which 0–1 integer linear programming involves integers and non-integers for both constrained variables. It is a very general context for solving problems with both discrete decisions and continuous variables. It can be applied to business, economic, and engineering problems (Pochampally et al., 2008).

4.5 Linear Physical Programming

Linear physical programming (LPP) is a multi-criteria decision-making tool that allows the decision maker (DM) to express ideas in a more realistic fashion for all criteria of interest
Most optimization problems fit one of two classifications: blind or physical optimization. Blind optimization happens when we wish to minimize (or maximize) a function subject to constraints and we do not have any knowledge about the physical meaning of the objective function, constraints, or decision variable. On the other hand, physical optimization takes place in the context of decision making that leads to the most satisfactory outcome (Alkhayyal and Gupta, 2015a; Messac et al., 1996). In LPP, there two classes of criteria, hard and soft, referring to sharpness of preference. The following four soft classes are used to express the DM preferences: smaller is better (1S), larger is better (2S), value is better (3S), and range is better (4S). For standard objective function, the four soft classes are illustrated in Figure 4.1. The most significant advantage of using PP is that no weights need to be specified for evaluation. The DM only needs to specify a preference structure for each criterion, which has a more physical meaning to the DM than weight that is randomly assigned to the criterion (Alkhayyal and Gupta, 2015a; Ilgin and Gupta, 2012; Messac et al., 1996).

Additionally, these classes have differing ranges of desirability and for illustration the case of class 1S shown in Fig. 4.1. is defined as the following (in decreasing order):

- **Ideal Range:**
  \[ g_p \leq t_{p1}^+ \]

- **Desirable Range:**
  \[ t_{p2}^+ \leq g_p \leq t_{p1}^+ \]

- **Tolerable Range:**
  \[ t_{p2}^+ \leq g_p \leq t_{p3}^+ \]

- **Undesirable Range:**
  \[ t_{p3}^+ \leq g_p \leq t_{p4}^+ \]

- **Highly Undesirable Range:**
  \[ t_{p4}^+ \leq g_p \leq t_{p4}^+ \]
• Unacceptable Range: \( g_p \geq t_{p5}^+ \)

The ranges parameters \( t_{p1}^+ \) through \( t_{p5}^+ \), represent the soft classes shown in Fig. 4.1 and the physically meaningful values that are specified by the DM to calculate the preferences associated with the \( p \)th design objective. On the other hand, the hard case has four subclasses which are:

- a) Class 1H: Must be smaller
- b) Class 2H: Must be larger
- c) Class 3H: Must be equal
- d) Class 4H: Must be in range

For example, let’s consider the operation of low-price toy factory. Assume that the DM wishes to:

- a) minimize a toy unit price \((P)\),
- b) minimize capital investment \((C)\),
c) minimize workforce \((W)\),

d) maximize a toy durability \((S)\), and

e) minimize risk \((R)\).

These criteria can be expressed in terms of a decision variable vector \(x\), under these conditions, the aggregate objective function is:

\[
\text{Min } J(x) = w_1 P(x) + w_2 C(x) + w_3 W(x) - w_4 S(x) + w_5 R(x)
\]  

(1)

Where \(w_i\) is a generic weight and the key difficulty with the above approach is, indeed determining the correct weights.

Consider for example the unit price above, the DM knows that a price of $15 or less is ideal; $19 desirable; $24 acceptable but undesirable, $29 is highly undesirable, and $34 or more, unacceptable. Thus, instead of attempting to find correct weights, the DM expresses the preference regarding the unit price as follows, using the LPP lexicon:

<table>
<thead>
<tr>
<th>Class</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ideal</td>
<td>&lt;$15</td>
</tr>
<tr>
<td>Desirable</td>
<td>$15-$19</td>
</tr>
<tr>
<td>Tolerable</td>
<td>$19-$24</td>
</tr>
<tr>
<td>Undesirable</td>
<td>$24-$29</td>
</tr>
<tr>
<td>Highly Undesirable</td>
<td>$29-$34</td>
</tr>
<tr>
<td>Unacceptable</td>
<td>&gt;$34</td>
</tr>
</tbody>
</table>

LPP explicitly and systematically employs this information as an integral part of its problem formulation.

The LPP formula consists of four different steps, Messac (2015):

1. Identify the class type for each objective (1S-4H)

2. Classify the ranges of desirability for each class (see Fig. 4.1)
3. Use the LPP weight algorithm to find the incremental weights, $\Delta w^+_{pr}$ and $\Delta w^-_{pr}$ (Messac et al., 1996).

4. Calculate the total score for each alternative, by solving the formula $J$, which is constructed as a weighted sum of deviations for all the ranges ($r = 2$ to $5$) and criteria ($p = 1$ to $P$), as follows:

$$J = \sum_{p=1}^{P} \sum_{r=2}^{5} (\Delta w^-_{pr} \cdot d^-_{pr} + \Delta w^+_{pr} \cdot d^+_{pr})$$

(2)

By using LPP there are no weights needed to be specified for the criteria of evaluation. The DM only needs to specify a preference structure for each criterion, which has a more physical meaning to the DM than weight that is randomly assigned to the criterion.

### 4.6 Economic Input-Output Life Cycle Assessment (EIO-LCA)

EIO-LCA is one of many process-based LCA and environmental assessment software tools available. This is a technique for estimating the materials and energy resources required for environmental emissions resulting from economic activities. The U.S. Bureau of Economic Analysis (BEA) releases every five years all the transaction information needed for all economic sectors (428 as of 2002). Simultaneously, the U.S. Environmental Protection Agency (EPA) gathers and publishes their emissions information under their industrial sectors. At the end, and to determine the effects of changing the output of a single sector, the EIO-LCA would combine the two data sources (EIO-LCA, 2016). Here, the EIO-LCA sector chosen for this study was the U.S. 2002 Benchmark for air conditioning, refrigeration, and warm air heating equipment manufacturing.
4.7 Conclusion

In this chapter, we introduced the multi-criteria tools used to solve various problems in strategic planning of reverse supply chains.
Chapter 5  A LINEAR PHYSICAL PROGRAMMING APPROACH TO EVALUATING COLLECTION CENTERS FOR END-OF-LIFE PRODUCTS

5.1 Abstract

The first research question of this dissertation is explored in this study through the integration of quantitative and qualitative attributes in a multi-criteria decision-making (MCDM) environment, within the context of a particular issue in the strategic “designing” level of the RSC process. The study employed an ANP to determine the performance indices of collection centers derived through qualitative criteria from the remanufacturing facilities that were interested in buying used products. The evaluating criteria was comprised as a four-level hierarchy: the first level contains objective of evaluation of the collection centers, the second level involves the main evaluation criteria taken from the perspective of a remanufacturing facility, the third level contains the sub-criteria under the main evaluation criteria, and the fourth level has the collection centers. ANP is presented herein as a matrix that is comprised of a list of all facets listed horizontally and vertically. This particular method is of value when key elements of a decision are difficult to quantify and contrast, and thus the identification of important facets and their incorporation into a linear programing environment is of value. To determine the quality of EOL products for transport from collection centers to remanufacturing facilities, a physical programming approach was applied. Four criteria and their satisfaction were focused upon: (1) maximizing the total value of purchase; (2) the minimization of the total cost of
transportation; (3) disposal; and (4) the purchase cost. A numerical example is explored in which three collection centers locations are included to determine the optimal collection center.

5.2 Introduction

Today environmental consciousness motivates both corporations and academics are giving more attention to environmental problems, which at the same time are being addressed by governmental regulations. Corporations across all industries are increasingly exploring ways to improve supply chain systems and efficiently and profitably meet consumer demands.

Reverse supply chain (RSC) is described as “an initiative that plays an important role in the global supply chain for those who seek environmentally responsible solutions for their end-of-life (EOL) products.” (Alkhayyal et al., 2016a). RSC involves all activities associated with EOL products including collection, transportation, recovery facilities, disassembly, recycling, remanufacturing, and disposal (Ilgin and Gupta, 2010).

The design of a successful RSC requires selection of the best collection center among the various candidate centers where EOL products are dropped off by consumers. Evaluation of the collection centers is the first stage in choosing the most profitable collection center. The evaluation of collection centers is a multi-criteria problem that require the use of one of several tools available, such as Goal Programming and Analytic Network Process.
5.3 Literature Review

Lu and Bostel (2007) employed a strategic design model for a closed-loop supply chain remanufacturing network. The model assumed that demand was deterministic and considered three types of facilities centers: intermediate, producer, and remanufacturing. A Lagrangian heuristic approach was used to solve the 0-1 mixed-integer programming problem.

Pochampally et al. (2004a), Pochampally et al. (2004b), and Pochampally and Gupta (2008) evaluated collection centers and recovery facilities for profit, consumer preference, and government preference (with respect to environmental consciousness). They calculated criteria weights using the Eigen vector method, and then employed the TOPSIS (technique for order preference by similarity to ideal solution) to find the success potential of each alternative evaluated. Lastly, Borda’s choice rule was applied to each alternative, combining individual success potentials into group success potential.

Pochampally et al. (2009b) and Nukala and Gupta (2007a) evaluated the metrics performance of a reverse and closed-loop supply chain with a mathematical model that used quality function deployment (QFD) and linear physical programming (LPP) to measure the "satisfaction level" of the supply chain with respect to each of the given metrics. They concluded that “developing the metrics for performance measurement of a supply chain is a difficult problem.” Pochampally and Gupta (2012), addressed the issues of selecting collection centers and evaluating the status of end-of-use products in recovery facilities with a multi-criteria decision making approach, employing fuzzy logic and Bayesian updating.
5.4 Problem Statement and Proposed Approach

5.4.1 Problem Statement

In this research, a scenario of evaluating collection centers based on efficiency is presented. Figure 5-1 shows the current stage of the RSC in this study. In this model, performance indices are determined using ANP (Pochampally et al., 2009).

![Figure 5-1: Current stage of the RSC for this study](image)

See Figure 5.2 for an exhibit of the ANP hierarchical structure, evaluating collection center candidates. Within ANP criteria, sub-criteria and alternative are perceived equally as facets within a network. Each facet may be contrasted with another, insofar as there is a relationship between them. Ranking alternatives may depend not only the weighting of criteria, but also the alternatives that are present, thereby influencing the application of weight upon the criteria. ANP is presented herein as a matrix that is comprised of a list of all facets listed horizontally and vertically. This particular method is of value when key elements of a decision are difficult to quantify and contrast, and thus the identification of important facets and their incorporation into a linear programing environment is of value. Within this chapter, a unique approach will be presented based on Linear Physical Programming (LPP) in order to produce a priority vector through an ANP framework.
The LPP approach was employed to determine the quantity of EOL products for transport from the candidate collection centers to remanufacturing facilities while satisfying the four criteria within the hierarchy. The criteria incorporate the maximization of the total value of purchase, and the minimization of disposal and transportation costs in addition to the minimization of the total cost of purchase. Following the application of this approach, a numerical example is explored through three candidate collection results. The results were realized through the LPP model, through which the selection of candidate collection centers was determined.
5.4.2 Linear Physical Programming Approach

Goal Programming involves attainment of pre-assigned goals or targets. Goals are assigned numerical weights and may be characterized by a utility function. Many scientists believe that utility functions offer the perfect way to solve a multi-criteria problem. But it is very difficult to obtain a mathematical representation of a utility function for a true decision maker (DM) preference. On the other hand, a utility function has a major advantage. If it is correctly expressed and used, it will practically guarantee the most satisfactory solution for the DM (Messac et al., 1996).

This is an issue of optimizing outcomes, and in general, optimization problems are classified as one of two problems, blind or physical. Blind optimization is realized when the desire to optimize a function, whether through minimization or maximization, is subject to constraints in terms of available information related to the physical meaning of the objective function, decision variable, or constraints. Physical optimization is realized within the context of decision making that results in the most satisfactory possible outcome (Messac et al., 1996).

5.4.2.1 Definition

Linear Physical Programming (LPP) is a multi-criteria decision-making tool that allows the decision maker (DM) to express ideas in a more realistic fashion for all criteria of interest (Messac et al., 1996; Messac, 2006). In LPP, there two classes of criteria, hard and soft, referring to sharpness of preference. The following four soft classes are used to express the DM preferences: smaller is better (1S), larger is better (2S), value is better (3S), and range is better (4S). For standard objective function, soft classes are illustrated in Figure 5-3. The most substantial benefit of employing LPP is the lack of having to specify
weights in order to achieve evaluation. It is only necessary that the DM specify a preference structure for each criterion given that they have a more tangible meaning to the DM than a randomly assigned weight to the criterion (Ilgin and Gupta, 2012).

5.4.2.2 Literature Review

The literature reported that the physical programming technique is used principally for network design of reverse and closed-loop supply chains and for disassembly system problems. Pochampally et al. (2003) used linear physical programming (LPP) to identify potential recovery facilities for a reverse supply chain network by considering multiple criteria (customer service rating of the recovery facility, ratio of throughput to supply of used products, multiplication of throughput by disassembly time, and quality of products at recovery facility). Pochampally and Gupta (2004b) developed a linear physical programming model to design a reverse supply chain in three stages. In stage I, cost-effective end-of-life (EOL) products for recycling or remanufacturing were selected from three candidate centers. Stage II involved selecting the best recovery facilities using the criteria defined, and stage III optimized the transportation of EOL products with the right transport quantities for the reverse supply chain.
5.4.3 Analytic Network Process Approach

The process applies an analytical network process (ANP) application, a multi-criteria analysis tool developed to present a simplification of the analytic hierarchy process (AHP) (Saaty, 1996). ANP may be structured as either hierarchical or nonhierarchical, and like AHP, allows interdependencies, outer-dependencies, and feedback within the various facets of the decision-making process (Ravi et al., 2005). ANP is of particular value to
RSC). Pochampally et al. used Analytic Network Process (ANP) to calculate the performance indices (efficiency scores) of candidate collection centers, with respect to qualitative criteria taken from the perspective of a remanufacturing facility interested in buying the EOL products. Then goal programming was used to determine the quantities of EOL products to be shipped from the candidate collection centers to the remanufacturing facility (Pochampally et al, 2009).

ANP is of value in that it effectively acknowledges the complex interrelationships between decision levels and attributes, particularly due to the fact that many decision problems may be structured hierarchically insofar as they involve interaction between and dependence on elements in a hierarchical structure of varying levels (Görener, 2012; Saaty, 1996). Through the application of ANP, the decision maker (DM) is able to make parallel judgments of independent criteria and alternative decisions, and is then capable of converting preferences into numeric scale priorities or weights. The prioritization enables the DM to rank alternatives on a scale of 1 to 9, with 1 demarcating equal importance while 9 indicates extreme importance, as exhibited in Table 5.1 (Saaty, 1980).

Table 5-1: Saaty’s Scale Ranges in Pair-wise Comparison

<table>
<thead>
<tr>
<th>Importance indicator</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
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<td>very strong importance</td>
</tr>
<tr>
<td>9</td>
<td>extreme importance</td>
</tr>
<tr>
<td>2, 4, 6, 8</td>
<td>intermediate importance values</td>
</tr>
</tbody>
</table>
5.5 Nomenclature

c_i \quad \text{Unit purchasing cost of used product at collection center } i

c_{di} \quad \text{Disposal cost of used product } i

t_i \quad \text{Cost of transporting one used product from collection center } i \text{ to remanufacturing facility } j

d_j \quad \text{Demand for used product } j

i \quad \text{Collection center index, } i = 1, 2, \ldots, s

k_i \quad \text{Capacity of collection center } i

p_i \quad \text{Probability of breakage of used products purchased from collection center } i

p_{\text{max}} \quad \text{Maximum allowable probability of breakage}

Q_i \quad \text{Decision variable representing the quantity to be purchased from collection center } i

s \quad \text{Number of candidate collection centers}

w_i \quad \text{Performance index of collection center } i \text{ obtained by carrying out ANP}

5.6 Problem Formulation

The focus here is to achieve the right quantities of used products to be transported from the candidate collection center to the remanufacturing facility within the RSC while satisfying these criteria: maximize total value of purchase, minimize total cost of purchase, transportation, and disposal. The decision-making criteria in this model are presented in terms of ranges of different degree of desirability. The following are the cost and revenue which are included in the methodology (Nukala and Gupta, 2006b).
5.6.1 Objective Functions

5.6.1.1 Physical Programming Classes and Constraints

Soft Classes:

Class-1S: Smaller-Is-Better – Min:

These are basically the cost criteria

Total Cost of Purchase \( g_1 \) given by

\[
g_1 = \sum c_i \times q_i \tag{5-1}\]

Total Transportation Cost \( g_2 \) given by

\[
g_2 = \sum t_i \times q_i \tag{5-2}\]

Disposal Cost \( g_3 \) given by

\[
g_3 = \sum (q_i \times p_i) \times c_d i \tag{5-3}\]

Class-2S: Larger-Is-Better – Max:

These are basically the revenue criteria

Total Value of Purchase \( g_4 \) given by

\[
g_4 = \sum w_i \times q_i \tag{5-4}\]

Goal constraints

\( h_1 \leq \text{RETMAX} \) (Retrieval cost is not more than maximum allowed value) \( (5-5) \)

\( g_p - d^+_{pr} \leq t^+_{p(r-1)} \) (Deviation is measured from corresponding target value) \( (5-6) \)

\( g_p \leq t^+_{p5} \) (Criterion value is in acceptable range) \( (5-7) \)

\( d^+_{pr} \geq 0 \) (Deviation is nonnegative number) \( (5-8) \)

System Constraints

Hard Classes:

Class-1H Must be smaller, i.e., \( g_p \leq t^+_{p,\text{max}} \)
\[ Q_i \leq k_i \quad \text{(Capacity constraint)} \quad (5-9) \]

**Class-2H Must be larger, i.e.,** \( g_p \geq t_{p,\text{min}} \)

\[ d_i \times p_{\text{max}} \geq \sum_{i=1}^{s} Q_i \times P_i \quad \text{(Quality constraint)} \quad (5-10) \]

\[ Q_i \geq 0 \quad \text{(Nonnegativity constraint)} \quad (5-11) \]

**Class-3H Must be equal, i.e.,** \( g_p = t_{p,\text{val}} \)

\[ \sum_{Q_i=a_j} \quad \text{(Demand constraint)} \quad (5-12) \]

### 5.7 Numerical Example

For lack of access to real-world DM data, this paper uses data used by Pochampally et al. (2009) in an attempt to simulate a real-world environment as closely as possible. These data were solved using goal programming. However, by involving the DM with the Physical Programming (PP) mechanism, results will be more realistic and satisfactory to the DM. The study considers three candidate collection centers. Table 5-1 shows the data used for the PP problem, the target values for each soft criterion are shown in Table 5-2, and the incremental weights obtained by LPP weight algorithm (Messac et al., 1996; Kongar and Gupta, 2002) are shown in Table 5-3.

#### 5.7.1 Numerical Data

<table>
<thead>
<tr>
<th>Collection center</th>
<th>S1</th>
<th>S2</th>
<th>S3</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Capacity</strong></td>
<td>300</td>
<td>650</td>
<td>750</td>
</tr>
<tr>
<td><strong>Unit purchasing cost</strong></td>
<td>1.2</td>
<td>0.9</td>
<td>1.0</td>
</tr>
<tr>
<td><strong>Breakage probability</strong></td>
<td>0.03</td>
<td>0.015</td>
<td>0.01</td>
</tr>
<tr>
<td><strong>Net demand for the product</strong></td>
<td>1,000</td>
<td>1,000</td>
<td>1,000</td>
</tr>
<tr>
<td><strong>Maximum acceptable breakage probability</strong></td>
<td>0.025</td>
<td>0.025</td>
<td>0.025</td>
</tr>
</tbody>
</table>
Table 5-3: Preference Table PP Model

<table>
<thead>
<tr>
<th>Criteria</th>
<th>$t_{p1}$</th>
<th>$t_{p2}$</th>
<th>$t_{p3}$</th>
<th>$t_{p4}$</th>
<th>$t_{p5}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$g_1$</td>
<td>900</td>
<td>1100</td>
<td>1300</td>
<td>1500</td>
<td>1700</td>
</tr>
<tr>
<td>$g_2$</td>
<td>150</td>
<td>250</td>
<td>290</td>
<td>450</td>
<td>600</td>
</tr>
<tr>
<td>$g_3$</td>
<td>70</td>
<td>150</td>
<td>250</td>
<td>300</td>
<td>450</td>
</tr>
<tr>
<td>$g_4$</td>
<td>400</td>
<td>500</td>
<td>600</td>
<td>700</td>
<td>800</td>
</tr>
</tbody>
</table>

5.7.2 Results

The ANP performance indices applied are presented in Table 5-4, which demonstrates S3 as the highest ranked among the collection centers considered. Barring any restriction in system restraints, a quantity of 750 units would be ordered from S3 prior to considering other collection center alternatives. Conversely, the results achieved through the MCDM tool LPP in Table 5-5 demonstrates that 620 units were ordered from S2 and the remaining 380 units were ordered from S3 in order to satisfy the demand of 1000 total units. This is due to the fact that the unit purchasing cost at S3 is higher than in S2, as exhibited in Table 5-1, however, this cost was not considered within the ANP analysis, in which collection centers were evaluated based upon qualitative criteria. Table 5.2 exhibits differing ranges of desirability as defined by the following Total Purchase Cost ($g_1$) in decreasing order:

1. Ideal Range: $g_1 \leq 900$
2. Desirable Range: $900 \leq g_1 \leq 1100$
3. Tolerable Range: $1100 \leq g_1 \leq 1300$
4. Undesirable Range: $1300 \leq g_1 \leq 1500$
5. Highly Undesirable Range: $1500 \leq g_1 \leq 1700$
6. Unacceptable Range: $g_1 \geq 1700$
Accounting for these ranges in terms of total purchase cost, the DM would consider these in concert with the other three criteria, resulting in having the output of LPP weight applied in the model, as exhibited in Table 5-3.

Table 5-4: Output of PP Weight Algorithm

<table>
<thead>
<tr>
<th>Criteria</th>
<th>$\Delta \omega_{p2}^+$</th>
<th>$\Delta \omega_{p3}^+$</th>
<th>$\Delta \omega_{p4}^+$</th>
<th>$\Delta \omega_{p5}^+$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$g_1$</td>
<td>0.025</td>
<td>0.085</td>
<td>0.132</td>
<td>0.024</td>
</tr>
<tr>
<td>$g_2$</td>
<td>0.017</td>
<td>0.011</td>
<td>0.026</td>
<td>0.479</td>
</tr>
<tr>
<td>$g_3$</td>
<td>0.013</td>
<td>0.031</td>
<td>0.881</td>
<td>0.012</td>
</tr>
<tr>
<td>$g_4$</td>
<td>0.225</td>
<td>0.950</td>
<td>0.521</td>
<td>0.018</td>
</tr>
</tbody>
</table>

Table 5-4 exhibits the overall performance indices of the ANP, while Table 5-5 exhibits the results that are realized through solving the problem using LINGO (v11). The total cost of purchase, comprised of the quantity ordered at each collection center multiplied by the unit cost, is $938. These findings indicate that the model selected was the most desirable range from amongst those the DM could choose from, with cost minimization found to be greatest at the higher ranges. Further, the total value of the purchase is achieved by multiplying the ANP rate by the quantity ordered at each collection center, amounting to 348, indicating that the model selected the ideal range from the DM ranges of desirability, while also endeavoring to lower the cost of the higher range.

It was found that the maximum rate in breakage probability was the same throughout the three collection centers considered, although they were different in accounting for the key detail associated with the used products they were interested in, that of breakage probability. Of the three, S1 had the greatest probability of breakage, in addition to the highest purchasing cost. Thus, the model was endeavoring to minimize costs while supporting desirability ranges. This is facilitated through the explicit and systematic employment of this information as a key element in the formulation of the problem. S2 had
a lower purchasing cost and a slightly higher level of breakage probability, although with
the purchase price as a higher priority, the model optimized S2 by making the most of its
capacity. The DM was tasked with specifying a preference structure for each criterion
beyond the weight that is randomly assigned to the criterion and the model integrated such
preferences in a viable way to accommodate the DM while minimizing the cost.

Table 5-5: overall performance indices

<table>
<thead>
<tr>
<th>Collection center</th>
<th>Performance index</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1</td>
<td>0.231</td>
</tr>
<tr>
<td>S2</td>
<td>0.232</td>
</tr>
<tr>
<td>S3</td>
<td>0.536</td>
</tr>
</tbody>
</table>

Table 5-6: Results

<table>
<thead>
<tr>
<th>Collection center</th>
<th>ANP rating</th>
<th>Quantity ordered</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1</td>
<td>0.231</td>
<td>0</td>
</tr>
<tr>
<td>S2</td>
<td>0.232</td>
<td>620</td>
</tr>
<tr>
<td>S3</td>
<td>0.536</td>
<td>380</td>
</tr>
</tbody>
</table>

5.8 Conclusion

The goal of the first research question was to determine both quantitative and qualitative
attributes in the MCDM environment to objectively evaluate multiple conflicting criteria
when confronting collection centers evaluation in the strategic “designing” level of RSC.
Evaluation of the collection centers is an important stage in choosing the most profitable
collection center.

ANP method has unique advantages when key elements of a decision are difficult
to quantify and compare, particularly through the application of these elements in a linear
programming environment. This allows the DM to conduct parallel judgments of
independent criteria and decision alternatives and to then convert preferences into numeric
scale priorities or weights that may be utilized the rank the alternatives on a scale of 1 to
9, with 1 indicating equal importance and 9 indicating extreme importance, as exhibited in Table 5.1.

In this instance, the LPP tool enables the DM to express ideas in a more realistic manner for all key criteria, providing a more tangible and physical meaning to the DM than randomly assigned weight to the criterion. Thus, the LPP model was employed to identify an efficient collection center in a region in which an RSC was to be designed and implemented. LPP was applied to determine the quantities of EOL products to be transported from the candidate collection centers to the remanufacturing facility, while simultaneously satisfying importance criteria on behalf of the remanufacturing facility as well. The results of the process identified the chosen collection center, exhibiting the value and advantages of LPP.
Chapter 6 OPTIMAL PRICING FOR REUSABLE AND RECYCLABLE PRODUCTS USING NONLINEAR PHYSICAL PROGRAMMING

6.1 Abstract

The second research question explores the tactical level and will be explored with an objective to determine and optimize the pricing policy of reusable and recyclable products to maximize the total profit while minimizing the product recovery costs. Physical programming is applied to solve MCDM related to the pricing of reusable and recyclable products. Pricing problems are non-linear due to the environment they operate in, although if boundaries are constrained to a smaller range, they may become linear. However, when all linear smaller problems are combined they may become non-linear due to the implications of the environmental effect. A non-linear physical programming model is developed and used to optimize the pricing policy for reusable and recyclable products that maximizes total profit while minimizing product recovery costs.

6.2 Introduction and Related Work

Along with the rise of consumer awareness of environmental consequences, quantities of products discarded by customers are increasing massively; this has led to legislation that holds the original equipment manufacturers (OEM) responsible for their end-of-life products (Vadde et al., 2006; Ilgin and Gupta, 2010). President Obama in his 2015 State of the Union address stated that "The best scientists in the world are all telling us that our
activities are changing the climate” (Park, 2015). This has encouraged third-party firms to enter the market to exploit the economic opportunity in discarded products, which allows them to compete with the brand new products of OEMs. The third-party firms, known as product recovery facilities (PRFs), are involved in collecting discarded products, implementing product recovery operations, and profiting through the sale of the recovered reusable and recyclable components in secondary markets (Vadde et al., 2006). The challenges faced by PRFs are: (1) competition between OEMs and other PRFs; (2) requirement of costly, skilled workers for product recovery operations; (3) valuation of environmental considerations for inclusion into economic optimization tools; (4) uncertainty of the arrival time and the quantity for the discarded products; (5) inventory levels of recovered components; and (6) promotional, markdowns, sales, and clearance price discounts to clear inventory (Vadde et al., 2006; Vadde et al., 2010).

Guide and Jayaraman (2000) conducted a survey and found that, to reduce the uncertainty of return quantity and quality, many remanufacturing firms in the United States have adopted a market-driven product acquisition management approach to collection of used products. For example, Green Citizen Company buys back Apple laptops, desktops, iPhones, and iPads. The world's first automated eWaste recycling station, ecoATM, provides instant cash for the responsible recycling of old cell phones, MP3 players, and tablets. As of July 2014, ecoATM had approximately 1100 kiosks located in shopping malls and select large retailers nationwide (Anonymous, 2014). Kodak controls the return quantity of used cameras with cash incentives (Ayres and Ayres, 2002). The Dell computer company dynamically adjusts prices based on inventory levels of products to improve supply chain efficiency (Agrawal and Kambil, 2000).
Pricing of remanufactured products has not been given any importance in the past, but the scale and unique processes of transforming used and recycled products to “like-new” conditions and recapturing missing values added to products during the manufacturing stage have made pricing an important subject of research (Atasu, Guide, and Wassenhove, 2010; Atasu, Sarvary, and Wassenhove, 2008).


An effective pricing model for reusable and recyclable products can address these challenges by managing inventory levels under stated conditions. The present work determines a pricing policy for reusable and recyclable products in a multi-criteria environment when PRFs passively accept discarded products and proactively acquire as needed, with a goal of maximizing revenue and minimizing product recovery costs. An empirical study is performed to investigate the effects of disposal cost, preparation cost, holding cost, disassembly cost, acquisition cost, and sorting cost. Although Vadde et al. (2006) have addressed issues in a multi-criteria environment for PRFs using genetic algorithms for pricing, this work is probably the first of its kind in the literature to provide a pricing model using Nonlinear Physical Programming (NPP) to satisfy multiple criteria.

In general, optimization problems are classified as one of two problems, blind or physical. Blind optimization is realized when the desire to optimize a function, whether through minimization or maximization, is subject to constraints in terms of available
information related to the physical meaning of the objective function, decision variable, or constraints. Physical optimization is realized within the context of decision making that results in the most satisfactory possible outcome (Messac et al., 1996).

NPP is a multi-criteria decision-making tool that allows the decision maker (DM) to express ideas in a more realistic fashion for each criteria of interest (Ilgin and Gupta, 2012; Messac, 2006, 2015; Messac et al., 1996). In PP, four different soft classes are used to help express DM preferences: smaller is better (1S), larger is better (2S), value is better (3S), and range is better (4S). The most significant advantage of using PP is that no weights need to be specified for evaluation. The DM only needs to specify a preference structure for each criterion, which has a more physical meaning to the DM than weight that is randomly assigned to the criterion (Ilgin and Gupta, 2012a; Ilgin and Gupta, 2012b; and Messac et al., 1996).

### 6.3 Notation

- $R_T$ Total revenue.
- $C_D$ Total disposal cost.
- $C_P$ Total preparation cost.
- $C_H$ Total holding cost.
- $C_A$ Total disassembly cost.
- $C_Q$ Total acquisition cost.
- $C_S$ Total sorting cost.
- $P_N$ Net profit.
- $n_r$ Number of unique reusable components in a discarded product.
- $n'_r$ Number of unique recyclable components in a discarded product.
$n_d$  Number of unique disposable components in a discarded product.

$m_{ri}$  Multiplicity of reusable component $i$.

$n'_{ri}$  Multiplicity of recyclable component $i$.

$m_{di}$  Multiplicity of disposable component $i$.

$w_{ri}$  Weight of reusable component $i$.

$w'_{ri}$  Weight of recyclable component $i$.

$w_{di}$  Weight of disposable component $i$.

$w_p$  Weight of discarded product.

$p_{ri}$  Selling price of remanufactured component $i$ ($/\text{unit}$).

$p'_{ri}$  Selling price of high quality recyclable component $i$ ($/\text{lb}$).

$p_{ai}$  Selling price of high grade as-is reusable component $i$ ($/\text{unit}$).

$p_{si}$  Price of scrap grade reusable component $i$ ($/\text{lb}$).

$p'_{si}$  Price of scrap quality recyclable component $i$ ($/\text{lb}$).

$p_p$  Price of discarded product ($/\text{lb}$).

$\lambda_{ri}$  Demand for remanufactured component $i$.

$\lambda'_{ri}$  Demand for high quality recyclable component $i$.

$\lambda_{ai}$  Demand for high grade as-is reusable component $i$.

$\lambda_{si}$  Demand for scrap grade reusable component $i$.

$\lambda'_{si}$  Demand for scrap quality recyclable component $i$.

$\lambda_p$  Demand for damaged discarded products.

$\beta$  Yield of sorting process.

$\gamma_{ri}$  Yield of high grade reusable component $i$.

$\gamma'_{ri}$  Yield of high quality recyclable component $i$. 
\( \theta_{ri} \) Yield of remanufacturable quality reusable component \( i \).

\( R_q \) Quantity of proactively acquired returns.

\( R_p \) Quantity of passively accepted returns.

\( C_s \) Cost to sort a discarded product.

\( C_r \) Cost to disassemble a product.

\( C_q \) Cost to acquire a discarded product (acquisition price) ($/unit).

\( C_{pi} \) Cost to remanufacture high grade reusable component \( i \).

\( C'_{pi} \) Cost to prepare (such as crushing) high quality recyclable component \( i \).

\( C_{ai} \) Cost to prepare high grade reusable component \( i \) for as-is sale.

\( C_{hi} \) Holding cost for high grade reusable component \( i \).

\( C'_{hi} \) Holding cost for high quality recyclable component \( i \).

\( C_{di} \) Cost to dispose reusable component \( i \).

\( C'_{di} \) Cost to dispose recyclable component \( i \).

\( C_{ddi} \) Cost to dispose the disposable component \( i \).

\( C_{dp} \) Cost to dispose the discarded product.

\( C_{oi} \) Penalty cost to dispose reusable component \( i \).

\( C'_{oi} \) Penalty cost to dispose recyclable component \( i \).

\( C_{odi} \) Penalty cost to dispose the disposable component \( i \).

\( C_{op} \) Penalty cost to dispose the discarded product.

\( D_{ri} \) Disposal limit for reusable component \( i \).

\( D'_{ri} \) Disposal limit for recyclable component \( i \).

\( D_{di} \) Disposal limit for disposable component \( i \).

\( D_p \) Disposal limit for damaged discarded products.
6.4 Problem Formulation

6.4.1 Categorize the Reusable and Recyclable Components

The current stage of the RSC in this study is exhibited in Figure 6-1. To assist in the categorizing of the reusable and recyclable components considered, the following four classes have been applied:

1. High grade reusable components: Good physical appearance and quality are key characteristics of these components, which may be further differentiated into first and second grade components, based upon further tests of their potential for reuse.
   a. First grade components possess greater economic value when remanufactured or refurbished (refurbished components will also be referred to as remanufactured components throughout this study).
   b. Second grade components (also referred to as high grade as-is reusable) are sold in as-is condition, although they may experience some cosmetic changes. Inventory is generally held in both grades of components.

2. Scrap grade reusable components: This grade of component is either physically blemished or functionally disabled, although such graded components are nevertheless good candidates for recycling.

3. High quality recyclable components: These components may be directly recycled, or may require minimal effort to obtain the actual recyclable components. Prior to stockpiling in the inventory, high-quality recyclable components are subjected to operations such as shredding and crushing to facilitate processing at the recycling stage.
4. Scrap quality recyclable components: Scrap quality components require greater 
effort and time to separate the actual recyclable components, and may hold lower 
recycling value.

To realize an effective economic model, PRFs generally sell the remanufactured 
components in the following order:

1. high grade as-is reusable,
2. high quality recyclable,
3. scrap grade reusable,
4. scrap quality recyclable.

Following the selling period and identification of saleable components, all reusable 
and recyclable leftover scrap components are disposed of. Disposal regulations may assign 
penalties insofar as the quantity exceeds the restricted limit.

Figure 6-1: Current stage of the RSC for this study

6.4.2 Physical Programming Classes

6.4.2.1 Soft Classes – Min

Class-1S: Smaller-Is-Better – Min:

These are basically the cost criteria

Total Disposal Costs ($g_i$):

$g_i$ of product $i$ is calculated by multiplying the component disposal cost by the number of 
component units disposed times the penalty cost to dispose the component.
\[ g_1 = \sum_{i=1}^{n_r} C_{di} + \sum_{i=1}^{n_r} d_i' + \sum_{i=1}^{n_d} c_{ddi} \] (6-1)

Total Preparation Costs \((g_2)\):

\(g_2\) of product \(i\) is the summation of the cost of:

1. remanufacture high grade reusable component \(i\),
2. prepare high quality recyclable component \(i\),
3. prepare high grade reusable component \(i\) for as-is sale.

\[ g_2 = \sum_{i=1}^{n_r} C_{pi} + \sum_{i=1}^{n_r} C_{pi}' + \sum_{i=1}^{n_r} C_{xi} \] (6-2)

Total Holding Costs \((g_3)\):

\(g_3\) of product \(i\) is the summation of both holding cost for high grade reusable component and high quality recyclable component.

\[ g_3 = \sum_{i=1}^{n_r} C_{hi} + \sum_{i=1}^{n_r} C_{hi}' \] (6-3)

Total Disassembly Costs \((g_4)\):

\(g_4\) of product \(i\) is calculated by multiplying the cost to disassemble a product by the sum of quantity of proactively acquired returns and the quantity of passively accepted returns.

\[ g_4 = Cr(\beta R_p + R_q) \] (6-4)

Total Acquisition Costs \((g_5)\):

\(g_5\) of product \(i\) is calculated by multiplying the cost to acquire a discarded product by the quantity of proactively acquired returns.

\[ g_5 = C_q R_q \] (6-5)

Total Sorting Costs \((g_6)\):

\(g_6\) of product \(i\) is calculated by multiplying the cost to sort a discarded product by the quantity of passively accepted returns.

\[ g_6 = C_s R_p \] (6-6)
Class-2S: Larger-Is-Better – Max:

Total Revenue \( g_7 \)

These are basically the revenue criteria

\( g_7 \) is the summation of: the selling price of remanufactured component \( i \) ($/unit), selling price of high quality recyclable component \( i \) ($/lb), selling price of high grade as-is reusable component \( i \) ($/unit), price of scrap grade reusable component \( i \) ($/lb), price of scrap quality recyclable component \( i \) ($/lb), and the price of discarded product ($/lb).

\[
g_7 = \sum_{i=1}^{n_{rr}} P_i Q_i + \sum_{i=1}^{n'_{rr}} P'_i Q'_i + \sum_{i=1}^{n_{rr}} P_i A_i + \sum_{i=1}^{n'_{rr}} P'_i S_i + \sum_{i=1}^{n_{rr}} P'_i F_i + P_{pj} \tag{6-7}
\]

6.4.2.2 Hard Classes – Max

Class-1H Must be smaller, i.e., \( g_p \leq t_{p,max} \)

It has six constrains: the quantity of proactively acquired returns and quantity of passively accepted returns larger or equal to the six types of demands:

1. Demand for remanufactured component \( i \).
2. Demand for high quality recyclable component \( i \).
3. Demand for high grade as-is reusable component \( i \).
4. Demand for scrap grade reusable component \( i \).
5. Demand for scrap quality recyclable component \( i \).
6. Demand for damaged discarded products.

Class-2H Must be larger, i.e., \( g_p \geq t_{p,min} \)

It has one constrain, which is, all the demands for discarded products are positive.
6.4.3 Goal Constraints

\[ h_1 \leq \text{RETMAX} \quad \text{(Retrieval cost is not more than maximum allowed value)} \]  
\[ g_{p} - d_{pr}^+ \leq t_{p(r-1)}^+ \quad \text{(Deviation is measured from corresponding target value)} \]  
\[ g_{p} \leq t_{p5}^+ \quad \text{(Criterion value is in acceptable range)} \]  
\[ d_{pr}^+ \geq 0 \quad \text{(Deviation is nonnegative number)} \]

6.4.4 NPP Problem Model

\text{MINIMIZE } J = \log_{10} \left\{ \frac{1}{n_{SC}} \sum zi \left[ \mu_i(x) \right] \right\} \quad \text{(for soft classes)}

Subject to

\[ \mu_i(x) \leq t_{i5}^+ \quad \text{(for class 1S objectives)} \]  
\[ \mu_i(x) \geq t_{-i5}^- \quad \text{(for class 2S objective)} \]  
\[ \mu_j(x) \leq t_{i, \text{max}} \quad \text{(for class 1H objectives)} \]  
\[ \mu_j(x) \geq t_{i, \text{min}} \quad \text{(for class 2H objectives)} \]  
\[ x_{j, \text{min}} \leq x_j \leq x_{i, \text{min}} \quad \text{(for design variables), where } t_{i, \text{max}}, t_{i, \text{min}}, \text{and } t_{i, \text{val}} = \text{specified preferences values for the } i^{th} \text{ hard objective; } t_{i, \text{min}} \text{ and } t_{i, \text{max}} = \text{minimum and maximum values, respectively, for } x_j; \text{ ranges of desirability, } t_{i5}^+ \text{ and } t_{-i5}^- \text{ are provided by the designer; and } n_{SC} = \text{number of soft objectives. In the above formulation, hard classes are treated as constraints and soft classes are part of the objective function (Messac, 2006).} \]

6.5 Numerical Example

Because of lack of access to real-world DM data, this paper uses data from Vadde et al. (2006) to simulate a real-world environment as closely as possible. These data were solved using genetic algorithms. However, allowing DM involvement in the decision using the
Physical Programming (PP) mechanism will lead to results that are more realistic and satisfactory to the DM. Consider that a PRF is processing discarded PCs according to configuration and data costs shown in Table 6-2 and Table 6-3. The weights were obtained by using Matlab Code for a PP algorithm (Messac, 2006), based on the DM preference ranges for μ in Table 6-1, which shows differing ranges of desirability defined: as the following for Total Disposal Cost (\( g_1 \)) in decreasing order (for more in Chapter 4.5). Let the data for the PC be, \( wp = 5.95 \text{ lb}, \beta = 0.8, Cs = $9, Cr = $15, Cdp = $15, Cop = $12, Dp = 300 \text{ lb}, Rp = 20, Rq = 8Cq, \lambda p = 30 - 2.4pp \). Linear demand functions are assumed for the case example: \( \lambda r1 = 125 - 1.2pr1, \lambda r2 = 120 - 2.4pr2, \lambda a1 = 70 - 2.5pa1, \lambda a2 = 65 - 3.2pa2, \lambda s1 = 18 - 5.2ps1, \lambda s2 = 19 - 4.1ps2, \lambda'r1 = 80 - 4.6p'r1, \lambda'r2 = 90 - 2.1p'r2, \lambda'r3 = 125 - 5.3 p'r3, \lambda'r4 = 110 - 8.5p'r4, \lambda'r5 = 105 - 3.5p'r5, \lambda'x1 = 18 - 2.2 p's1, \lambda'x2 = 12 - 1.9 p's2, \lambda'x3 = 19 - 3.7 p's3, \lambda'x4 = 11 - 4.5 p's4, \lambda'x5 = 17 - 3.5 p's5, \lambda p = 30 - 2.5 Pp

<table>
<thead>
<tr>
<th>Criteria</th>
<th>( t_{p1}^+ )</th>
<th>( t_{p2}^+ )</th>
<th>( t_{p3}^+ )</th>
<th>( t_{p4}^+ )</th>
<th>( t_{p5}^+ )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( g_1 )</td>
<td>6</td>
<td>8</td>
<td>10</td>
<td>12</td>
<td>14</td>
</tr>
<tr>
<td>( g_2 )</td>
<td>5</td>
<td>7</td>
<td>9</td>
<td>11</td>
<td>13</td>
</tr>
<tr>
<td>( g_3 )</td>
<td>0.3</td>
<td>0.6</td>
<td>0.9</td>
<td>1.1</td>
<td>1.3</td>
</tr>
<tr>
<td>( g_4 )</td>
<td>600</td>
<td>700</td>
<td>800</td>
<td>900</td>
<td>1000</td>
</tr>
<tr>
<td>( g_5 )</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
</tr>
<tr>
<td>( g_6 )</td>
<td>100</td>
<td>200</td>
<td>300</td>
<td>400</td>
<td>500</td>
</tr>
<tr>
<td>( g_7 )</td>
<td>1300</td>
<td>1100</td>
<td>900</td>
<td>700</td>
<td>500</td>
</tr>
</tbody>
</table>

The following for Total Disposal Cost (\( g_1 \)) DM desirable ranges in decreasing order:

1. Ideal Range: \( g_1 \leq 6 \)
2. Desirable Range: \( 6 \leq g_1 \leq 8 \)
3. Tolerable Range: \( 8 \leq g_1 \leq 10 \)
4. Undesirable Range: \( 10 \leq g_1 \leq 12 \)
5. Highly Undesirable Range: \( 12 \leq g_1 \leq 14 \)
6. Unacceptable Range: $g_l \geq 14$

### 6.5.1 Numerical Data

Table 6-2: Product configuration

<table>
<thead>
<tr>
<th>Index (i)</th>
<th>Component</th>
<th>Multiplicity</th>
<th>Weight</th>
<th>Yield</th>
<th>Yield</th>
<th>Disposal Limit (lb)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Recycle)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>14&quot; FHD</td>
<td>1</td>
<td>1.10</td>
<td>0.85</td>
<td>n/a</td>
<td>26</td>
</tr>
<tr>
<td>2</td>
<td>Chassis</td>
<td>1</td>
<td>0.68</td>
<td>0.95</td>
<td>n/a</td>
<td>38</td>
</tr>
<tr>
<td>3</td>
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<td>0.70</td>
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</tr>
<tr>
<td>4</td>
<td>64MB RAM</td>
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<td>0.02</td>
<td>0.80</td>
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<td>20</td>
</tr>
<tr>
<td>5</td>
<td>1.44MB FD</td>
<td>1</td>
<td>0.68</td>
<td>0.75</td>
<td>n/a</td>
<td>19</td>
</tr>
<tr>
<td>(Reuse)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>24x CD-ROM</td>
<td>1</td>
<td>0.90</td>
<td>0.90</td>
<td>0.50</td>
<td>50</td>
</tr>
<tr>
<td>2</td>
<td>10GB HD</td>
<td>2</td>
<td>1.30</td>
<td>0.70</td>
<td>0.60</td>
<td>90</td>
</tr>
<tr>
<td>(Dispose)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>2.80 GHz Processor</td>
<td>1</td>
<td>0.40</td>
<td>n/a</td>
<td>n/a</td>
<td>120</td>
</tr>
</tbody>
</table>

Table 6-3: Cost data

<table>
<thead>
<tr>
<th>Preparation Cost</th>
<th>As-Is Cost</th>
<th>Holding Cost</th>
<th>Disposal Cost</th>
<th>Disposal Penalty</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Recycle)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>n/a</td>
<td>1.02</td>
<td>8</td>
<td>9</td>
</tr>
<tr>
<td>9</td>
<td>n/a</td>
<td>1.01</td>
<td>9</td>
<td>6</td>
</tr>
<tr>
<td>8</td>
<td>n/a</td>
<td>0.95</td>
<td>7</td>
<td>4</td>
</tr>
<tr>
<td>9</td>
<td>n/a</td>
<td>1.03</td>
<td>7</td>
<td>6</td>
</tr>
<tr>
<td>8</td>
<td>n/a</td>
<td>1.04</td>
<td>7</td>
<td>7</td>
</tr>
<tr>
<td>(Reuse)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>12</td>
<td>3</td>
<td>1.05</td>
<td>6</td>
<td>8</td>
</tr>
<tr>
<td>8</td>
<td>5</td>
<td>1.04</td>
<td>9</td>
<td>6</td>
</tr>
<tr>
<td>(Dispose)</td>
<td>n/a</td>
<td>n/a</td>
<td>10</td>
<td>14</td>
</tr>
</tbody>
</table>

### 6.5.2 Results and Discussion

Having determined these ranges for the DM in terms of the total disposal cost, exhibited in Table 6-1, in addition to three other criteria, the output of LPP weight that will be applied within the LPP model is identified, as demonstrated in Table 6-4.
Table 6-4: Output of PP Weight Algorithm

<table>
<thead>
<tr>
<th>Criteria</th>
<th>$\Delta \omega_2^+$</th>
<th>$\Delta \omega_3^+$</th>
<th>$\Delta \omega_4^+$</th>
<th>$\Delta \omega_5^+$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$g_1$</td>
<td>0.013</td>
<td>0.031</td>
<td>0.781</td>
<td>0.015</td>
</tr>
<tr>
<td>$g_2$</td>
<td>0.113</td>
<td>0.025</td>
<td>0.016</td>
<td>0.462</td>
</tr>
<tr>
<td>$g_3$</td>
<td>0.723</td>
<td>0.387</td>
<td>0.496</td>
<td>0.082</td>
</tr>
<tr>
<td>$g_4$</td>
<td>0.225</td>
<td>0.950</td>
<td>0.521</td>
<td>0.018</td>
</tr>
<tr>
<td>$g_5$</td>
<td>0.823</td>
<td>0.521</td>
<td>0.783</td>
<td>0.913</td>
</tr>
<tr>
<td>$g_6$</td>
<td>0.021</td>
<td>0.657</td>
<td>0.052</td>
<td>0.134</td>
</tr>
<tr>
<td>$g_7$</td>
<td>0.023</td>
<td>0.085</td>
<td>0.132</td>
<td>0.025</td>
</tr>
</tbody>
</table>

Table 6-5 demonstrates the results that are obtained through solving the problem by applying LINGO (v11). The total revenue ($g_7$) is $1187.98, which is the summation of: the selling price of remanufactured component i ($/unit), selling price of high quality recyclable component i ($/lb), selling price of high grade as-is reusable component i ($/unit), price of scrap grade reusable component i ($/lb), price of scrap quality recyclable component i ($/lb), and the price of discarded product ($/lb). This demonstrates that the model selected the desirable range for the DM from amongst the ranges of desirability, while also endeavoring to minimize the cost to higher ranges. Further, total acquisition costs ($g_5$), calculated by multiplying the cost to acquire a discarded product by the quantity of proactively acquired returns, is $4.10. The resulting cost is within the tolerable/undesirable range, exhibited through the model’s identifying the criteria to satisfy and optimize others. For example, total disassembly cost ($g_4$) is $732 (tolerable/acceptable range), and total sorting cost ($g_6$) is $180 (desirable range).

Given these findings, the pricing policy is capable of effectively minimizing costs while maximizing revenues. The costs are comprised of the acquisition cost of returns, disassembly cost of recovering components, processing and holding costs of the remanufactured, high grade as-is reusable, and high quality recyclable components,
disposal costs of scrap quality products, scrap grade reusable, and scrap quality recyclable components. Revenues are comprised of sales from the four classes of components, in addition to scrap quality discarded products. This particular model holds a unique means through which desirability ranges are accommodated. This information is then systematically employed as a key facet of the problem formulation process. Essentially, the DM was tasked with specifying a preference range for the criterion rather than randomly assigning weight to each individual criterion, with the model integrating these preferences in a more realistic manner to accommodate the DM while minimizing costs.

Table 6-5: Results obtained from executing the NPP algorithm

<table>
<thead>
<tr>
<th>Component</th>
<th>Price</th>
<th>Inventory</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>High grade/</td>
<td>As-Is High</td>
</tr>
<tr>
<td></td>
<td>quality($/lb)</td>
<td>grade/quality(lb)</td>
</tr>
<tr>
<td></td>
<td>Scrap grade/</td>
<td>As-Is (S)</td>
</tr>
<tr>
<td></td>
<td>Quality($/lb)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>High grade/</td>
</tr>
<tr>
<td></td>
<td></td>
<td>quality(lb)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>As-Is (units)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Disposed (lb)</td>
</tr>
<tr>
<td>14&quot; FHD</td>
<td>9.52</td>
<td>6.15</td>
</tr>
<tr>
<td>Chassis</td>
<td>31.52</td>
<td>6.23</td>
</tr>
<tr>
<td>128MB RAM</td>
<td>24.08</td>
<td>5.94</td>
</tr>
<tr>
<td>64MB RAM</td>
<td>12.57</td>
<td>3.02</td>
</tr>
<tr>
<td>1.44MB FD</td>
<td>24.81</td>
<td>4.07</td>
</tr>
<tr>
<td>24x CD-ROM</td>
<td>90.42</td>
<td>3.13</td>
</tr>
<tr>
<td>10GB HD</td>
<td>40.03</td>
<td>0.76</td>
</tr>
<tr>
<td>2.80GHz Processor</td>
<td>n/a</td>
<td>14.09</td>
</tr>
<tr>
<td>Computer</td>
<td>n/a</td>
<td>4.02</td>
</tr>
</tbody>
</table>

6.6 Conclusion

This research employed LPP to solve a MCDM problem involving the pricing of recyclable and reusable products, and focused on the tactical level of RSC, in line with the goal of the second research question.

The variance between the return flow of discarded products and demand or reusable and recyclable components, the source of potentially extreme inventory level differences was explored, to determine impacts on the costs associated with product recovery. Linear
programming was employed to optimize the utilization of resources, where the relationships between resource limitations and objectives are linear. For example, machine capacity and production manufacture levels are directly proportional to one another. This relationship however is not omnipresent, as with pricing problems given that they have non-linear relationships. However, given the environment in which they operate, even when boundaries are constrained to smaller ranges, they may become linear.

Within this work, PRFs passively accept discarded products on a regular basis, although at times proactively acquire them as necessary to reduce the mismatch between product returns and component demand. The price of reusable and recyclable components of varying grades and acquisition prices of discarded products are determined through a multi-criteria setting in which the PRF is tasked with maximizing its financial returns. This is accomplished by simultaneously minimizing various product recovery costs such as those associated with disposal, disassembly, preparation, holding, acquisition, and sorting. Therefore, this work provides a novel assessment from within the available literature.

This work recommends and it is capable of extending the current analytical model to multi-type products and is exhibited in a multi-period case. To study the effect of sorting and disassembly yields on pricing and inventory levels, the traditional deterministic assumption will be relaxed. Price and acquisition issues are explored through which remanufactured product demand is found to vary with a multiplicative random variable. It is found that a consideration of the stochastic demand for recovered components, customer price reservation, and monopoly of PRFs may enrich the analytical model in the illustration of their impact on pricing decisions and strategies.
Chapter 7 MANAGING TRANSPORTATION OF PRODUCTS AND GREENHOUSE GAS EMISSIONS IN REVERSE SUPPLY CHAINS

7.1 Abstract

The third research question of this dissertation is explored in this study through which a deterministic model is employed to explore the effects of internalizing a cost of RSC GHG emissions into optimization models. Variations in optimal facility use, pricing/profit margins, and transportation logistics were compared against a variable cost of carbon, employing a case study method established through the inclusion of actual data from sites in the Boston area. RSC is described as “an initiative that plays an important role in the global supply chain for those who seek environmentally responsible solutions for their EOL products”. The economic and environmental benefits of RSC are influenced by costs and emissions during collection, transportation, recovery facilities, disassembly, recycling, remanufacturing, and disposal of unrecoverable components. In this research, a mixed-integer linear programming model for reverse supply chains with full valuation of emissions is used to determine the optimal flow of parts among multiple remanufacturing centers that will maximize total profit and minimize CO₂ emissions, based on actual sites in the Boston area. The proposed model considers a mid-size LG brand air conditioning (A/C) unit with a refurbished market price of $288. Valuation of emissions is done using a direct carbon tax with the value varied according to ranges proposed at the 21st Climate Change Conference (COP21) in Paris, to determine how proposed policy will influence
profit margins for remanufactured goods. In the absence of a carbon tax, the profit margin for the A/C unit is 25%; a USEPA-recommended $40/ton CO2 equivalent (tCO2e) tax reduces the profit margin to 22%.

### 7.2 Introduction and Related Work

The number of products discarded by consumers has been gradually growing, which has led to legislations in various countries that hold the original equipment manufacturers (OEM) responsible for the end-of-life processing of products. In addition, the supply chain field has been influenced by consumer awareness of environmental issues (Vadde et al., 2006; Ilgin and Gupta, 2010).

Climate change, disposal capacities, finite resources, growing populations, quality of life improvement, increasing emissions, and rising energy prices have motivated both corporations and academics to develop strategies based on corporate social responsibilities and sustainable supply chains (Carter, 2008; Nagurney et al., 2007). While the concept of integrating sustainability into supply chains is relatively new, its implementation continues to increase (Paul et al., 2005; Seuring et al., 2008).

Nowadays, products are still moving in the direction of the end customer, but there is also increasing reverse flow of products. This is occurring for all industries (for instance, electronic products, pharmaceuticals, beverages). As an example, the automobile industry is busy changing the physical and practical supply chain to smooth end-of-life vehicle recovery and the U.S. vehicle-recycling infrastructure (Boon et al., 2000; Ferguson and Browne, 2001).

Reverse supply chain (RSC) processing is an initiative that plays an important role in the global supply chain for those who seek environmentally responsible solutions for
end-of-life (EOL) products. The relative economic and environmental benefits of RSC are influenced by costs and emissions during collection, transportation, recovery facilities, disassembly, recycling, remanufacturing, and disposal of unrecoverable components (Alkhayyal and Gupta, 2015; Gupta 2013).

Seuring and Muller (2008) defined sustainable supply chain management as “the management of materials, information, and capital flows, as well as cooperation among companies along the supply chain while taking goals from all three dimensions of sustainable development, viz., economic, environmental and social, into account which are derived from customer and stakeholder requirements.”

A literature review is conducted by Mexiell and Gargeya (2005) on economic considerations of supply chain design. A comprehensive review of the published literature on sustainable supply chain is presented by Seuring and Muller (2008), and Srivastava (2007).

Gungor and Gupta (1999) addressed the issues of environmentally conscious manufacturing and product recovery with an extensive review of the literature. The study looked at the product recovery process from environmentally conscious manufacturing point of view, and included the common issues in both environmentally conscious manufacturing and product recovery (viz. environmentally conscious design, environmentally conscious production, recycling and remanufacturing, and production planning and inventory control). Ilgin and Gupta (2010) further extended this literature review through 2010. There are several other authors who reported on product recovery designs under certain legislation and regulations (Das, 2002; Bellmann and Khare, 2000; Dekker et al, 2013; Fleischmann, 2000; Guide et al., 1999; Guide, 2000; Henshaw, 1994).
7.2.1 Greenhouse Gas Emissions in Reverse Supply Chains

Recent literature reviews consider different aspects of supply chain sustainability, including energy use (Dotoli, 2005), GHG emissions reduction (Guillen-Gosalbez and Grossmann, 2009), green design (Hugo and Pistikopoulos, 2005), production planning and control for remanufacturing (Hugo and et al., 2005), product recovery (Jayaraman, 2006), reverse logistics (Sheu, 2008), and waste management (Guillen-Gosalbez and Grossmann, 2009).

Reducing emissions generated by a supply chain has become an important goal. The “trade-offs in the supply chain are no longer just about cost, service and quality, but also about cost, service, quality and carbon,” (Chaabane and et al., 2012). A "closed-loop supply chain" considered by Paksoy et al. (2011), focused on transportation costs and GHG emissions, to explore the trade-off between operational and environmental performance measures. Abdallah et al. (2012), meanwhile, investigated greenhouse gas emissions as a consequence of supply chain network design and supplier selection using a life cycle assessment (LCA) approach.

A mixed-integer programming model was formulated by Diabat and Simichi-Levi (2010) to find an optimal strategy for companies to meet their carbon cap while minimizing costs. Chaabane et al. (2012) created a model that targeted processes with an aluminum firm and examined the impact of greenhouse gas emissions on designing a sustainable CLSC network based on LCA principles; it also evaluated the trade-offs between economic and environmental dimensions under various costs and strategies. The issues surrounding facility location with a trading price of GHG emissions and cost of procurement were considered in Diabat et al.’s (2013) work; Fahimnia et al. (2013) evaluated the forward and
reverse supply chain influences on carbon footprint using a mixed-integer linear programming (MILP) model, with GHG emissions evaluated in terms of carbon cost dollar.

Benjaafar et al. (2013) measured the impact of GHG emissions when a series of lot-sizing models were integrated into operations decisions, and how significant emissions reductions without cost increases can be achieved by operational adjustments alone. A supply chain and transportation mode selection study for a major retailer, based on carbon policies, was reported by Jin et al. (2014).

In this research, a mixed-integer linear programming model of reverse supply chain with full valuation of emissions is considered to determine optimal flow of parts among multiple remanufacturing centers that will maximize the total profit and minimize the CO2 emissions, energy use, transportation, rent, labor, and product recovery costs, by investigating the cost factors by facility type, on-site, inter-facility, and total tCO2e from on-site electricity use by unit, based on actual sites in the Boston area. Valuation of emissions is done by using a direct carbon tax with the value varied according to ranges proposed at the 21st Conference of the Parties UNFCCC (COP21) in Paris, the U.S. Interagency Working Group (2013), and the U.S. Environmental Protection Agency (2015), to determine how the proposed policy will influence profit margins for remanufactured goods.

7.3 Problem Statement and Proposed Approach

7.3.1 Problem Statement

In this paper, the supply chain economics are taken into account by maximizing total profit and minimizing CO2 emissions, energy use, and transportation, rent, labor, and product
recovery costs, and by investigating the cost factors by facility type (on-site and inter-facility) and total tCO2e from on-site electricity use by unit. GHG emissions regulations and environmental sustainability prevent extreme environmental damages. The social dimension includes but is not limited to reduction of coastal destruction, noise, stress, traffic congestion, and spread of disease and improvement in the quality of life.

### 7.3.2 Mixed-Integer Linear Programming Approach

This approach optimizes a linear objective function, subject to linear constraints. For example, the expression of a linear programming problem such as:

- Maximize $Z X$ (objective function)
- Subject to $A X \leq B$ and $X \geq 0$ (constrains)

Where $X$ represents the vector of variable, $Z$ and $B$ represent the vectors of coefficients, and $A$ is the matrix of coefficients. When the variables of this linear problem are restricted to integers, the model is called a linear integer problem. Mixed-integer linear programming (MILP) is a special case, in which 0–1 integer linear programming involves integers and non-integers for both constrained variables. It is a very general context for solving problems with both discrete decisions and continuous variables. It can be applied to business, economic, and engineering problems (Pochampally et al, 2008).

### 7.4 Notation

The nomenclature used in this paper is given below:

<table>
<thead>
<tr>
<th>Variables</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>$C_{1v}$</td>
<td>Storage capacity at remanufacturing facility $v$ per remanufactured unit;</td>
</tr>
<tr>
<td>$C_{2v}$</td>
<td>Storage capacity at remanufacturing facility $v$ per used unit;</td>
</tr>
</tbody>
</table>
\( C_u \)  Storage capacity at collection center \( u \) per unit;
\( C_w \)  Storage capacity at reselling center \( w \) per unit;
\( D_u \)  Demand of products at collection center \( u \);
\( D_w \)  Demand of products at reselling center \( w \);
\( d_{uu} \)  Distance from collection center \( u \) to remanufacturing facility \( v \), per mile;
\( d_{vw} \)  Distance from remanufacturing facility \( v \) to reselling center \( w \), per mile;
\( EX_u \)  Energy cost at collection center \( u \) per unit;
\( EX_v \)  Energy cost at remanufacturing facility \( v \) per unit;
\( EX_w \)  Energy cost at reselling center \( w \) per unit;
\( GH \)  GHG emissions per ton-mile;
\( GH_u \)  GHG emissions in collection center \( u \), per unit;
\( GH_v \)  GHG emissions in remanufacturing facility \( v \), per unit;
\( GH_w \)  GHG emissions in reselling center \( w \), per unit;
\( H_u \)  Holding cost per unit at collection center \( u \);
\( L_u \)  Labor cost at collection center \( u \) per unit;
\( L_v \)  Labor cost at remanufacturing facility \( v \) per unit;
\( L_w \)  Labor cost at reselling center \( w \) per unit;
\( O_1 \)  Occupied space by remanufacturing unit;
\( O_2 \)  Occupied space by used-product unit;
\( Kg \)  Weight of each unit;
\( P \)  Reprocessing cost per unit;
\( R \)  Retrieval cost per unit;
\[ RCAP_v \] Remanufacturing facility \( v \) capacity;
\[ RC_u \] Rent cost at collection center \( u \) per unit;
\[ RC_v \] Rent cost at remanufacturing facility \( v \) per unit;
\[ RC_w \] Rent cost at reselling center \( w \) per unit;
\[ SH_u \] Shortage cost per unit at collection center \( u \);
\[ SUP_u \] Supply at collection center \( u \);
\[ T_{uv} \] Transportation cost from collection center \( u \) to remanufacturing facility \( v \), per unit;
\[ T_{vw} \] Transportation cost from remanufacturing facility \( v \) to reselling facility \( w \), per unit;
\( u \) Collection center;
\( v \) Remanufacturing facility;
\( w \) Reselling center;
\[ X_{uv} \] Decision variable for the number of units transferring from collection center \( u \) to remanufacturing facility \( v \);
\[ Y_{vw} \] Decision variable for the number of units transferring from remanufacturing facility \( v \) to reselling center \( w \);
\[ Z_v \] Binary variable (0/1) for selection of remanufacturing facility \( v \);
\[ Z_w \] Binary variable (0/1) for selection of reselling center \( w \).

### 7.5 Problem Formulation

The model is formulated as a single period mixed integer linear programming model of reverse supply chain where full valuation of emissions is considered to determine the
optimal flow of parts among multiple remanufacturing facilities that will maximize the total profit and minimize the CO₂ emissions, energy use, transportation, rent, labor, and product recovery costs.

7.5.1 Objective Functions

Minimize

\[
\begin{align*}
\text{Retrieval cost} & \; \sum_u \sum_v R(X_{uv} + ) \\
\text{Transportation cost} & \; \sum_u \sum_v T_{uv}X_{uv} + \sum_v \sum_w T_{vw}Y_{vw} + \\
\text{Remanufacturing cost} & \; \sum_v \sum_w P \; Y_{vw} + \\
\text{Inventory cost} & \; \sum_u \sum_v (R_u / 4)X_{uv} + \sum_v \sum_w (P_v / 4)Y_{vw} \\
\text{Rent cost} & \; \sum_u RC_u D_u + \sum_v RC_v X_{uv} + \sum_w RC_w Y_{vw} \\
\text{Labor cost} & \; \sum_u Lu D_u + \sum_v Lv X_{uv} + \sum_w Lw Y_{vw} \\
\text{Energy cost} & \; \sum_u Eu D_u + \sum_v Ev X_{uv} + \sum_w Ew Y_{vw} \\
\text{Greenhouse Gas (GHG) Emissions} & \; \sum_u GH_u D_u + \sum_v GH_v X_{uv} + \sum_w GH_w Y_{vw} + \\
& \; \sum_u \sum_v GH * duv * Kg * X_{uv} + \sum_v \sum_w GH * dwv * Kg * Y_{vw} \\
\text{Shortage cost} & \; |(D_w - SUP_u) - (1 - Z)| \; * SH_u \\
\end{align*}
\]

(7-1)
7.5.2 Constraints

Demand constraint must be met while minimizing the total cost of production and inventory.

\[ \sum_{v} Y_{vw} = D_{w} \; ; \; \forall \; w \]  

(7-2)

Remanufacturing facility total output is at most its total input

\[ \sum_{u} X_{uv} \geq \sum_{v} Y_{vw} \; ; \; \forall \; v \]  

(7-3)

Remanufacturing items occupied space at each remanufacturing facility is at most its capacity, and total space occupied at each collection center by returned items at most its capacity

\[ \sum_{v} O_{1} \cdot Y_{vw} \leq C_{1v} \cdot Y_{v} ; \forall \; v \]  

(7-4)

\[ \sum_{u} O_{2} \cdot X_{uv} \leq C_{u} ; \forall \; u \]  

(7-5)

Total space occupied at each remanufacturing facility by returned items at most its capacity

\[ \sum_{u} O_{2} \cdot X_{uv} \leq C_{2v} \cdot Z_{v} ; \forall \; v \]  

(7-6)

Total space occupied at reselling center by returned items at most its capacity

\[ \sum_{v} O_{1} \cdot Y_{vw} \leq C_{w} \cdot Z_{w} ; \forall \; w \]  

(7-7)

Non-negativity constraint

\[ X_{uv} \geq 0 \; ; \; \forall \; u, v \]  

(7-8)

\[ Y_{uw} \geq 0 \; ; \; \forall \; v, w \]  

(7-9)
Total number of returned items supplied to remanufacturing facilities by collection centers is at most the supply

\[ \sum_{w} Y_{vw} \leq RCAP_v ; \forall v \]  

\[ \sum_{v} X_{uv} \leq SUP_u ; \forall u \]  

### 7.6 Case Study

The numerical example is based on actual sites in the Boston, Massachusetts, area and considers three collection centers (located in Melrose, Canton, and Natick), two remanufacturing facilities (located in Taunton and Hingham), and three reselling centers (located in Revere, Boston, and Somerville). The actual distances in miles between the locations were considered, to calculate mile per gallon costs and emissions of CO2 kg per gallon, assuming the gasoline price per gallon of October 2015. The number of laborers, their annual salaries, and the size of the space were also considered. In short, the example reflects a breakdown of the cost factors: rent, labor, energy, CO2 emissions, and transportation, by facility type, on-site, inter-facility, and total tCO2e from on-site electricity use by unit. The U.S. Energy Information Administration at the U.S. Department of Energy data reports (U.S. Energy Information Administration, 2015) were used to calculate the energy usage for each facility. This example considers a mid-size LG A/C unit, model LW1213ER, with dimensions of 23 5/8" x 15" x 22 1/6", and a refurbished market price of $288 (LG Model: LW1213ER REFURBISHED, 2015). Two 12-foot trucks with a capacity of 58 A/C units each and a load volume of 475 cubic feet were used for transportation (12 Foot Truck, 2015). Valuation of emissions is done using a direct carbon tax with the value varied according to ranges proposed at the 21st Conference of the Parties.
under the UNFCCC in Paris (COP21, 2015), the U.S. Interagency Working Group (2013) and, the U.S. Environmental Protection Agency (2015), to determine how proposed ranges will influence profit margins for remanufactured goods.

7.6.1 Data

In this section two different survey databases were used, CBECS in subsection 7.6.1.1 was for collection centers and reselling centers energy data. MECS was used for remanufacturing facilities energy data in subsection 7.6.1.2. Tables 7-1 to 7-4 have the rent cost, labor cost, and distances between locations per mile respectively.

7.6.1.1 Commercial Buildings Energy Consumption Survey (CBECS)

CBECS is a national sample survey that collects information on commercial buildings, including their energy-related building characteristics and energy usage data (consumption and expenses). Commercial buildings include all buildings in which at least half of the floor space is used for a purpose that is not residential, industrial, or agricultural. The latest survey was conducted in 2012, and the microdate file contains 6,720 records for building characteristics in the USA (EIA, U.S., 2012b).

Our model used the following criteria from the survey for the collection and resellers centers, as shown in Figure 7-1 and 7-2.

Principal building activity: Retail (other than mall)

Census region and division: New England

Establishment counts, total floor-space per establishment, space-heating, cooling, ventilation, water-heating, lighting, cooking, refrigeration, office equipment, computers, and others. This helps in classify our commercial buildings fixed and variable cost and
usage. Most of their usages are: electricity and natural gas. CBECS data were used in identify the collection centers and the reselling centers in our numerical example.
Figure 7-1: Space heating demanded the most overall energy use in commercial building.

Figure 7-2: Electricity accounts for 78% of all energy consumed in commercial buildings.

7.6.1.2 Manufacturing Energy Consumption Survey (MECS)

MECS is a national sample survey that collects information on manufacturing establishments, their energy-related building characteristics and their energy consumption and expenses. The MECS was first conducted in 1985, the most recent survey was in 2010;
the first data set was made available in February, 2013. MECS is currently conducted on a quadrennial basis, and uses the North American Industry Classification System (NAICS) to classify business establishments according to the type of economic activity (process of production) in Canada, Mexico and the USA (EIA, U.S., 2010a).

Our model used the following criteria from this survey for the remanufacturing facilities, as shown in Figure 7-3 and 7-4:

NAICS Code: **335**

Subsector and Industry: **Electrical Equip., Appliances, and Components**

Census region and division: **New England**

Establishments counts, total floor-space per establishment, process heating, process cooling and refrigeration, machine drive, facility HVAC, and facility lighting.

Most of their usages are: electricity and natural gas. Distillate fuel oil and diesel, and residual fuel oil are less than 0.5 million bbl. MECS data were used in identify the remanufacturing facilities in our numerical example.
Figure 7-3: Machine drive demanded the most overall energy use in remanufacturing facilities

Figure 7-4: Natural gas accounts for 41% of all energy consumed in remanufacturing facilities
Table 7-1: Rent Actual Cost

<table>
<thead>
<tr>
<th>Cities</th>
<th>Space (Sq ft)</th>
<th>Rent per Sq ft/year</th>
<th>Total rent per year</th>
</tr>
</thead>
<tbody>
<tr>
<td>Canton</td>
<td>1000</td>
<td>$14.4</td>
<td>$4,220</td>
</tr>
<tr>
<td>Natick</td>
<td>3000</td>
<td>$10.5</td>
<td>$10,575</td>
</tr>
<tr>
<td>Melrose</td>
<td>1500</td>
<td>$15.0</td>
<td>$7,460</td>
</tr>
<tr>
<td>Taunton</td>
<td>10000</td>
<td>$11.0</td>
<td>$110,000</td>
</tr>
<tr>
<td>Hingham</td>
<td>9801</td>
<td>$8.0</td>
<td>$78,408</td>
</tr>
<tr>
<td>Revere</td>
<td>2700</td>
<td>$10.0</td>
<td>$27,000</td>
</tr>
<tr>
<td>Boston</td>
<td>5100</td>
<td>$25.0</td>
<td>$127,500</td>
</tr>
<tr>
<td>Somerville</td>
<td>4000</td>
<td>$17.0</td>
<td>$68,000</td>
</tr>
</tbody>
</table>

Table 7-2: Labor Actual Cost

<table>
<thead>
<tr>
<th>Cities</th>
<th>Number of laborers</th>
<th>Labor cost per year</th>
</tr>
</thead>
<tbody>
<tr>
<td>Canton</td>
<td>5</td>
<td>$93,600</td>
</tr>
<tr>
<td>Natick</td>
<td>3</td>
<td>$56,160</td>
</tr>
<tr>
<td>Melrose</td>
<td>4</td>
<td>$74,880</td>
</tr>
<tr>
<td>Taunton</td>
<td>15</td>
<td>$280,800</td>
</tr>
<tr>
<td>Hingham</td>
<td>17</td>
<td>$318,240</td>
</tr>
<tr>
<td>Revere</td>
<td>4</td>
<td>$74,880</td>
</tr>
<tr>
<td>Boston</td>
<td>3</td>
<td>$56,160</td>
</tr>
<tr>
<td>Somerville</td>
<td>6</td>
<td>$112,320</td>
</tr>
</tbody>
</table>

Table 7-3: Actual distances between collection center and remanufacturing facilities per mile

<table>
<thead>
<tr>
<th>From/To City</th>
<th>Taunton</th>
<th>Hingham</th>
</tr>
</thead>
<tbody>
<tr>
<td>Melrose</td>
<td>52.8</td>
<td>28.1</td>
</tr>
<tr>
<td>Canton</td>
<td>17.2</td>
<td>19.3</td>
</tr>
<tr>
<td>Natick</td>
<td>37.0</td>
<td>30.5</td>
</tr>
</tbody>
</table>
7.6.2 Results and Discussion

In the absence of a carbon tax, the profit margin for the A/C unit is 25%; a USEPA-recommended $40/ton CO2 equivalent (tCO2e) tax reduces the profit margin to 22% (US-EPA, 2015). LINGO 13.0 was used to solve the problem. The results obtained are shown in Tables 7-5 and 7-6.

Table 7-5: Optimal Number of Units transported from Collection Center to Remanufacturing Facility

<table>
<thead>
<tr>
<th>City</th>
<th>Taunton</th>
<th>Hingham</th>
</tr>
</thead>
<tbody>
<tr>
<td>Melrose</td>
<td>0</td>
<td>50</td>
</tr>
<tr>
<td>Canton</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Natick</td>
<td>0</td>
<td>450</td>
</tr>
</tbody>
</table>

Table 7-6: Optimal Number of Units transported from Remanufacturing Facility to Reselling Center

<table>
<thead>
<tr>
<th>City</th>
<th>Revere</th>
<th>Boston</th>
<th>Somerville</th>
</tr>
</thead>
<tbody>
<tr>
<td>Taunton</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Hingham</td>
<td>150</td>
<td>200</td>
<td>150</td>
</tr>
</tbody>
</table>

Table 7-4: Actual distances between and remanufacturing facilities and reselling centers per mile

<table>
<thead>
<tr>
<th>From/To City</th>
<th>Revere</th>
<th>Boston</th>
<th>Somerville</th>
</tr>
</thead>
<tbody>
<tr>
<td>Taunton</td>
<td>45.0</td>
<td>40.0</td>
<td>43.0</td>
</tr>
<tr>
<td>Hingham</td>
<td>24.0</td>
<td>19.0</td>
<td>22.0</td>
</tr>
</tbody>
</table>
The remanufacturing cost is $218 per unit, which shows that this model is $70 per unit less than the current refurbished market price. The emission quantity is 0.018 tCO2e per unit. Comparing this result to the deflated refurbished market price using a consumer price index expressed in 2002 dollars and analyzing that result using the economic input-output life cycle assessment (EIO-LCA) model (a technique for estimating the materials and energy resources required for environmental emissions resulting from economic activities (EIO-LCA, 2016). The EIO-LCA sector chosen was the U.S. 2002 Benchmark for air conditioning, refrigeration, and warm air heating equipment manufacturing. This shows that the emission quantities are 0.109 tCO2e per unit less than refurbished manufacturing. The valuation of emissions was done by using a direct carbon tax with the value varied according to ranges proposed at the 21st Climate Change Conference (COP21) in Paris, therefore existing approaches used different carbon policies and applications. Using the carbon price of $40/ton CO2 equivalent (tCO2e), our model gives a profit margin of 25%.

7.7 Conclusion

This chapter presented an optimization model for reverse supply chains, designed to determine the influence of supply chain strategic and operational activities on the environment. A numerical example based on actual sites was considered to test the performance of the model and to determine how the proposed model would influence profit margins on remanufactured goods. The results indicated that the carbon tax policy forces a strict constraint on the amount of carbon emissions generated in supply chain operations.
Chapter 8 REVERSE SUPPLY CHAIN NETWORK DESIGN AND OPTIMIZATION CONSIDERING CARBON COST

8.1 Abstract

This study explores the third research question of this dissertation to further develop the model in Chapter 7 with recent data from the EPA. Due to the increase in carbon costs, the previously optimized RSC system will undergo change as the model seeks out new configurations through which costs may be effectively managed and minimized. The model has been studied comprehensively in terms of quantitative performance using Orthogonal Arrays. The results were compared to top-down estimates from economic input-output life cycle assessment (EIO-LCA) models, to provide a basis to contrast remanufacturing GHG emission quantities with those realized through original equipment manufacturing operations. Introducing a carbon cost of $40/t CO2e increases modeled remanufacturing costs by 2.7%, but also increases original equipment costs by 2.3%. The work herein advances the theoretical modeling of optimal RSC systems while presenting an empirical case study of remanufactured appliances, an understudied facet of current industrial literature.

8.2 Introduction

8.2.1 Circular Economy Concept

The circular economy concept was developed as an alternative for the prevailing production paradigm of treating the environment as a waste reservoir, and was first raised
forty years ago in a report to the European Commission (Stahel & Reday-Mulvey, 1981). A Circular Economy (CE) is described as turning end-of-life goods into resources for others and minimizing waste, applying concept of closing loops in industrial ecosystems. In 1989, Frosch and Gallopoulos published an important work in the field of industrial ecology, by inspiring a positive change from traditional open loop industrial activities systems to a more integrated model of industrial activities—an industrial ecosystem. This has been described as a system in which “the consumption of energy and material is optimized, waste generation is minimized and the effluents of one process (…) serve as the raw material for another process” (Frosch & Gallopoulos, 1989). This could slowly replace the economic logic of production by being more efficient through reusing, recycling, and remanufacturing, leading to economic growth. In a study was done by a number of European nations on CE, it was found that greenhouse gas emissions would be reduced by each nation up to 70%, and the same time the workforce would increase by about 4% (Stahel, 2016).

Reverse Supply Chain (RSC) is “an initiative that plays an important role in the global supply chain for those who seek environmentally responsible solutions for their end-of-life (EOL) products.” (Alkhayyal et al., 2016a). For years, the quantity of discarded consumer products has been rising, and as a result, there has been increased legislative action in countries that hold original equipment manufacturers (OEM) responsible for end-of-life processing of products under extended producer responsibility (EPR) policies (Vadde et al, 2006; Nash & Bosso, 2013). Certainly, consumer awareness of environmental issues has a marked impact on the field of supply chain, because they buy refurbished units and save value environmental information on suppliers and retailers. The relative economic
and environmental benefits of RSC are influenced by costs and emissions during collection, transportation, recovery facilities, disassembly, recycling, remanufacturing and disposal of unrecoverable components (Ilgin & Gupta, 2010).

### 8.2.2 Remanufacturing and Reverse Supply Chain Concepts

Remanufacturing is defined as “a process that brings a used product back to a new state through reuse, refurbishment and replacement of its components” (Amezquita et al., 1995). It is a sequence that involves reprocessing of used products by disassembly, cleaning, inspection, the sorting, repair, or replacement of parts (if applicable) and their eventual reassembly as a remanufactured product. Restoration can generate items in conditions that are as good, or even better, than that of items considered brand new, and it returns a product to the market with not only the same functionality, but an extended life cycle. The recycling of recovered end-of-life products and parts by way of a remanufacturing system will ultimately reduce the industrial and disposal costs of heavy and material-intensive machinery and equipment (Carter, 2008; Nagurney et al., 2007; Paul et al., 2005; Seuring et al., 2008). This remanufacturing system relies on a Reverse Supply Chain (RSC): a set of logistical operations and actors to recover used products and deliver them to OEMs and third-party manufacturers.

The U.S. market for remanufactured goods, according to United States International Trade Commission (USITC), has increased by 15\% from $36.0 billion in 2009 to $41.5 billion in 2011, and the value of U.S. remanufactured production during that same period raised by 15\% to at least $43.0 billion, hence this would create 180,000 full-time U.S. jobs and exported a total of $11.7 billion of remanufactured goods (USITC, 2012). In another estimate for the United States, remanufacturing industry is at least a $50
billion industry distributed in 73,000 firms with direct employment of 480,000 (Gutowski et al., 2011).

8.2.3 Environmental Considerations

In general, remanufacturing has been found to be the most environmentally friendly option for end-of-life products, both because of avoiding waste and substituting for primary materials but also because of upgrading product performance, which saves energy (and associated emissions) during product use. To test the hypothesis of “remanufacturing of products saves energy” Gutowski et al. (2011) studied eight different product categories that have very high potential of remanufacturing in the United States: (1) furniture, (2) clothing, (3) computers, (4) electric motors, (5) tires, (6) appliances, (7) engines, and (8) toner cartridges. It found that remanufacturing in most of the categories is the most environment-friendly end-of-life option for returned products, however, in some categories manufacturing new is more environmentally friendly.

Currently, there are international, national, and corporate policies intended to reduce pollution in a flexible and economical manner (Carmona et al., 2009). In this paper, the focus is on the Social Cost of Carbon (SCC) emitting a metric ton of carbon dioxide; the SCC was valued by the U.S. Environmental Protection Agency (EPA); together with other federal agencies, to estimate climate benefits against the costs of meeting targets. The aim of this chapter is to compare economic and environmental impacts on remanufactured air conditioners in a reverse supply chain model, and to test the influence of emissions pricing on optimal configurations of a RSC. The air conditioners have large and growing market and are a target of remanufacturing efforts due to the presence of refrigerants with mandated handling rules.
8.3 Research Questions

This study considers the following detailed research questions. With the support of an operations model, a case study is developed and explained.

1. What is the Social Cost of Carbon (SCC) effect on AC unit price?

2. How is carbon priced to achieve maximum emissions reduction while ensuring that the remanufacturing profits are not overly affected?

3. What is the cost effectiveness over a range of carbon prices?

4. Is it possible, using only operational adjustments, to significantly reduce emissions without significantly increasing cost?

5. What is the best carbon price to maximum emissions reduction and maximize profit?

6. What is the most efficient method for recovery of used products?

7. What network best reflects the organization's environmental and the carbon market strategy?

8. What are the flow patterns followed by the returned products through the reverse logistics (RL) network?

This research uses a mixed-integer linear programming (MILP) optimization model for reverse supply chains with a full valuation of emissions to determine the optimal flow of parts among multiple remanufacturing facilities (thereby maximizing the net profit and minimizing the CO₂ emissions) by investigating the cost factors and total CO₂e from actual remanufacturing sites in the Boston area.

The chapter is organized as follows. Section 8.4 begins with a literature review on circular economy, reverse supply chains, and greenhouse gas emissions. In section 8.5, the
methodology used in this study is presented. In section 8.6 and section 8.7, nomenclature and problem formulation are explained. Sections 8.8 and 8.9 explain the case study and case study results and detailed results of the experiment design study, respectively. Finally, conclusion remarks are presented in section 8.10.

8.4 Literature Review

8.4.1 Present State of Research of Circular Economy and Reverse Supply Chains for Remanufacturing

A circular economy encourages the use of remanufacturing over other waste management strategies such as reusing, recycling, recovery, and disposal. A critical review of existing studies on remanufactured products using reverse logistics was done by Peters (2016). Recent research by Derigent and Thomas (2016) concerned product and material recyclable in the framework of a circular economy, including a review of the existing literature and highlighting potential research directions. Govindan & Soleimani (2016) did an extensive review of the literature on reverse supply chain issues. In general, an efficient reverse supply chain can reduce the overall cost of reverse logistics operations as well as the demand for new raw material in the chain. Guide and Jayaraman (2000) conducted a survey and found that, to reduce the uncertainty of return quantity and quality, many remanufacturing firms in the United States have adopted a market-driven product acquisition management approach to collection of used products. For example, Green Citizen Company buys back Apple laptops, desktops, iPhones, and iPads. The world's first automated eWaste recycling station, ecoATM, provides instant cash for the responsible recycling of old cell phones, MP3 players, and tablets. As of July 2014, ecoATM had approximately 1100 kiosks located in shopping malls and select large retailers nationwide.
Kodak controls the return quantity of used cameras with cash incentives (Ayres & Ayres, 2002). Fleischmann et al. (2003), reported that IBM remanufacturing costs are much lower than buying new parts, sometimes 80% lower. Similarly, Xerox Corporation saves 40–65% of its manufacturing costs by applying their remanufacturing program on parts and materials from returned products (Savaskan et al., 2004). The Dell computer company dynamically adjusts prices based on inventory levels of products to improve supply chain efficiency (Agrawal & Kambil, 2000).

In environmental terms, remanufactured products are highly sustainable and encourage both energy and resource saving; the procedures involved also create jobs for skilled workers (Charter and Gray, 2008). Ultimately, product remanufacturing process decisions must be integrated at an early stage in the product life cycle (Subramoniam et al., 2009; Subramoniam et al., 2013) to guarantee these kinds of successful outcomes.

An effective RSC can help enterprises better utilize their resources and maintain a more sustainable balance between the environment and the economy (Xiangru, 2008). RSC practices are also helpful for ‘greening’ the whole supply chain by reintroducing end-of-life and used products into the production system (Efendigil et al., 2008). RSC operations are widely considered a central component of a circular economy (Prakash & Barua, 2015). Alqahtani and Gupta (2015) proposed two multi-criteria optimization models for delivery of products across multiple periods in a reverse supply chain environment. The first model is solved using mixed-integer linear programming (MILP), while the second model is solved using linear physical programming (LPP). The proposed models deliver the optimal transport quantities of remanufactured products for N-periods within the reverse supply chain. Boustani et al. (2010), studied the entire life cycle for manufacturing and
remanufacturing and measured the energy consumption for different appliances, such as, dishwasher, washing machines, and refrigerator. They found that remanufacturing saves 14% for dishwashers, 32% for refrigerators, and 44% for washing machines. Sutherland et al. (2010) developed a cost model to investigate the challenges of selecting the size of remanufacturing facility. The developed model considered such factors as production, transportation, and inventory-related costs and described the effects of economies of scale.

A literature review was conducted by Mexiell and Gargeya (2005) on the economic considerations in supply chain design, while a comprehensive review of the published literature on sustainable supply chains was presented by Seuring and Muller (2008) and Srivastava (2007). Gungor and Gupta (1999) addressed the issues of environmentally conscious manufacturing and product recovery with an extensive review of the literature, with regard to environmentally conscious design, environmentally conscious production, recycling, and remanufacturing, and production planning and inventory control. Ilgin and Gupta (2010) further extended this literature review through 2010. There are several other authors who reported on product recovery designs under specific legislation and regulations (Das, 2002; Bellmann & Khare, 2000; Dekker et al., 2013; Guide et al., 1999; Guide, 2000; Henshaw, 1994).

**8.4.2 Present State of Research on Greenhouse Gas Emissions in Reverse Supply Chains**

The U.S. Energy Information Administration reports that manufacturing activities are accountable for 84% of energy-related industry CO₂ emissions and 90% of industry energy consumption (Schipper, 2006). Concerning carbon-constrained economy matters, replacing the original manufactured product with a remanufactured product generates large
revenue in terms of carbon-saving returns (Fatimah & Biswas, 2016). Usually, original equipment manufacturer (OEM) refers to the company that originally manufactured the product and/or used virgin materials. Many studies have confirmed, however, that remanufacturing is more profitable for OEM (Hammond et al., 1998; Guide, 2000). In Japan, at least 80% of air conditioner materials are recycled under the home appliance recycling law. In 2014 alone, Japan recovered about 230,000 products, totaling 10,783 tons, with an 89% recycling ratio (Daikin, 2015).

Recent literature reviews considering different aspects of supply chain sustainability include: energy use (Dotoli, 2005) GHG emissions reduction (Guillen-Gosalbez & Grossmann, 2009), green design (Hugo & Pistikopoulos, 2005), production planning and control for remanufacturing (Hugo et al., 2005), product recovery (Jayaraman, 2006), reverse logistics (Sheu, 2008), and waste management (Guillen-Gosalbez & Grossmann, 2009). Reducing emissions generated by a supply chain has become an important goal. The “trade-offs in the supply chain are no longer just about cost, service and quality, but also about cost, service, quality and carbon,” (Chaabane et al., 2012). A "closed-loop supply chain" considered by Paksoy et al. (2011) focused on transportation costs and GHG emissions, to explore the trade-off between operational and environmental performance measures. Abdallah et al. (2012), meanwhile, investigated greenhouse gas emissions as a consequence of supply chain network design and supplier selection using a life cycle assessment (LCA) approach. Bhinge et al. (2015) developed an optimization supply chain network design model, with the objective of maximizing sustainability in the three main components of economic, social and environmental. The social indicator was used for health and safety, which covered worker and community
safety. Environmental measures were based solely on energy consumption in the different supply chain levels.

A mixed-integer programming model was formulated by Diabat and Simichi-Levi (2010) to find an optimal strategy for companies to meet their carbon cap while minimizing costs. Similarly, a mixed-integer linear programming model was formulated by Alkhayyal et al. (2016a, 2016b) to find the optimal flow of parts among multiple remanufacturing centers under a specific carbon tax while minimizing costs. Chaabane et al. (2012) created a model that targeted processes with an aluminum firm and examined the impact of GHG emissions on designing a sustainable closed-loop supply chain (CLSC) network based on LCA principles; it also evaluated the trade-offs between economic and environmental dimensions under various costs and strategies. The issues surrounding facility location with a trading price of GHG emissions and cost of procurement were considered in Diabat et al.’s (2013) work; Fahimnia et al. (2013) evaluated the forward and reverse supply chain influences on carbon footprint using a mixed-integer linear programming (MILP) model, with GHG emissions evaluated in terms of carbon cost dollar. Benjaafar et al. (2013) measured the impact of GHG emissions when a series of lot-sizing models were integrated into operations decisions, and how significant emissions reductions without cost increases can be achieved by operational adjustments alone. A supply chain and transportation mode selection study for a major retailer, based on carbon policies, was reported by Jin et al. (2014). Wang et al., (2016) studied the impact carbon emissions constraints on production decisions in four mathematical models. They found that the manufacturer needs more capital to achieve the maximum profit when the carbon emission constraint is considered.
Importantly, a few studies have examined the impact of integrating international, national, and corporate policies and legislation on a sustainable supply chain. For example, Nagurney et al. (2006) addressed carbon taxes in electric power supply chains, and Subramanian et al. (2010) proposed adding and integrating environmental considerations within the overall agenda. Biswas et al. (2013) compared the environmental impacts among repaired, remanufactured, and new air compressors. The results showed that a remanufactured air compressor led to a 96% reduction in GHG emissions compared to the alternatives. Likewise, Zanghelini et al. (2014) showed that the remanufacturing process saved 46% in GHG emissions when compared to newly manufactured air compressor production systems. Seuring and Muller (2008) defined sustainable supply chain management as “the management of materials, information, and capital flows, as well as cooperation among companies along the supply chain while taking goals from all three dimensions of sustainable development, viz., economic, environmental and social, into account which are derived from customer and stakeholder requirements.”

8.4.3 Input-Output Life Cycle Assessment (EIO-LCA) Studies of Remanufacturing

Latham (2016) used the EIO-LCA method to study the economic and environmental impact of manufactured traditional vehicles and remanufactured new vehicles. The results showed that in every EIO-LCA category remanufactured vehicles were a better alternative than manufactured vehicles both economically and environmentally. EIO-LCA was used to study statistical data on U.S. cellular phone shipments and average bills of material from 2003 and 2004 with respect to the environmental impact of upstream cellular phone production chains, such as, air pollutants, energy use, and greenhouse emissions (Zhou and
Schoenung, 2006). They concluded that reusing, recycling, refurbishing, and remanufacturing cellular phones and their components were better alternatives for environmental risk reduction. Mihelcic et al. (2003) studied the life cycle stages of products. In most cases, reusing and remanufacturing were preferred since they required fewer natural resources, less energy and time, and lower costs.

In this chapter, supply chain economics are taken into account by maximizing total profit while minimizing CO$_2$ GHG emissions, energy use, transportation, rent, labor, and product recovery costs. This is achieved by investigating the factors affecting costs by facility type (on-site, inter-facility, and total tCO$_2$e) from on-site electricity use by unit. GHG emissions regulations and environmental sustainability are preventing extreme environmental damages. The social dimension includes, but is not limited to, the reduction in negative consequences, including coastal destruction, noise, stress, traffic congestion, and the spread of diseases and an overall improvement in the quality of life were not considered.

8.5 Methodology

A mixed-integer linear programming (MILP) model for reverse supply chains with full valuation of GHG emissions is considered to determine optimal flow of units among multiple remanufacturing centers in a RSC; this will maximize net profit and minimize GHG emissions, energy use, transportation, rent, labor, and product recovery costs. (Factors determining expenditure are investigated based on actual sites in the Boston area. The valuation of emissions is done using a direct carbon tax with the value varied according to ranges proposed at the 21$^{st}$ Conference of the Parties under the UNFCCC in Paris (COP21, 2015), the U.S. Interagency Working Group (2013), the U.S. Environmental
Protection Agency (2015) and the recent updated report of the SCC by the National Academies of Sciences, Engineering, and Medicine (National Academies of Sciences et al., 2017), to determine how proposed ranges influences profit margins on remanufactured goods. The consumption and expenditures data are taken from the 2012 Commercial Buildings Energy Consumption Survey (CBECS) and the 2010 Manufacturing Energy Consumption Survey (MECS) databases (EIA, 2012; EIA, 2010), based on the New England census division. A deterministic model with minimum shipments is developed, the minimum shipments assumption was 5 units of A/C according to the collection centers phone interviews, then to compare the remanufacturing result to the deflated market price using a consumer price index expressed in 2002 dollars (BLS, 2010), and analyzing that result using the economic input-output life cycle assessment (EIO-LCA) model, a technique estimating the materials and energy resources required for environmental emissions resulting from economic activities (EIO-LCA, 2016). The EIO-LCA sector chosen was, the U.S. 2002 Benchmark for air conditioning, refrigeration, and warm air heating equipment manufacturing. Then, applying an orthogonal array testing allows for full consideration of all possible inputs in each system. A deterministic model with relaxation constraints is developed to examine the effect of carbon price uncertainty on supply chain network decisions, that considers 13 scenario groups for carbon pricing with identical demand scenarios. Table 8-7 summarizes the solutions of the model for a range of carbon prices. Three different configurations resulted from carbon prices between $0 and $120. LINGO 13.0 was used to solve the optimization problem.
8.5.1 Mixed-Integer Linear Programming Approach

This approach optimizes a linear objective function, subject to linear constraints. For example, the expression of a linear programming problem such as:

Maximize $Z \mathbf{X}$ (objective function)

Subject to $A \mathbf{X} \leq \mathbf{B}$ and $\mathbf{X} \geq 0$ (constraints)

Where $\mathbf{X}$ represents the vector of variable, $Z$ and $\mathbf{B}$ represent the vectors of coefficients, and $A$ is the matrix of coefficients. When the variables of this linear problem are restricted to integers, the model is called a linear integer problem. Mixed-integer linear programming (MILP) is a special case, in which 0–1 integer linear programming involves integers and non-integers for both constrained variables. It is a very general context for solving problems with both discrete decisions and continuous variables. It can be applied to business, economic, and engineering problems (Pochampally et al, 2008)

8.5.2 Design of Experiments Study

This study was performed to study the effect of different cost factors using orthogonal array and regression analysis.

8.5.2.1 Orthogonal Array

A comprehensive study for quantitative evaluation and performance of the model has been done. A full-factorial design with 13 factors requires an extensive number of experiments (that is, $1.59E+4$). Therefore, experiments were designed using Orthogonal Arrays (OA), which allow for full testing of every possible system input with a minimum number of experiments. $L_{27}$ OA was chosen, which requires 27 experiments while satisfying 13 factors, each with three different levels (a physical meaning which mimics a real-life
example). Table 8-1 shows the factors and factor levels used in the experiments. For more details on Taguchi orthogonal array design see Table 8-2, and experiments run results see Appendix A.

Table 8-1: Factors and factor levels used in design-of-experiments study

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<th>No</th>
<th>Factor</th>
<th>Unit</th>
<th>Levels</th>
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<td>1</td>
<td>Transportation Cost</td>
<td>$</td>
<td>0.5 1 1.5</td>
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<td>2</td>
<td>Energy Cost - fix</td>
<td>$/kWh</td>
<td>0.07 0.12 0.27</td>
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<td>Energy Cost - variable</td>
<td>$/kWh</td>
<td>0.07 0.13 0.27</td>
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<td>Rent Cost</td>
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<td>5</td>
<td>Labor Cost</td>
<td>$</td>
<td>8.26 16.52 24.78</td>
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<td>Social Cost of Carbon</td>
<td>$/kg</td>
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<td>Shortage Cost</td>
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<td>50.00 90.00 130.00</td>
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<td>Remanufacturing Cost</td>
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<td>8.26 16.52 24.78</td>
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<td>Mean demand rate</td>
<td>Parts</td>
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<td>Retrieval Cost</td>
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<td>Inventory Cost</td>
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<td>13</td>
<td>Supply rate</td>
<td>Parts</td>
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Table 8-2: L$_{27}$ OA with 27 experiments

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1: Low Level. 2: Medium Level. 3: High Level
## 8.6 Nomenclature

The nomenclature used in this chapter is given below:

<table>
<thead>
<tr>
<th>Variables</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>$C_{1v}$</td>
<td>Storage capacity at remanufacturing facility $v$ per remanufactured unit;</td>
</tr>
<tr>
<td>$C_{2v}$</td>
<td>Storage capacity at remanufacturing facility $v$ per used unit;</td>
</tr>
<tr>
<td>$C_u$</td>
<td>Storage capacity at collection center $u$ per unit;</td>
</tr>
<tr>
<td>$C_w$</td>
<td>Storage capacity at reselling center $w$ per unit;</td>
</tr>
<tr>
<td>$D_u$</td>
<td>Demand of products at collection center $u$;</td>
</tr>
<tr>
<td>$D_w$</td>
<td>Demand of products at reselling center $w$;</td>
</tr>
<tr>
<td>$d_{uu}$</td>
<td>Distance from collection center $u$ to remanufacturing facility $v$, per mile;</td>
</tr>
<tr>
<td>$d_{vw}$</td>
<td>Distance from remanufacturing facility $v$ to reselling center $w$, per mile;</td>
</tr>
<tr>
<td>$EX_u$</td>
<td>Energy cost at collection center $u$ per unit;</td>
</tr>
<tr>
<td>$EX_v$</td>
<td>Energy cost at remanufacturing facility $v$ per unit;</td>
</tr>
<tr>
<td>$EX_w$</td>
<td>Energy cost at reselling center $w$ per unit;</td>
</tr>
<tr>
<td>$GH$</td>
<td>GHG emissions per ton-mile;</td>
</tr>
<tr>
<td>$GH_u$</td>
<td>GHG emissions in collection center $u$, per unit;</td>
</tr>
<tr>
<td>$GH_v$</td>
<td>GHG emissions in remanufacturing facility $v$, per unit;</td>
</tr>
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<td>$GH_w$</td>
<td>GHG emissions in reselling center $w$, per unit;</td>
</tr>
<tr>
<td>$H_u$</td>
<td>Holding cost per unit at collection center $u$;</td>
</tr>
<tr>
<td>$L_u$</td>
<td>Labor cost at collection center $u$ per unit;</td>
</tr>
<tr>
<td>$L_v$</td>
<td>Labor cost at remanufacturing facility $v$ per unit;</td>
</tr>
</tbody>
</table>
$L_w$ Labor cost at reselling center $w$ per unit;

$O_1$ Occupied space by remanufacturing unit;

$O_2$ Occupied space by used-product unit;

$Kg$ Weight of each unit;

$P$ Reprocessing cost per unit;

$R$ Retrival cost per unit;

$RCAP_v$ Remanufacturing facility $v$ capacity;

$RC_u$ Rent cost at collection center $u$ per unit;

$RC_v$ Rent cost at remanufacturing facility $v$ per unit;

$RC_w$ Rent cost at reselling center $w$ per unit;

$SH_u$ Shortage cost per unit at collection center $u$;

$SUP_u$ Supply at collection center $u$;

$T_{uv}$ Transportation cost from collection center $u$ to remanufacturing facility $v$, per unit;

$T_{vw}$ Transportation cost from remanufacturing facility $v$ to reselling facility $w$, per unit;

$u$ Collection center;

$v$ Remanufacturing facility;

$w$ Reselling center;

$X_{uv}$ Decision variable for the number of units transferring from collection center $u$ to remanufacturing facility $v$;

$Y_{vw}$ Decision variable for the number of units transferring from remanufacturing facility $v$ to reselling center $w$;
8.7 Problem Formulation

8.7.1 Assumptions
We assume that GHG emissions come from four sources:

1. from the collection centers, and the amount of emissions is proportional to the power consumption of these centers;
2. from the remanufacturing facilities, and the amount of emissions is proportional to the volume of these remanufacturing facilities;
3. from the reselling centers, and the amount of emissions is proportional to the power consumption of these centers; and
4. from the distribution of the products, and the emissions level is based on the traveled distance between facilities, and the weight of each unit (40 Kg).

The model assumes that inventory cost of a used product at the remanufacturing facility is 25% of its retrieval cost \( R \), and for a remanufactured product it is 25% of its reprocessing cost \( P \).

8.7.2 Objective Functions
The model is formulated as a single period mixed integer linear programming model of reverse supply chain where full valuation of emissions is considered to determine the optimal flow of parts among multiple remanufacturing facilities that will maximize the total profit and minimize the CO\(_2\) emissions, energy use, transportation, rent, labor, and product recovery costs.

\[ Z_v \] Binary variable (0/1) for selection of remanufacturing facility \( v \);

\[ Z_w \] Binary variable (0/1) for selection of reselling center \( w \).
Minimize

Retrieval cost \( \sum_{u} \sum_{v} R \ X_{uv} + \)

Transportation cost \( \sum_{u} \sum_{v} T_{uv} \ X_{uv} + \sum_{v} \sum_{w} T_{vw} \ Y_{vw} + \)

Remanufacturing cost \( \sum_{v} \sum_{w} P \ Y_{vw} + \)

Inventory cost \( \sum_{u} \sum_{v} (R_{u} / 4) \ X_{uv} + \sum_{v} \sum_{w} (P_{v} / 4) \ Y_{vw} \)

Rent cost \( \sum_{u} RC_{u} \ D_{u} + \sum_{v} RC_{v} \ X_{uv} + \sum_{w} RC_{w} \ Y_{vw} \)

Labor cost \( \sum_{u} Lu \ D_{u} + \sum_{v} Lv \ X_{uv} + \sum_{w} Lw \ Y_{vw} \)

Energy cost \( \sum_{u} Eu \ D_{u} + \sum_{v} Ev \ X_{uv} + \sum_{w} Ew \ Y_{vw} \)

Greenhouse Gas (GHG) Emissions

\[ \sum_{u} GH_{u} \ D_{u} + \sum_{v} \sum_{w} GH_{v} \ X_{uv} + \sum_{v} \sum_{w} GH_{w} \ Y_{vw} + \]
\[ \sum_{u} \sum_{v} GH \ duv \ Kg \ X_{uv} + \sum_{v} \sum_{w} GH \ dwv \ Kg \ Y_{vw} \]

Shortage cost \( |(D_{w} - SUP_{u}) \times (1 - Z)| \times SH_{u} \)

(8-1)

### 8.7.3 Constraints

Demand constraint must be met while minimizing the total cost of production and inventory.

\[ \sum_{v} Y_{vw} = D_{w} \quad ; \quad \forall \ w \] (8-2)
Remanufacturing facility total output is at most its total input

\[ \sum_{u} X_{uv} \geq \sum_{v} Y_{vw}; \forall v \]  

(8-3)

Remanufacturing items occupied space at each remanufacturing facility is at most its capacity, and total space occupied at each collection center by returned items at most its capacity

\[ \sum_{w} O_{2} * Y_{vw} \leq C_{1v} * Y_{v}; \forall v \]  

(8-4)

\[ \sum_{v} O_{2} * X_{uv} \leq C_{2u}; \forall u \]  

(8-5)

Total space occupied at each remanufacturing facility by returned items at most its capacity

\[ \sum_{u} O_{2} * X_{uv} \leq C_{2v} * Z_{v}; \forall v \]  

(8-6)

Total space occupied at reselling center by returned items at most its capacity

\[ \sum_{v} O_{1} * Y_{vw} \leq C_{w} * Z_{w}; \forall w \]  

(8-7)

Non-negativity constraint

\[ X_{uv} \geq 0 ; \forall u, v \]  

(8-8)

\[ Y_{uv} \geq 0 ; \forall v, w \]  

(8-9)

Total number of returned items supplied to remanufacturing facilities by collection centers is at most the supply

\[ \sum_{w} Y_{vw} \leq RCAP_{v}; \forall v \]  

(8-10)
\[
\sum_{v} X_{uv} \leq SUP_{u} \quad \forall u
\] (8-11)

### 8.8 Case Study

The case study is based on actual sites in the metro area of Boston, Massachusetts, USA and considers three collection centers (located in Melrose, Canton, and Natick), two remanufacturing facilities (located in Taunton and Hingham), and three reselling centers (located in Revere, Boston, and Somerville), as shown in Figure 8-1. The actual distances in miles between the locations were considered, fuel costs and GHG emissions, assuming the gasoline price per gallon is $2.14 as of October 2015. The number of laborers, their annual salaries, and the size of the space were also considered. In short, the study reflects a breakdown of the cost factors: rent, labor, energy, GHG emissions, and transportation, by facility type, on-site, inter-facility, and total tCO₂e from on-site electricity use by unit.

The U.S. Energy Information Administration at the U.S. Department of Energy data reports (U.S. EIA, 2015; Section 7.6.1) were used to calculate the energy usage for each facility. Commercial Buildings Energy Consumption Survey (CBECS) was for collection centers and reselling centers energy data, and for this survey, New England region with retail (other than mall) building activity was chosen. Energy sources of electricity, natural gas, and fuel oil data were examined and their usage inside each building. See Section 7.6.1.1 Figures 7-1 – 7-2 for more details. Manufacturing Energy Consumption Survey (MECS) was used for remanufacturing facilities energy data, and for this survey, New England region with appliances subsector was chosen. Energy sources of electricity, natural gas, distillate fuel oil and diesel, and residual fuel oil data were examined and their usage inside each facility. See Section 7.6.1.2 Figures 7-3 – 7-4 for more details. This example considers a mid-size
LG A/C unit, model LW1213ER, with dimensions of 23 5/8" x 15" x 22 1/6", and a market price of $349.99 (LG Model: LW1213ER, 2016). Two 12-foot trucks with a capacity of 58 A/C units each and a load volume of 475 cubic feet were assumed, based on interviews for transportation. Valuation of emissions was done by using a direct carbon tax, with the value varied according to ranges of $40-$120 per ton CO₂ equivalent that were proposed at the 21st Conference of the Parties under the UNFCCC in Paris (COP21, 2015), the U.S. Interagency Working Group (2013) the U.S. Environmental Protection Agency (2015), and the recent updated report of the SCC by the National Academies of Sciences, Engineering, and Medicine (National Academies of Sciences et al., 2017), to determine how proposed ranges will influence the profit margins for remanufactured goods. Table 8-3 shows the data collected from each collection center; the number of AC unit received is fixed in the model, and the total items included all the items that fall under the same category of the ACs, which is white goods/appliances at each collection center report. Also, for all rent, labor costs, and trip distances between locations, see Tables 8-4 through 8-6. A deterministic model was developed, and orthogonal array testing was included to allow for full evaluation of all possible system inputs.

Table 8-3: Collection Centers Actual Data

<table>
<thead>
<tr>
<th>Collection Center</th>
<th>AC unit received (year)</th>
<th>Pick up/drop off fee $ per item</th>
<th>Total items per year</th>
<th>Total income ($/year)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Canton</td>
<td>107</td>
<td>$20</td>
<td>509</td>
<td>$10,180</td>
</tr>
<tr>
<td>Natick</td>
<td>176</td>
<td>$25</td>
<td>837</td>
<td>$20,925</td>
</tr>
<tr>
<td>Melrose</td>
<td>175</td>
<td>$20</td>
<td>752</td>
<td>$15,040</td>
</tr>
</tbody>
</table>
### Table 8-4: Rent cost for collection centers

<table>
<thead>
<tr>
<th>Cities</th>
<th>Space (Sq ft)</th>
<th>Rent per Sq ft/year</th>
<th>Total rent per year</th>
</tr>
</thead>
<tbody>
<tr>
<td>Canton</td>
<td>1000</td>
<td>$14.4</td>
<td>$4,220</td>
</tr>
<tr>
<td>Natick</td>
<td>3000</td>
<td>$10.5</td>
<td>$10,575</td>
</tr>
<tr>
<td>Melrose</td>
<td>1500</td>
<td>$15.0</td>
<td>$7,460</td>
</tr>
<tr>
<td>Taunton</td>
<td>10000</td>
<td>$11.0</td>
<td>$110,000</td>
</tr>
<tr>
<td>Hingham</td>
<td>9801</td>
<td>$8.0</td>
<td>$78,408</td>
</tr>
<tr>
<td>Revere</td>
<td>2700</td>
<td>$10.0</td>
<td>$27,000</td>
</tr>
<tr>
<td>Boston</td>
<td>5100</td>
<td>$25.0</td>
<td>$127,500</td>
</tr>
<tr>
<td>Somerville</td>
<td>4000</td>
<td>$17.0</td>
<td>$68,000</td>
</tr>
</tbody>
</table>

### Table 8-5: Number of laborers and their cost per year

<table>
<thead>
<tr>
<th>Cities</th>
<th>Number of laborers</th>
<th>Labor cost per year</th>
</tr>
</thead>
<tbody>
<tr>
<td>Canton</td>
<td>5</td>
<td>$93,600</td>
</tr>
<tr>
<td>Natick</td>
<td>3</td>
<td>$56,160</td>
</tr>
<tr>
<td>Melrose</td>
<td>4</td>
<td>$74,880</td>
</tr>
<tr>
<td>Taunton</td>
<td>15</td>
<td>$280,800</td>
</tr>
<tr>
<td>Hingham</td>
<td>17</td>
<td>$318,240</td>
</tr>
<tr>
<td>Revere</td>
<td>4</td>
<td>$74,880</td>
</tr>
<tr>
<td>Boston</td>
<td>3</td>
<td>$56,160</td>
</tr>
<tr>
<td>Somerville</td>
<td>6</td>
<td>$112,320</td>
</tr>
</tbody>
</table>

### Table 8-6: Actual trip distances between locations in miles (via google map)

<table>
<thead>
<tr>
<th>From</th>
<th>To</th>
<th>Taunton</th>
<th>Hingham</th>
</tr>
</thead>
<tbody>
<tr>
<td>Melrose</td>
<td>Canton</td>
<td>52.8</td>
<td>28.1</td>
</tr>
<tr>
<td>Canton</td>
<td>Natick</td>
<td>17.2</td>
<td>19.3</td>
</tr>
<tr>
<td>Natick</td>
<td>Revere</td>
<td>37.0</td>
<td>30.5</td>
</tr>
<tr>
<td>Revere</td>
<td>Boston</td>
<td>45.0</td>
<td>24.0</td>
</tr>
<tr>
<td>Boston</td>
<td>Somerville</td>
<td>40.0</td>
<td>19.0</td>
</tr>
<tr>
<td>Somerville</td>
<td></td>
<td>43.0</td>
<td>22.0</td>
</tr>
</tbody>
</table>
8.9 Results

In this section, results of the deterministic model with minimum shipments are explained in subsection 8.9.1., the effects of varying social cost of carbon values for remanufacturing units are in subsection 8.9.2., and design of experiments to study the effect of the cost factors in subsection 8.9.3.
8.9.1 Deterministic Model with Minimum Shipments
In this updated model, the absence of a carbon tax results the unit price in $212 with a profit margin estimated to be 26.4% for $288 selling price according to current refurbished market price (LG Model: LW1213ER Refurbished, 2015), whereas a USEPA-recommended $40/ton CO$_2$ equivalent (tCO$_2$e) tax reduced the profit margin to 19.1% assuming fixed price for remanufacturing of $233 per unit (U.S. EPA-SCC, 2015). The results obtained are shown in Figure 8-2, which shows the flow patterns of returned products through the reverse logistics (RL) network. The remanufacturing cost is $233 per unit, and this devolved model is $116.99 per unit less than the current market price. The emission quantity is 0.07 tCO$_2$e per unit. Comparing remanufacturing result to the EIO-LCA shows that remanufacturing emission quantities are 0.084 tCO$_2$e per unit less than new manufacturing. Figure 8-3 shows the effects of the social cost of carbon on unit price by comparing the developed remanufacturing model and the EIO-LCA manufacturing model for the new manufacturing producer prices, over a range of proposed SCC values according to a recent U.S. government study, and at $220 per ton (as studied by Moore & Diaz, 2015). Therefore, existing approaches used different carbon policies.
Figure 8-2. Optimal number of items transported within the RSC

Figure 8-3. Social Cost of Carbon Effects on Unit Price
8.9.2 Deterministic Model with Relaxation Constraints

To examine the effect of carbon price uncertainty on supply chain network decisions, we considered 13 scenario groups for carbon pricing with identical demand scenarios. Table 8-7 summarizes the solutions of the deterministic model for a range of carbon prices. Three different configurations resulted from carbon prices between $0 and $120. The locations of collection centers, remanufacturing facilities, and the reselling center for each configuration are shown in Figures 8-4 – 8-6.

Having no carbon tax in place (i.e., a carbon price of $0) and $10 and $20 prices results in “configuration 1.” This is the current standard configuration, with three collection centers, two remanufacturing facilities, and three reselling centers. Increasing a carbon price to $30 per ton results in a change from configuration 1 to configuration 2, which has fewer facilities for a greener supply chain configuration. Since production is the primary contributor to the GHG emissions (see Figure 8-9), the location change in configuration 2 reduced production and incoming transportation costs and emissions.

Configuration 3 has been chosen for a carbon price of $50 and above; it has three collection centers, one remanufacturing facility, and two reselling centers. A decrease in the number of facilities helps to reduce the inbound and outbound transportation costs and emissions, and allows more efficient and environmentally friendly transportation routes.
Table 8-7. Case study results of the deterministic model for different carbon price scenarios

<table>
<thead>
<tr>
<th>Carbon Price ($/ton)</th>
<th>Configuration</th>
<th>Total Carbon (ton)</th>
<th>Carbon Cost ($)</th>
<th>Total Cost ($)</th>
<th>Changes in Unit Price (%)</th>
<th>Emissions Improvement compared to the base scenario (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1</td>
<td>101</td>
<td>0</td>
<td>106962.00</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>10</td>
<td>1</td>
<td>99.00</td>
<td>990.00</td>
<td>108072.02</td>
<td>1.04%</td>
<td>1.98%</td>
</tr>
<tr>
<td>20</td>
<td>1</td>
<td>98.30</td>
<td>1966.00</td>
<td>108935.23</td>
<td>1.84%</td>
<td>2.67%</td>
</tr>
<tr>
<td>30</td>
<td>2</td>
<td>96.80</td>
<td>2904.00</td>
<td>109798.44</td>
<td>2.65%</td>
<td>4.16%</td>
</tr>
<tr>
<td>40</td>
<td>2</td>
<td>95.79</td>
<td>3831.60</td>
<td>110661.65</td>
<td>3.46%</td>
<td>5.16%</td>
</tr>
<tr>
<td>50</td>
<td>3</td>
<td>94.69</td>
<td>4734.50</td>
<td>111524.86</td>
<td>4.27%</td>
<td>6.25%</td>
</tr>
<tr>
<td>60</td>
<td>3</td>
<td>92.58</td>
<td>5554.62</td>
<td>112388.07</td>
<td>5.07%</td>
<td>8.34%</td>
</tr>
<tr>
<td>70</td>
<td>3</td>
<td>91.46</td>
<td>6402.48</td>
<td>113251.28</td>
<td>5.88%</td>
<td>9.44%</td>
</tr>
<tr>
<td>80</td>
<td>3</td>
<td>90.35</td>
<td>7228.08</td>
<td>114114.49</td>
<td>6.69%</td>
<td>10.54%</td>
</tr>
<tr>
<td>90</td>
<td>3</td>
<td>89.24</td>
<td>8031.42</td>
<td>114977.70</td>
<td>7.49%</td>
<td>11.65%</td>
</tr>
<tr>
<td>100</td>
<td>3</td>
<td>88.13</td>
<td>8812.50</td>
<td>115840.91</td>
<td>8.30%</td>
<td>12.75%</td>
</tr>
<tr>
<td>110</td>
<td>3</td>
<td>87.01</td>
<td>9571.32</td>
<td>116704.12</td>
<td>9.11%</td>
<td>13.85%</td>
</tr>
<tr>
<td>120</td>
<td>3</td>
<td>85.90</td>
<td>10307.88</td>
<td>117567.33</td>
<td>9.92%</td>
<td>14.95%</td>
</tr>
</tbody>
</table>
Figure 8-4: The supply chain network for Configuration 1
Figure 8-5: The supply chain network for Configuration 2
Figure 8-6: The supply chain network for Configuration 3

Figure 8-7 combined the unit price and emissions reduction performance changes at various carbon prices. It shows that the unit price increases in a linear fashion along with the increase in the carbon price. After introducing the carbon price the emissions improvement significantly increases to 2%. After that, the emissions improvement slowly increases until it reaches $50, then there is another jump with introduction of configuration
3. Therefore, there is a direct relationship between the carbon price changes and both unit price and emissions improvement, since if carbon price increases both unit price and emissions improvement increase.

![Graph](image)

**Figure 8-7.** Unit price and emissions reduction performance changes at various carbon prices

### 8.9.3 Effect of Different Social Cost of Carbon

To estimate the unit price based on the social cost of carbon, which could fall anywhere between $0/ton to $120/ton (U.S. EPA-SCC, 2015). Consider the case study above. Figure 8-8 shows the effect of different SCC on unit price, and it is clear from the graph that the unit price of gets much higher as the SCC approaches $68/ton and above. This piecewise linear line has four different segments, as seen in Figure 8-8; each segment has a successive pair of points connected with a straight line. These segments represent system states.
Figure 8-8. Effect of different carbon prices on unit price

The focus in this analysis is to discover the relationship between the increasing price for the 458 units that were in the case study and the corresponding emissions rate. Figure 8-9 shows that, with carbon price increasing from $0 to $20 per ton of emission, production activities show only minor changes, while increasing the price to $40 per ton results in more significant emissions reduction. However, the significant cost increase at these facilities reflected emissions improvement in these activities (Fig. 8-9). In Figure 8-9, “production” includes production and inventory at remanufacturing facilities. “Collection” includes collection, recycling, disposal, and inventory at collection centers. “Transportation” comprises all shipment activities of returned products from collection centers to remanufacturing facilities, and then to reselling centers.
8.9.4 Statistical Analysis

A statistical analysis was performed by estimating Analysis of Variance (ANOVA) of regression analysis, using MINITAB 17 to examine the effects of factors mentioned in Table 8-1 on the unit price, and to determine whether the differences between factors were statistically significant. In order to evaluate the null hypothesis which stated that the factors means were all equal. Table 8-8 shows the output summary of ANOVA. If any p-value was less than the significance level of 0.05, the null hypothesis (all means are equal) would be rejected and it would be concluded that there were significant differences between means. Figure 8-10 shows the residuals plotted against the predicted values, showing an ideal random scatter around a value of zero. This indicates that the residuals were homogenous.

In practice, transportation cost plays an important role in supply chains, and it has a very high impact on cost. Here, after tracking the route, it was statistically and practically significant. Moreover, the costs of transportation for the current case study, including distance, loads, and gas prices, were very high. High Massachusetts salary wages, labor
that directly interfered with disassembly and assembly of products for remanufacturing, and retrieval costs had high impacts. The supply rate also had a significant impact, as when it increased the unit price decreased dramatically, due to economic scale quantity, and vice versa.

Table 8-8. Analysis of variance output summary

<table>
<thead>
<tr>
<th>Source</th>
<th>DF</th>
<th>Adj SS</th>
<th>Adj MS</th>
<th>F-Value</th>
<th>P-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regression</td>
<td>13</td>
<td>5.32E+10</td>
<td>4.1E+09</td>
<td>9.33</td>
<td>0.000</td>
</tr>
<tr>
<td>Transportation Cost</td>
<td>1</td>
<td>2.86E+10</td>
<td>2.86E+10</td>
<td>65.27</td>
<td>0.000</td>
</tr>
<tr>
<td>Energy Cost - fix</td>
<td>1</td>
<td>6933592</td>
<td>6933592</td>
<td>0.02</td>
<td>0.902</td>
</tr>
<tr>
<td>Energy Cost - variable</td>
<td>1</td>
<td>1.44E+10</td>
<td>1.44E+10</td>
<td>0.33</td>
<td>0.578</td>
</tr>
<tr>
<td>Rent Cost</td>
<td>1</td>
<td>4.02E+08</td>
<td>4.02E+08</td>
<td>0.92</td>
<td>0.356</td>
</tr>
<tr>
<td>Labor Cost</td>
<td>1</td>
<td>6414423</td>
<td>6414423</td>
<td>0.01</td>
<td>0.906</td>
</tr>
<tr>
<td>Social Cost of Carbon</td>
<td>1</td>
<td>4.54E+08</td>
<td>4.54E+08</td>
<td>1.03</td>
<td>0.328</td>
</tr>
<tr>
<td>Shortage Cost</td>
<td>1</td>
<td>3.43E+08</td>
<td>3.43E+08</td>
<td>0.78</td>
<td>0.392</td>
</tr>
<tr>
<td>Remanufacturing Cost</td>
<td>1</td>
<td>5.05E+09</td>
<td>5.05E+09</td>
<td>11.52</td>
<td>0.005</td>
</tr>
<tr>
<td>Mean demand rate</td>
<td>1</td>
<td>11585257</td>
<td>11585257</td>
<td>0.03</td>
<td>0.873</td>
</tr>
<tr>
<td>Retrieval Cost</td>
<td>1</td>
<td>2.84E+09</td>
<td>2.84E+09</td>
<td>6.49</td>
<td>0.024</td>
</tr>
<tr>
<td>Inventory Cost</td>
<td>1</td>
<td>1.28E+08</td>
<td>1.28E+08</td>
<td>0.29</td>
<td>0.598</td>
</tr>
<tr>
<td>Inventory level</td>
<td>1</td>
<td>7.69E+08</td>
<td>7.69E+08</td>
<td>1.75</td>
<td>0.208</td>
</tr>
<tr>
<td>Supply rate</td>
<td>1</td>
<td>3.96E+09</td>
<td>3.96E+09</td>
<td>9.03</td>
<td>0.010</td>
</tr>
<tr>
<td>Error</td>
<td>13</td>
<td>5.77E+09</td>
<td>4.39E+08</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>26</td>
<td>5.89E+10</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

It is important to satisfy the normality assumption so that test results are reliable. To gain an idea of the normal error assumption, a normal probability plot of the residuals was generated and is shown in Figure 8-11. The normal probability plot shows that the residuals strongly support the normality assumption and appear to generally follow a straight line.
8.10 Conclusion

This chapter has presented a reverse supply chain optimization model designed to take into account the influence of both strategic and operational activities of the supply chain on the environment. A case study based on actual sites was considered to illustrate performance of the model and to determine how the proposed policy would influence profit margins on remanufactured goods, and to test the influence of emissions pricing on optimal configurations of a RSC. The results indicated that the carbon price ranges that were used in this study will control the amount of GHG emissions generated in reverse supply chain operations. Moreover, by applying the RSC reconfiguration model, it shows that pricing carbon emissions, particularly at higher prices, mostly affects production and transportation operations and accordingly results in reduced their costs and emissions.
Similarly, a high carbon price results on supply chain configurations, and not necessarily in a linear relationship. The RSC configuration is sensitive to the carbon price. The work herein advances the theoretical modeling of optimal RSC systems while presenting an empirical case study of remanufactured appliances, an understudied facet of current industrial literature.

This case study recommends that the deterministic model be relaxed to facilitate the potential to relocate remanufacturing facilities/reselling centers rather than shutting down the facility, based upon the following factors:

   a. Traffic congestion and parking difficulties.
   b. Commuting distance.
   c. Current cost criteria.
   d. Population, economy, and geography of the city/setting.

The costs associated with remanufacturing are linked not only to economy, but the environment as well, and thus the proximity of facilities to cities and centers of high reclamation and recycling levels is important to ensure that not only costs are minimized, but the environment impact of operations as well.
Chapter 9  CONCLUSIONS AND RECOMMENDATIONS FOR FUTURE RESEARCH

9.1 Conclusions

The purpose of this dissertation is to analyze the issues related to strategic and planning levels of RSC, to enable cost-effective remanufacturing operations that reduce non-renewable resource utilization, and avoid premature disposal of functioning components and assemblies. A key facet of such efforts is the development of RSC systems capable of facilitating a reverse flow of used products from consumers back to manufacturers, at which point they may be refurbished or remanufactured to realize both environmental and economic benefits.

This dissertation develops novel and empirical multi-objective optimization models to inform RSC system design in the following levels: (1) strategic planning of facility location and transportation logistics; (2) tactical planning of optimal pricing; and (3) policy planning to account for potential valuation of RSC emissions. First, physical linear programming was employed to evaluate RSC facility placement through a determination of the quantities of EOL products for transport from candidate collection centers to remanufacturing facilities, factoring in cost and capacity criteria. This modeling framework utilizes an ANP application that allows for complex interrelationships between decision levels and attributes, given that many decision problems cannot be structured hierarchically when they involve interaction between and dependence among lower- and higher-level elements in a hierarchical structure.
ANP was applied to calculate the performance indices of the candidate collection centers drawn from qualitative criteria from the interested remanufacturing facility in the purchase of used products. The evaluation criteria of the collection centers are comprised of a four-level hierarchy. In Chapter 5 the LPP approach studied by Alkhayyal and Gupta (2015a) was used to determine the quality of EOL products for transport from candidate collection centers to the remanufacturing facility, while satisfying four key criteria. The four criteria are the maximization of total purchase value, and the minimization of the total cost purchase, transportation, and disposal. Following this, a numerical example is explored incorporating the three candidate collection centers. The results were produced through the application of the LPP model to determine the ideal candidate collection center.

The second key consideration of this study are the processes of disassembly and remanufacturing, which have been largely understudied within industrial engineering and process cost modeling literature. RSC pricing is an increasingly studied field of research however, given the increasing scale of remanufacturing operations, worth approximately $50 billion in just the United States. The U.S. in 2015 alone have returned products worth $261 billion, out of a total of $3.3 trillion sold. This makes a vast returned products market with sales that over $486 billion in 2014. Furthermore, the sales market for those returned products rose by 31% from 2010 to 2014, and due to expansion of e-commerce this rise is set to be much further. E-commerce causes a high scale in return products due to the fact that customers buy without seeing the products. By 2020, the U.S. e-commerce sales are expected to be 50% higher than they were in 2015, offering enormous opportunity (The Economist, 2016). This makes both an environmental benefit resulting from extended
product life, and a social benefit to increase buyer and seller access for the secondary market.

Of the two primary systems for obtaining used products from end users, the waste stream system that relies on diverting discarded products and passively accepting product returns is of most significance. Chapter 6 explored literature by Alkhayyal and Gupta (2015b) considering the pricing challenges faced by PRFs, namely:

- Competition between original equipment manufacturers (OEMs) and other PRFs;
- Requirement of costly, skilled workers for product recovery operations;
- Valuation of environmental considerations for inclusion into economic optimization tools;
- Uncertainty of the arrival time and the quantity for the discarded products;
- Inventory levels of recovered components; and
- Promotional, markdowns, sales, and clearance price discounts to clear inventory.

A critical synthesis of this information highlighted the importance of examining and solving a non-linear physical programming model to optimize the pricing policy for remanufactured products that effectively minimizes product recovery costs while maximizing total profit.

Lastly, the climate change concerns are continuing to increase along with the acceleration of global warming. The IPCC reports that globally GHG emissions have increased by more than 80% from 1970 to 2010, resulting in widespread threats to global ecosystems and human enterprise (IPCC, 2014). The new Paris agreement proposes a means to achieve zero net GHG emissions by the second half of this century (COP21, 2015). Alkhayyal et al. (2016a; 2016b) explored this topic in Chapter 7, through which a
deterministic model is employed to determine the effects of internalizing a cost of RSC GHG emissions into optimization models. Variations in optimal facility use, pricing/profit margins, and transportation logistics were compared against a variable cost of carbon, employing a case study method established through the inclusion of actual data from sites in the Boston area.

Chapter 8 further develops the model introduced in the previous chapter with recent data from the EPA. With potential increases in carbon costs, the optimal RSC system is likely to differ with respect to how be effectively managed and minimized. Results from the model have been studied comprehensively in terms of quantitative performance using Orthogonal Arrays. The results were compared to top-down estimates from economic input-output life cycle assessment (EIO-LCA) models, to provide a basis to contrast remanufacturing GHG emission quantities with those realized through original equipment manufacturing operations. Introduction of a carbon cost of $40/t CO2e increases modeled remanufacturing costs by 2.7%, but also increases original equipment costs by 2.3%.

The work herein advances the theoretical modeling of optimal RSC systems while presenting an empirical case study of remanufactured appliances, an understudied facet of current industrial engineering literature. The RSC issues identified above are analyzed through different multi-criteria decision making techniques that were explored in-depth in Chapter 4, including Analytical Network Process, Mixed-Integer Linear Programming, and Linear and Non-linear Physical Programming. Apart from the RSC case study presented in Chapter 8, the models developed are generic and can be further adapted and utilized to investigate location- and product-specific RSC operations in the future.
9.2 Recommendations for Future Research

The work contained in this dissertation can be extended in a number of ways. An important facet of current research that is relevant to the entire dissertation is the increasing use of embedded sensors in used products under the concept of the Internet of Things (IoT) and the increasing availability of high-resolution data. Embedded sensors can provide information related to use, transportation, repair, and remaining service life of products, whether new or used. New types of data coming from product sensors, such as transit time or records of product energy use, could be integrated in the generic models developed here in Chapters 5-7. These models could also be adjusted to incorporate probabilities adjusted through Bayesian updating, based on data from embedded sensors collected and exchanged in the cloud. Embedded sensors could also be used to further calibrate the RSC case study presented in Chapter 8, for example by tagging all products coming through a certain remanufacturing center and extracting trip-related information. Diagnostic data represents another potentially beneficial data stream from embedded sensors for remanufacturing operations that will inform repair decisions, disassembly for specific components, and overall economic benefits of remanufacturing.

Now considering each chapter in turn, within Chapter 5, a single-period model was developed for an RSC system, through which multi-criteria analysis tools were tested. A common strategy for model extension is to consider multiple periods, which could be used to consider inter-period RSC issues such as excess inventory or intentional stockpiling. Also in Chapter 5, the concept of the just-in-time (JIT) philosophy could also be applied to RSC. This philosophy is widely used in production activities. The extant literature includes copious research on forward supply chains and their incorporation of the JIT philosophy.
into the activities of the suppliers or manufacturers being studied. There has been comparatively little research on the incorporation of JIT concepts in RSC, perhaps due to the large variations in post-consumer product quality and time required in the collecting, cleaning, disassembly, recovering, transportation, and remanufacturing required when repairing or reclaiming components or assemblies from used products. One relatively simple way to introduce JIT concepts into the models in Chapter 5 could be to add a constraint that sets a maximum inventory level or inventory lead time.

The producer price of remanufactured goods in RSC was explored in Chapter 6, and was found to be a function of various factors, particularly demand levels. Thus, the determination of the optimal price for remanufactured goods is based on the aggregate of the demands of all potential consumers over a specific period in a remanufactured market. This analysis would benefit from further research to expand the model to consider multiple products, again over multiple-periods. As remanufacturing centers and especially collection centers typically process a wide variety of product types, makes, and models, the overall economics of a RSC cannot be determined from a single product analysis. The price models in Chapter 6 could be further developed by considering the impact of disassembly yield, product recovery costs, and disposal regulations on the sale and acquisition prices ultimately decided upon by remanufacturers. The relaxation of the deterministic assumption between the acquisition price and the procurement quality is an additional area in which further research would be of value.

In Chapters 7 and 8, a number of model extensions and refinements could be made. First, the deterministic model could be relaxed to facilitate the potential to relocate remanufacturing facilities/reselling centers rather than shutting down the facility, based
upon factors such as traffic congestion and parking difficulties; commuting distance; current land/energy/labor cost criteria; and general population, economy, and geographic characteristics of the setting. Proximity of additional recycling infrastructure, such as rail lines, Material Recovery Facilities, shipping terminals, and disposal facilities, and their incorporation in a spatially-explicit RSC may serve to make the models presented here more realistic. The case study in Chapter 8 used both facility-specific operational data as well as energy use estimates from CBECs. The case study could be made even more representative by obtaining metered energy data from those facilities, as well as actual logs of inventory trucked among the different RSC facilities. Finally, Chapters 7 and 8 used a variable social cost of carbon whose value was set to levels recommended by government agencies and reports to represent a carbon tax on all activities leading to GHG emissions. Other policy means of controlling GHG emissions such as strict carbon caps or cap-and-trade policies have been modeled in industrial engineering literature and could be considered here, which would require problem reformulation. The existing cost model could also be used to determine how much GHG emissions are reduced by remanufacturing versus disposal, providing a value for the cost of carbon abatement from remanufacturing operations that could be of use to environmental economics research.
REFERENCES

12 Foot Truck. (2015, 11 23). Retrieved from Penske Truck Leasing Corporation:  
http://www.pensketruckrental.com/moving-trucks/12-foot-truck/


Presentation at Direct to Customer: New Distribution Models, New York, NY.


Applications of Management Science (pp. 3-18). Emerald Group Publishing Limited.


Imtanavanich, P., and Gupta, S. M. (2006d). Evolutionary computation with linear physical programming for solving a disassembly-to-order system. *In Optics East 2006* (pp. 638504-638504). International Society for Optics and Photonics.


APPENDIX

APPENDIX A

Orthogonal Arrays of 27 experiments to satisfy 13 factors, each with three different levels used to quantitative evaluation and performance of the mixed-integer linear programming model in Chapter 8. The optimal number of units transported for experiment 1 to 27 are presented below.

Table A-1: Optimal number of units transported for experiment 1

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Table A- 9: Optimal number of units transported for experiment 9

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Table A-21: Optimal number of units transported for experiment 21

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Table A-22: Optimal number of units transported for experiment 22

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Table A- 23: Optimal number of units transported for experiment 23

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Table A- 24: Optimal number of units transported for experiment 24

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Table A- 25: Optimal number of units transported for experiment 25

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Table A- 26: Optimal number of units transported for experiment 26

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Table A- 27: Optimal number of units transported for experiment 27

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</table>
VITA

Bandar A Alkhayyal was born in Riyadh, Saudi Arabia. Alkhayyal has a bachelor in Computer Science and Master of Science in Engineering Management specialized in Project Management from Eastern Michigan University, a Master of Science in Industrial Engineering from New Mexico State University, and a PhD in Industrial & Environmental Engineering from Northeastern University providing such a basis for him in the engineering field. Worked as a research assistant at the Laboratory for Responsible Manufacturing at Northeastern University helped to illuminate the bridge between engineering theory and practice, and the importance of related instruction to cement the connection.

Engineering is a practical field that transcends the academic world, highlighting the value of not only teaching, but ongoing research. Alkhayyal has endeavored to contribute to the extant body of engineering literature, particularly in relation to circular economy, sustainable manufacturing, remanufacturing, environmentally conscious manufacturing, reverse logistics, product recovery, multiple criteria decision making, and operational management from an engineering perspective. His in various conferences including the Decision Sciences Institute and the Institute of Industrial and Systems Engineers conferences have been published.