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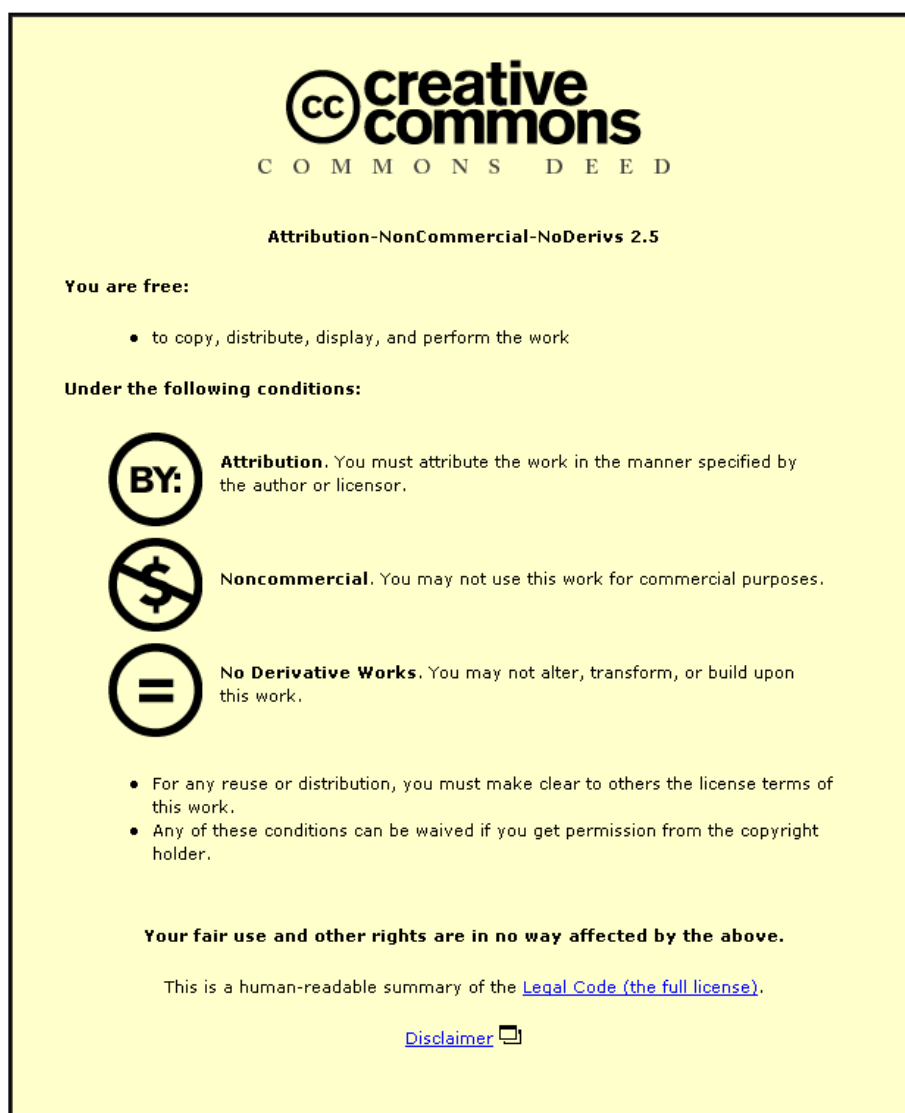
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SELECTION OF RETURN CHANNELS AND RECOVERY OPTIONS FOR USED PRODUCTS

By

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ABSTRACT

Due to legal, economic and socio-environmental factors, reverse logistics practices and extended producer responsibility have developed into a necessity in many countries. The end results and expectations may differ, but the motivation remains the same. Two significant components in a reverse logistics system -product recovery options and return channels - are the focus of this thesis. The two main issues examined are allocation of the returned products to recovery options, and selection of the collection methods for product returns. The initial segment of this thesis involves the formulation of a linear programming model to determine the optimal allocation of returned products differing in quality to specific recovery options. This model paves the way for a study on the effects of flexibility on product recovery allocation. A computational example utilising experimental data was presented to demonstrate the viability of the proposed model. The results revealed that in comparison to a fixed match between product qualities and recovery options, the product recovery operation appeared to be more profitable with a flexible allocation. The second segment of this thesis addresses the methods employed for the initial collection of returned products. A mixed integer nonlinear programming model was developed to facilitate the selection of optimal collection methods for these products. This integrated model takes three different initial collection methods into consideration. The model is used to solve an illustrative example optimally. However, as the complexity of the issue renders this process ineffective in the face of larger problems, the Lagrangian relaxation method was proposed to generate feasible solutions within reasonable computational times. This method was put to the test and the results were found to be encouraging.

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CHAPTER 1
INTRODUCTION

1.1 Introduction

This chapter touches on the research background, objectives, organisation, significance, scope and direction of this study. Also included are the motivating factors behind this endeavour.

1.2 Research Background

Minimizing environmental pollution and industrial waste is a major concern of many countries. Developed countries such as Japan, the United States and the European Union (EU) have already enacted legislation on these issues. It is also noteworthy that other related problems such as scarcity of natural resources in certain industries, limited landfill capacities, and the negative effect of discarded products have worsened over the years.

For some companies, engagement in environmental preservation and management of industrial waste is no longer an option. According to Sasikumar, Kannan, and Haq (2010), many companies are now engaged in the product recovery business due to increasing government pressure, environmental deterioration, economic pressure, resource depletion and social responsibilities.

Some governments are of the opinion that the management of products that have outlived their usefulness is the responsibility of the company that produced

them. Inderfurth, de Kok and Flapper (2001) stated that legislation aimed at environment-benign production makes it obligatory for manufacturers to reclaim their discarded products from end-users. Generally, companies are compelled to manage their product returns due to regulatory and economic reasons as well as pressure from their consumers.

Government regulations concerning product take-back such as a specific minimum level of product returns (minimum percentage of products that firms need to take back) play a major role in the promotion of product recovery. This regulation is now widely practiced in many EU nations and other developed countries such as the United States and Japan. With the enforcement of environmental laws, firms are obliged to come up with suitable ways to manage their discarded products.

Other than the requirement to comply with product take-back regulations, there is also the need for firms to devise effective and efficient ways to do so. And this is where the economic factor comes into play. An increasing number of firms are beginning to appreciate the fact that reverse logistics and product recovery management can lead the way towards the realization of business objectives such as profit maximization, cost minimization, resource utilization and production efficiency. Major firms such as Canon, Xerox, Hewlett-Packard, Agfa, Kodak, Daimler-Chrysler, BMW, and Visteon are practicing product recovery management to enhance their profitability and cost competitiveness (while complying with environmental regulations), factors that could lead to

better competitive positioning in the market. This brings us to the third driver – consumer pressure.

The consumers of today are increasingly environmentally conscious. Termed 'the green consumers' they can be expected to frown on products and firms that are not environmentally friendly. Their influence is gaining in strength, and with the current level of business competition, firms are understandably concerned about their image. Thus, it is not surprising that many firms have implemented environmental campaigns with product recovery themes such as shopping bag recycling (Tesco, Aldi, Carrefour, etc.) and free take back of used products such as personal computers, washing machines and mobile phones. Some firms even go a step further by offering refund payments in a bid to encourage more returns. The above factors are further discussed in the following chapter.

In the meantime, the emergence of reverse logistics as the most significant recovery approach in environmental management within the broad supply chain context has long been recognized. The role of reverse logistics in the environmentally-conscious society of today is clearly vital. Implementation of an effective reverse logistics system involving management of product return flows is seen as one of the primary ways of enhancing the competitiveness and profitability of firms (as explained in the previous paragraphs). In other words, the current application of this system in many industries is not only for the purpose of complying with environmental laws but also as a profitable and sustainable business strategy (Du and Evans, 2007).

Briefly, according to Srivastava and Srivastava (2006), environmental issues, sustainable development and legal regulations have resulted in organizations becoming increasingly responsive to reverse logistics and specifically, product recovery management. Persistent problems related to declining landfill capacities and the negative impact of product disposal on the environment have also coerced more nations into employing environmentally-friendly measures such as the implementation of a product take-back policy and extending the scope of producer responsibility.

The factors mentioned above have significantly encouraged the management of firms to seriously consider the management of product returns which includes product take back and recovery. These are the focal points of this study which comprises two sections. The first section involves a discussion on the selection of product recovery options and the maximum benefits firms can gain from them, while in the second section an investigation is conducted on the ways firms can optimise their profits through the assignment of a location-allocation strategy for product returns.

1.3   Brief introduction to Reverse Logistics and Product Recovery

Rogers and Timbke-Lembke (1999) define reverse logistics as the process of planning, implementing and controlling the efficient, cost effective flow of materials, in-process inventory, finished goods and related information from the point of consumption to the point of origin for the purpose of recapturing value or

proper disposal. They also consider remanufacturing and refurbishing activities to be included in the definition of reverse logistics. Reverse logistics can also be defined as a process of moving goods/products (such as used products, damaged items, seasonal inventory and salvaged products) from end customers back to its original manufacturer through various return channels and mechanisms.

Product Recovery Management (PRM) is defined as 'the management of all used and discarded products, components, and materials for which a manufacturing company is legally, contractually or otherwise responsible' (Thierry, Salomon, van Nunen and van Wassenhove, 1995). This definition suggests that product recovery management can be considered part of the reverse logistics system. In the PRM process, returned products can be recovered based on four levels; the product, module, part and material levels. According to Krikke, van Harten and Schuur (1998), the aim of product recovery management is to salvage the maximum economic as well as ecological value of used products, components and materials and in the process reduce the quantity of waste to a minimum.

There are also five options for product recovery: repairing, refurbishing, remanufacturing, cannibalizing and recycling (Thierry et al., 1995). Minor repair or the replacement of parts is for the purpose of restoring the used product to working order. The disassembly for this type of recovery is at the product level. Refurbishing involves returning used products back to a specified quality level through critical module and technological upgrading. The amount of recovery

work for this type of recovery option is less rigorous than for new products, but more when compared to the repair option.

The third recovery option is remanufacturing. This is the most rigorous form of recovery because it involves disassembly, inspection of all modules and parts, as well as technological and module upgrading. The objective of remanufacturing is to raise the quality of used products to the level of new products. Cannibalizing involves the recovery of a limited set of reusable parts from return products. These retrieved parts are then reused in repair, refurbishing or remanufacturing of other return products, modules and parts. Finally, recycling is a process whereby materials from return products are reused. The recycled materials can be used as it is or for other alternative applications.

1.4   Research Motivation

The importance of reverse logistics and product recovery are well documented in both theoretical and practical domains. The motivation for manufacturers to be actively involved in product recovery activities is apparent. Numerous researches in conceptual, empirical and modelling forms have been carried out to address issues related to reverse logistics and product recovery management. There are many players, components, processes and stages within a reverse logistics framework. Each is inter-connectedly as well as independently significant. Product recovery options and product return channels are two important components within the reverse logistics process.

In the industrial field, product recovery involves decisions on appropriate re-processing methods for returned products. Relevant factors such as quality and

volume of returns, market demand, costs and the capability of a manufacturer in this area play a pivotal role in these decisions. The selection of a recovery method is crucial as it plays a decisive role in the cost management or profit-making performance of the manufacturer. In some countries, manufacturers are also required by law to fulfil minimum collection and recovery rates for selected products. Product recovery is also boosted by the upsurge in market demand for recovered products as an alternative to virgin products.

A significant research avenue for the improvement of a reverse logistics framework is flexibility assignment. Theoretically, while validation is required, flexible assignment involving various quality classes of returned products and multiple recovery options may lead to a superior outcome when compared to a conventional approach. As research in this area is lacking, this study intends to fill this void through an empirical examination by employing the modelling approach.

It has been noted that there are three identified product return methods. In practice, customers return unwanted products via mail, drop-off or pick-up facilities provided by manufacturers or independent third parties. As these return channels initiate the contact between customers and collectors, decisions regarding these channels significantly influence the ability of manufactures to achieve their collection targets. It is also worth noting that collection activities affect recovery operations in the later stages. A pressing predicament for firms in some countries is the requirement to comply with the minimum collection rate.

As a consequence, the need for more available options and better decisions in product return channels are becoming progressively crucial. However, while

awareness on the urgency of the situation is noted, relevant information from previous research on these three collection methods is still sorely lacking. Another notable omission from previous investigations is the viability of mail return as an alternative to the other two return methods. Empirical evidence is needed to examine the feasibility of mail return in the reverse logistics network. Its potential linkages with the drop-off and pick-up methods also present substantial research opportunities. Hitherto, existing research regarded collection problems as location and routing problems. Decisions such as those concerning the selection of effective collection methods and available customer zones require further investigation.

1.5 Research Objectives

As previously stated, this study intends to examine two important components of a reverse logistics system. These are the product recovery options and return channels. This undertaking includes the development of models to help organizations make correct decisions in their selection of optimal recovery options and product return channels. The following are the specific objectives of this study:

1. *To determine optimal product recovery options.*

This study aims to investigate optimal assignment of product recovery options and the impact of allowing for flexibility in the decision-making process. A mathematical model will be formulated to optimize the profit of a firm by considering all recovery options (repair, refurbish, remanufacture, cannibalization and recycling). Specifically, a linear programming model will be developed to

attain an optimal assignment of returned products in different quality classes to specific recovery options with the allowance for flexibility included in the decision-making policy.

2. *To identify the best collection methods of returned products*

The second part of this study addresses problems in the product return channels. Pick up, drop-off and mail return are the three collection methods considered here. The aim is to develop an assignment model (profit maximization) for the collection channels of the manufacturer. A mixed integer non-linear programming model integrating the three collection methods is proposed to achieve this objective.

3. *To develop better solution methods via heuristic algorithm*

As in the second objective, the third objective also emphasises on product return channels. The necessity of a heuristic algorithm can be attributed to the complexity of the problem and the unavailability of a precise method to generate optimal solutions effectively. To overcome these obstacles, a Lagrangian Relaxation method is applied to provide alternative choices for the optimal solution and to enhance the practicality of the solutions. A heuristic procedure is formulated to achieve this third objective.

1.6 Significance of the study

In terms of theoretical contributions, the first part of this study offers a novel approach to the allocation of product recovery options. This approach

involves an investigation into the benefits that can be derived by allowing for flexibility in the allocation of product recovery options. Unlike previous studies, the model developed in this study provides a more comprehensive quality classification of returned products. Due to the allowance for flexibility, products from various quality classes can be assigned to different recovery options for as long as it is feasible to do so. Practicality is another important contribution from the proposed model. It is cost-effective and while it requires less computation time, this does not compromise its ability to generate optimal solutions under challenging circumstances.

The second part of this study also delves into the collection of returned products where the focus is on the collection stage of product return channels, an area that has been largely overlooked by previous studies. Three collection methods (drop-off, pick up and mail return) are studied and their potential for integration examined. This examination will go a long way in filling the void in relevant literature on product return channels and in the process unveil a new optimization model that simultaneously considers all three collection methods together. The proposed model incorporates more practicality and also provides a very comprehensive analysis regarding the collection of returned products compared to previous relevant research. Another significant contribution of this research is the examination of mail return as one of the collection avenues.

The third part of this study focuses on an investigation of the proposed model utilising a heuristic algorithm (Lagrangian Relaxation) to determine the best alternative solution to the original solution. The Lagrangian Relaxation

approach is also employed to strengthen the applicability of the proposed model when exposed to various problematic situations. The algorithm is also expected to produce feasible solutions in a situation where the inadequacies of the exact model render it incapable of overcoming medium and high level problems. A desirable result from this heuristic algorithm will establish a strong foundation for the potential application of the proposed model in the industrial field.

1.7   Scope and Direction of the research

The emphasis of this study is on product recovery options and product return channels. For product recovery options, the proposed model is based on five recovery methods: repair, refurbish, remanufacture, cannibalisation and recycling. The proposed model is deterministic in nature and the objective here is to examine the potential application of flexible allocation of product recovery options. Other related factors such as end-of-life product inventory, government incentives and subsidy, decision making levels and information system, forecasting, and transportation facilities were excluded from the analysis.

As for the product return channels, the focus is on three initial collection methods for returned products; pick up, drop-off and mail return delivery. The decision making levels or the flow of information involving centralisation or decentralisation decisions within product return channels are not considered. The main consideration is the viability of integrating all three collection methods into a single model. The routing problem is also excluded from the main analysis.

1.8   Chapter Feature and Organization

This thesis comprises eight chapters. The other sections of this study are organized as follows:

Chapter 2 discusses relevant literature review on reverse logistics, product recovery management and product returns channels. Key literature and significant research gaps are highlighted. Other relevant researches are also discussed in this chapter.

Chapter 3 presents a discussion on the methodologies used in this study. This chapter examines optimization methods that may be used for problems in this study and provides an explanation on the choice of methods used.

Chapter 4 discusses product recovery options. A mathematical model is developed, tested and analysed in this chapter in order to highlight optimal allocation of product recovery options and to achieve the first objective of this study.

Chapter 5 addresses the problem of returned products collection methods. A mixed integer non-linear model integrating all collection methods is formulated and tested. The computation works and results are presented.

Chapter 6 highlights the application of a heuristic method to obtain solutions based on the previous problem addressed in chapter 5. A Lagrangian relaxation method is employed to achieve this goal. The findings are discussed at the end of the chapter.

Chapter 7 discusses key findings from each chapter and highlights important managerial implications and recommendation for future research.

Chapter 8 presents an overall conclusion to this study.

CHAPTER 2
REVIEW OF LITERATURE

2.1   Introduction

This chapter reviews relevant research on reverse logistics, with particular attention to related literature on product recovery management and product return channels. The chapter starts with a broad discussion on reverse logistics and product recovery management before emphasizing the components and other relevant factors. The second half of the chapter addresses product return channels. At the end of this chapter, the research summarizes the literature reviews by identifying relevant gaps and associating them with the main purpose of this study.

2.2   The Concept of Reverse Logistics & Product Recovery Management

The concept of reverse logistics is sometimes confused with other related terms such as reverse supply chain, closed-loop supply chain, green logistics and waste management. Reverse supply chain covers a bigger scope than reverse logistics as it involves the following five groups of activities: (1) collection, (2) inspection/separation, (3) re-processing, (4) disposal, and (5) re-distribution. Kumar and Malegeant (2006) defined collection as all the activities that are required to collect returned products and to physically move them to a certain point for further recovery processes. This involves activities such as product acquisition, transportation and storage. Inspection and separation involve used

product testing (to determine the quality level), disassembly, shredding, sorting and storage.

Re-processing, on the other hand, is engagement with repair activities such as disassembly, shredding, remanufacturing, replacement, and recycling. Disposal (non-recovery processes) means that the non-reusable items are disposed of to either incinerators or landfills. Re-distribution focuses on activities directing reusable items to be re-marketed to new or existing markets, and physically moving them to new users. Activities such as sales and marketing, transportation and storage fall under re-distribution processes.

On the other hand, the closed-loop supply chain emphasizes on coordinating the forward and reverse supply chain (inclusive of forward and reverse logistics), and this system also includes various product recovery and disposal options. Reverse logistics is different from green logistics as the latter considers the environmental aspects in all logistics activities and focuses specifically on forward logistics (Rodrigue, Slack and Comtois, 2001). According to de Brito and Dekker (2004), reverse logistics also differs from waste management as the latter mainly refers to collecting and processing waste (products for which there is no new use) efficiently and effectively.

Unlike traditional forward logistics, reverse logistics focuses on the backward flow of logistical activities and processes starting from the end customers moving upstream towards the manufacturer. The European Working Group on Reverse Logistics (REVLOG) defines reverse logistics as:

"The process of planning, implementing and controlling backward flows of raw materials in process inventory, packaging and finished goods from a manufacturing, distribution or use point, to a point of recovery or point of proper disposal." (REVLOG, 1998)

The Council of Logistics Management characterises reverse logistics as "the role of logistics in recycling, waste disposal and management of hazardous materials; a broader perspective includes all relating to logistics activities carried out in source reduction, recycling, substitution, reuse of materials and disposal." However, the most common definition (widely used and most accepted in the literature) of reverse logistics is given by Rogers and Tibben-Lembke (1999):

"Reverse logistics refers to the process of planning, implementing and controlling the efficient, cost-effective flow of raw materials, in-process inventory, finished goods and related information from the point of consumption to the point of origin for the purpose of recapturing value or proper disposal. Thus, product recovery activities such as remanufacturing, recycling and refurbishing are included in the definition of reverse logistics"

Based upon the aforementioned definitions, it is obvious that product recovery management plays a pivotal role in reverse logistics. Apart from managing the basic logistical aspects of the reverse supply chain such as transportation and distribution, reverse logistics is significantly involved in the value recovery of returned products. De Brito and Dekker (2004) presented important characteristics that are used to show the diversity of reverse logistics systems: (1) the driving factors (economical, ecological and legislation), (2) the

types of items involved in reverse logistics such as spare parts, packages and consumer goods, (3) the form of reuse (such as direct reuse, repair, recycling and remanufacturing) and relevant processes such as collection, inspection and re-processing, and (4) the involved actors (members of forward channels or specialized parties). They also provide a framework for the basic understanding of reverse logistics based on four perspectives, which are:

WHY are things returned? : refers to the factors driving companies to be involved in reverse logistics and the reasons for products going back into the supply chain.

HOW are returned products processed? : refers to the overall activities in a reverse logistics process, particularly product recovery options.

WHAT is being returned? : analyses product characteristics for reverse logistics (types and classification).

WHO are executing the reverse logistic activities? : refers to the actors/players in reverse logistics and their respective roles.

On the 'why' question, de Brito and Dekker (2004) differentiated three driving forces for reverse logistics: economics (profit-making and cost minimization), legislation (laws and regulations that require companies to take back their products at the end of their usage) and corporate citizenship (company feels socially responsible to do it). 'How' refers to all the processes involved in reverse logistics such as the collection of returned products (through various return channels), 'gate-keeping' activities such as quality inspection, selection

and the sorting process, re-processing activities that include recovery options (disassembly, segregation, repair, refurbishment, remanufacturing, recycling, and cannibalization), and re-distribution.

'What' looks on the product characteristics, which include three main features: (1) product composition, (2) the deterioration process, and (3) the used patterns. Fleischmann, Bloemhof-Ruwaard, Dekker, van Der Laan, van Nunen and van Wassenhove (1997) classified products into seven types, namely (1) civil objects, (2) consumer goods, (3) industrial goods, (4) ores, oil and chemical, (5) packaging and distribution items, (6) spare parts, and (7) other materials such as pulp, glass and scraps. Meanwhile, Fuller and Allen (1995) presented a list of actors in reverse logistics and divided them into three major categories: (1) forward supply chain actors (suppliers, manufacturers, wholesalers and retailers), (2) specialized reverse chain players (such as jobbers, recycling specialists, remanufacturers, etc.), and (3) opportunistic players such as charity organizations. The forward and reverse logistics function as well as the scope of the product recovery management within the supply chain management function can also be illustrated in the following figures 2.1 and 2.2.

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                                                    │       Centralized        │
                                                    │      Direct/Indirect     │
                                                    │    Collection Channels   │
                                                    └─────────────────────────┘

┌──────────────┐
│  Secondary   │                                    ┌─────────────────────────┐
└──────────────┘                                    │  Initial Collection      │
                                                    │  Points:                 │
┌──────────────┐  ┌──────────────┐ ┌──────────┐ ┌──────────┐ │  Drop-off        │
│ Manufacturer │→ │  Distributor │→│ Retailer │→│ Customer │ │  Pick-up         │
└──────────────┘  └──────────────┘ └──────────┘ └──────────┘ │  Mail return     │
                                                    └─────────────────────────┘

                        ┌──────────────────────────┐  ┌─────────────────────────┐
                        │   CAPACITY DECISIONS     │  │ Decentralized Direct/    │
                        │                          │  │ Indirect                 │
                        │  • Product Recovery      │  │ Collection Channels      │
                        │    Facility              │  └─────────────────────────┘
┌──────────────────┐    │  • Reuse                 │
│ STORAGE CAPACITY │    │  • Remanufacturing       │
│                  │    │  • Refurbishment         │
│ Finished         │    │  • Cannibalization       │
│ Repairable       │    │  • Recycling             │
│ Goods Storage    │    │                          │  ┌─────────────┐
└──────────────────┘    └──────────────────────────┘  │  DISPOSAL   │
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Figure 2.1: The Forward and Reverse logistics Framework
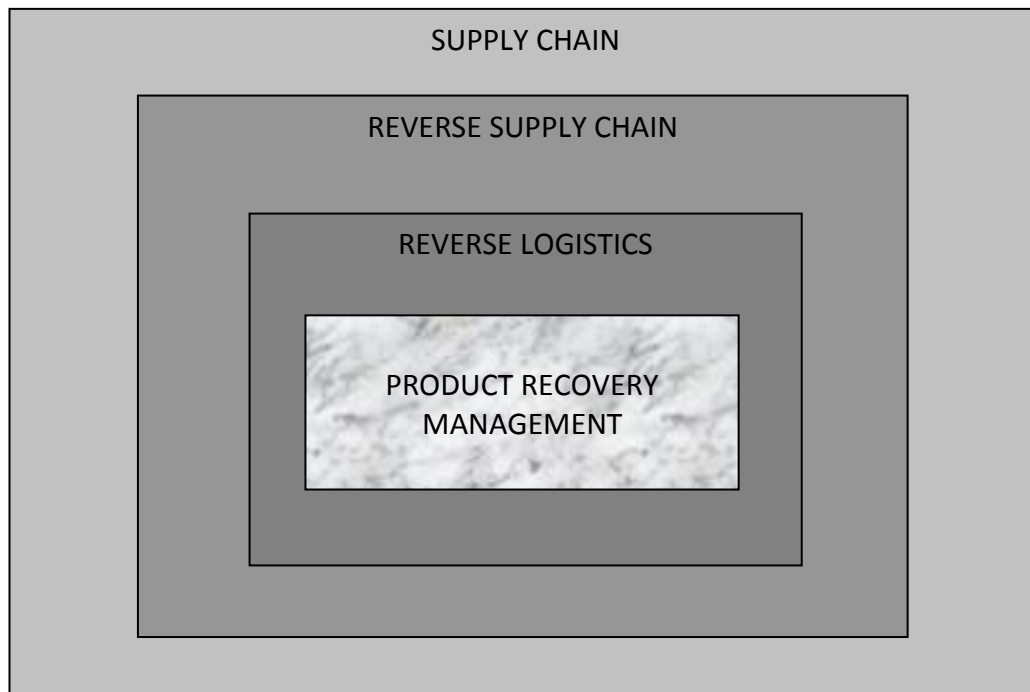
Figure 2.2: The Scope of Product Recovery Management and Reverse Logistics

2.3   Product Recovery Management

According to Thierry et al. (1995), Product Recovery Management (PRM) is the process of managing all used and discarded products, parts, components and materials returned by customers. Baenas, Hojas De Castro, Battistelle and Junior (2011) added to the above definition of product recovery management by including the legal responsibility of the manufacturing firms. The purpose of product recovery management is to recover (recapture) the economic and ecological value of returned products as much as possible while at the same time minimizing waste and disposal.

Generally, returned products can be either recovered or disposed (incinerated or landfilled). There are five recovery options for returned products

(Thierry et al., 1995; Sasikumaret al., 2010): repair, refurbish, remanufacturing, cannibalization and recycling (the recovery options are listed according to the required degree of disassembly). Thierry et al. (1995) distinguished the five recovery options into the following characteristics:

a. ***Repair***: This recovery option requires limited disassembly processes and the quality of the repaired products is also lower than that of the new products. Repair involves fixing or replacing only certain parts or components of a product, whereas other parts/components are basically in good condition. The purpose of repair is to return the used products to 'working order'.

b. ***Refurbish***: The aim of refurbishment is to return the used products to a specified quality level which is, however, still lower than the quality of the new products. It involves inspection, fixing and replacement of some critical modules (following disassembly of the returned products into modules). Approved modules are then reassembled into refurbished products and it also involves technology upgrading such as replacing outdated modules with new ones that come with better technology.

c. ***Remanufacturing***: The objective of remanufacturing is to bring used products up to a quality standard that is as good as the new product. Used products are entirely disassembled with all the modules, parts and components inspected, replaced with new ones (if necessary), fixed and tested. The process involved in remanufacturing is as rigorous as the process of making a new product and it may also involve technological upgrading.

d. ***Cannibalization***: The purpose of cannibalization is to recover a limited set of components or parts that are still reusable. Cannibalization involves selective disassembly of used products and inspection of potentially reusable parts or components. Subsequently, these parts or components are reused in other recovery processes (repair, refurbishment or remanufacturing) depending on their quality level.

e. ***Recycling***: The purpose of recycling is to reuse materials from used products and components. The recycled materials are reused in the production of other components or parts (it can be used in the production of its original products or in other products). It begins when used products and components are disassembled into parts. These parts are then separated into certain material categories before they are eventually used in the production of other new parts or components.

Krikke et al. (1998) distinguished product recovery options based on the level of disassembly, quality requirements and resulting product as shown in the following table.

According to Jayaraman (2006), there are seven characteristics that complicate the management and control of product recovery in the reverse supply chain: (1) uncertainty in timing, quantity and quality of returns, (2) the need to balance demands with returns, (3) the need to disassemble the returned products, (4) uncertainty in materials recovered from returned products, (5) the requirement for a reverse logistics network, (6) the complication of material matching

restrictions, and (7) the problem of stochastic routings and variable processing times. Figure 2.3 illustrates the product recovery sequence involving product returns (collection), inspection/separation (quality classification), and re-processing (recovery) activities. In the collection decisions, '*dc*' refers to '*direct centralized*' while '*dd*' means '*direct decentralized*'. For indirect collection channels, '*Ic*' refers to '*indirect centralized*' while '*Id*' means '*indirect decentralized*" collection.

Table 2.1: Product Recovery Options based on Disassembly Level and Quality Requirements

Recovery options	Level of disassembly	Quality requirements	Resulting product
Repair	To product level	Restore product to working order	Some parts repaired or replaced
Refurbishment	To module level	Inspect and upgrade critical modules	Some modules repaired or replaced
Remanufacturing	To part level	Inspect all modules/parts and upgrade	Used and new modules/parts in new product
Cannibalization	Selective retrieval of parts	Depends on use in other product recovery options	Some parts reused, others disposed of or recycled
Recycling	To material level	Depends on use in remanufacturing	Materials used in new products

Source: Krikke et al. (1998)
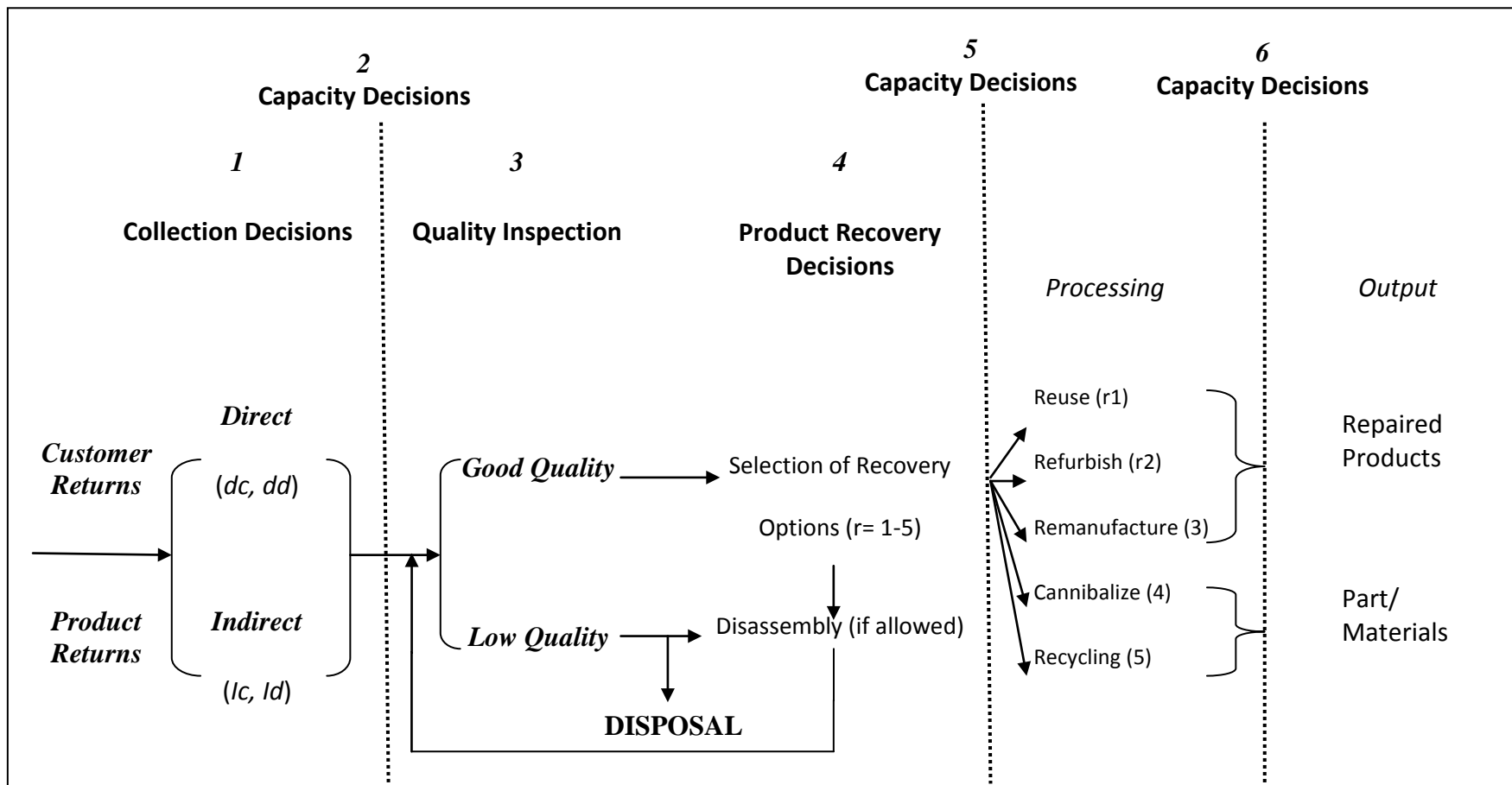
Figure 2.3: Structure of the Six Steps Product Recovery Decision Processes

Krikke et al. (1998) were among the first researchers to address the optimality of all product recovery options in one particular study. The study focused on a problem in which the firm needed to determine to what extent returned products must be recovered for reuse or disposal (incineration or landfill) and to decide on which sort of recovery options were suitable to be used. The study also included a quality classification scheme of returned products (limited to $q1$ = good condition and $q2$ = malfunctioning with conditional probability) as well as technical, commercial and ecological criteria (see Table 2.2 for examples of feasibility criteria) to determine the viability of the product recovery and disposal options. It also tried to choose an optimal relation between the disassembly strategy, quality classification, and feasible recovery and disposal options.

Krikke et al. (1998) used the classification of recovery options by Thierry et al. (1995): repair, refurbishing, remanufacturing, cannibalization and recycling. The analysis was based on the tactical management level, excluding disassembly sequencing from the model, focused on the product level and dealt with OEM products with high return volume (three types of TV). A special subroutine was also developed to determine the optimal combination for the recycling strategy (recycling has different optimization characteristics compared to other reuse options). The overall idea was that for each assembly j in class q a set of recovery and disposal options was generated, after which the feasibility of these recovery and disposal options was assessed (Krikke et al., 1998). A stochastic dynamic programming algorithm was used for the optimization (2-phased optimization procedures and based on net profit) and the model was tested with a TV case. The

result revealed a classification scheme and a set of conditional assignment rules based on the abovementioned feasibility criteria on the product level.

Table 2.2: Examples of Feasibility Criteria

Product Level	Product Group Level
1. Technical Feasibility Criteria • Processability • Technical state • Separability of materials • Processing properties of materials • Presence and removability of hazardous contents	*1. Technical Feasibility Criteria* • Capacities of transportation, recovery and disposal facilities • Availability of collection systems
2. Commercial Feasibility Criteria • Technological status • Recovery costs • Secondary market prices • Lost sales in primary market • Quality of returned products, components and materials	*2. Commercial Feasibility Criteria* • Perception of consumers towards secondary products, components and materials • Limited volumes of secondary end markets
3. Ecological Feasibility Criteria • Disposal bans • Obligatory removal of hazardous contents	*3. Ecological Feasibility Criteria* • Legislative recovery targets

Source: Krikke et al. (1998)

Krikke, van Harten and Schuur (1999) also applied their previous theoretical models (Krikke et al., 1998) in another study involving a municipal waste company in Rotterdam which had to deal with the recycling of PC-

monitors. They used a two-step procedure (product level and group level) for optimizing a recovery strategy for durable consumer products in a multi-product situation. The solution approach that was used in this case (a municipal company) was in fact largely based on their previous model, except for several adjustments that needed to be made in accordance with the product specification (the previous model was tested using a TV product while this case study focused on PC-monitors). Mostly, the recovery options in this case study (Krikke et al., 1999) were limited to the recycling processes due to the specifications of the product and its parts and components. The approaches taken to obtain the optimal product recovery strategy were: Group Recovery Disposal 1 (allowing partial disassembly, mixed and separate recycling) and Group Recovery Disposal 2 (full disassembly and separate recycling). The results showed that Group Recovery Disposal 1 (GRD 1) was cheaper than GRD 2 due to better capacity utilization, additional cost savings and coverage of fixed costs (GRD 1 produced a lower fixed cost per monitor).

Teunter (2006) presented an improvised stochastic dynamic programming algorithm for determining the optimal disassembly and recovery strategy based on the previous model developed by Krikke et al. (1998). The difference between his study and the one proposed by Krikke et al. (1998) was the generalization of the disassembly options: there could be multiple disassembly processes and partial disassembly was also allowed. Teunter (2006) also included disassembly tree (assemblies-subassemblies relationships), the process-dependent quality distributions of assemblies, and the quality-dependent recovery options in his models. Although it was based on the model by Krikke et al. (1998), he only

considered two recovery options: remanufacturing and recycling. The quality classification was also incomprehensive with only two categorizations: high or low quality, while the disassembly was divided into two types, destructive and non-destructive. The solution gave specific disassembly and product recovery strategies that were selected for each assembly (product and its components) that would maximize profits. Although the inclusion of more disassembly options in the product recovery strategy was very good and practical, Teunter (2006) failed to address other related issues in his model such as capacity limitations, and uncertainties in terms of product returns and the impact of a collection channel strategy.

Georgiadis and Vlachos (2004) studied the effects of environmental parameters on product recovery, focusing on the long term behaviour of a single product reverse supply chain with product recovery under various ecological awareness influences. They considered the capacity of remanufacturing facilities as a design parameter, and the environmental issues examined were the green image effect on customer demand, the effect of state environmental protection policies (such as the take-back obligation imposed from legislation) and the state campaigns for the proper disposal of used products. They used a two-phased dynamic simulation model (based on the principles of System Dynamics methodology) to analyse the behaviour of the system. They also considered the model to be useful in facilitating decisions on environmental and remanufacturing capacity policies.

Georgiadis and Vlachos (2004) also considered the following operations in their model: supply, production, distribution, use, collection, inspection, remanufacturing and waste disposal, with particular attention given to inventory and capacity (production, collection and remanufacturing capacity) variables. Eighty scenarios over a period of 300 weeks were simulated involving all possible combinations of 5 environmental protection policy indices, 4 market behaviours and 4 remanufacturing capacity adding strategies. The study showed that the 'leading' or 'matching' remanufacturing capacity adding strategy improved the green image that led to an increase in demand. Strengthening efforts on environmental protection also led to higher collection rates of returned products. However, this paper could be improved by incorporating more analysis on the operational aspects of the system as well as on analysing more recovery options such as recycling and refurbishment. It focused more on the external aspects of the system (the green image, protection policies, market behaviour and state campaign) even though there was some inclusion of functional parameters.

Salema, Barbosa-Povia and Novais (2007) also addressed capacity issues in their study. They also incorporated another two problems related to product recovery within the reverse logistics network: multi-product management and uncertainty in demands and returns. However, the capacity issues in their model were not comprehensively analysed because the main focus was the development of an optimal recovery network. Their study was actually an extension of a previous study by Fleischmann, Beullens, Bloemhof-Ruwaard and van Wassenhove (2001) that developed the Recovery Network Model (RNM) using Mixed Integer Linear Programming (cost minimization). The main contribution

(and aim) of their paper was the inclusion of the aforementioned problems into the model which made it more realistic and generalisable. Salema et et al. (2007) carried out an analysis using four situations (basic single product network, recovery network with capacity constraints, multi-products recovery network, and uncertainty in demands and returns) based upon the case of an office document company in the Iberian market. The model considered five factory locations, eight warehouse locations, five disassembly centres and fifteen clusters of customers. The first three situations were analysed using the MILP technique, while the fourth case, involving uncertainty in demands and returns, was additionally analysed using the scenario-based approach. The results for each situation showed how customer demands/returns were being served by various factories, warehouses and disassembly centres in an optimal combinatorial recovery network (that could lead to cost minimization).

Mangun and Thurston (2002) developed a design decision model regarding component reuse, remanufacturing, recycling and disposal over several product lifecycles for a portfolio of products. The model integrated (and considered trade-offs between) costs, environmental impact, reliability of components, product lifecycles and three different types of market segments (technophiles, utilitarian and green) and was formulated using a constrained multi-attribute optimization problem. Four design decisions (reuse, remanufacture, recycle and new) and eight operations (material processing, manufacturing, assembly, collection, disassembly, remanufacturing, recycling and disposal) were considered in the development of the model. The aim was to maximize the overall utility of the entire product portfolio over several lifecycles.

The researchers also used the special lifecycle assessment software, SimaPro 4.0, to help them in estimating the total environmental impact. The model was then tested on a case study of a single manufacturer producing personal computers (involving 88 separate components) using a nonlinear programming solver. However, all the input parameters including costs, reliability and environmental data were estimated (industry average values) and did not reflect those of any specific manufacturer or product. Four scenarios were analysed: a single product approach with new products (no reuse options), single product under closed-loop approach, product portfolio under closed-loop and product selling approach, and product portfolio under closed-loop with service-selling approach. The results showed that the product portfolio approaches generated better results (higher total portfolio utility) than single product approaches, with the service selling approach producing the highest total portfolio utility. Nevertheless, the inclusion of leasing arrangements (service selling approach) in the model was not comprehensively explained and its effect on product consumptions needs to be further studied. The model itself has several assumptions that need to be relaxed to further improve its practicality, such as the inclusion of demand uncertainty, capacity limitation and other recovery options (refurbishment and cannibalization).

Guide, Muyldermans and van Wassenhove (2005) worked with Hewlett-Packard on how to manage time-sensitive returned products and to unlock its potential in generating maximal profit for the company. The researchers focused on two main HP products, namely personal computers and notebooks, for the analysis. After understanding the current system in HP (the reverse supply chain

flow and how they manage returned products before reselling it to the secondary market), the researchers developed multi-period linear programming models based on network-flow principles to explore alternative scenarios and to maximize HP profits. The researchers also emphasized two important issues, the quality and the age of the returned products, when developing their models.

They also included bottleneck issues, outsourcing considerations, peak season demands, production lead times and inventory costs in their models. Their findings showed that the company could increase their profits significantly through the implementation of the proposed models, which convinced HP to implement the new models/policy. However, their study only focused on two recovery options: reuse and refurbishment (PCs and notebooks are comprised of many parts and components that can also be recycled, cannibalized or remanufactured). The model also did not include transportation/logistics costs, the pricing effect (trade-off) between HP and the outsourcing firm that carried out the repair activities for the company, and the disposal options (the model did not consider the disposal options as all the rejected items went to the brokers).

2.4   Drivers for Product Recovery

Several drivers have been noted as significant forces for product recovery. These drivers consist of legal requirements, consumer pressure/ green awareness, and economic factors.

2.4.1 Legal Requirements

Extended producer responsibility is becoming increasingly common around the world (Alumur, Nickel, Saldanha-da-Gama and Verter, 2012; Ozdemir, Denizel and Guide, 2012). Communities, governments, businesses, international agencies and non-governmental organizations are increasingly concerned with the establishment of sustainable development within the context of the business community (Tsoulfas and Pappis, 2006). Qin and Ji (2010) stated that government regulations and the environmental consciousness of consumers are the main reasons for product recovery.

Due to increased environmental pollution levels and reduced solid waste processing capacities, environmental regulations and take-back laws are being adopted in the nation and around the world (Toffel, 2003). The German Recycling and Waste Control Act requires that manufacturers actively seek techniques and products that avoid waste and the reuse of non-avoidable wastes (Rembert, 1997). The European Union (EU) has also enacted a special regulation requiring producers (manufacturing firms) to take back their products at the end-of-life (Krikke, Bloemhof-Ruwaard and van Wassenhove, 2003). Some European countries, namely Austria, Belgium, Finland, France, Italy, The Netherlands, Spain and Sweden, have also passed stringent laws on reuse (Rembert, 1997).

Inderfurth et al. (2001) stated that legislation aimed at environment-benign production forces manufacturers to take back their products from end-users after they discard them. Governments around the globe have started enacting laws prohibiting landfilling or incineration of certain products that could potentially

have a negative impact on the environment. Japan, Taiwan and the EU have enacted directives to regulate the collection and processing of EOL vehicles (Johnson and Wang, 2002; Lee, 1997).

2.4.2 Consumer pressure/Green awareness

Increasing consumer awareness on the issues of environmental preservation has made product take-back and recovery an important aspect to be dealt with. According to Fleischmann, Krikke, Dekker and Flapper (2000), customer expectations urge companies to reduce the environmental burden of their products. A 'green' image (environmentally friendly company) has also become an important marketing element (Rogers and Tibben-Lembke, 1999). Apart from that, the implementation of manufacturers' corporate social responsibility within the reverse logistics context also plays an important role (Sarkis, Helm and Hervani, 2010). Hence, firms need to comply with the strict environmental regulations and produce 'green' products as well as demonstrate good corporate citizen practices in order to enhance their 'green image' and marketability (Jayaraman, Patterson and Rolland, 2003).

2.4.3 Economic factors

Environmental management within business boundaries could critically lead to massive cost reductions and enhance potential profits as proven by some of the major companies in the world (Savaskan and van Wassenhove, 2006). It is also economically beneficial for the company due to the cheaper and cost effective materials, and added value recovery (Fleischmann et al., 2000). Hence, the

motivation to perform an environmentally-aligned business strategy is no longer solely driven by external factors such as governments, NGOs and consumer pressures as more and more companies have reaped the 'internal benefits' of achieving significant cost reduction, improved process efficiency and operating profit. According to Akdogan and Coskun (2012), processing returned or used products provide substantial gains to the companies both directly and indirectly. In fact, they also concluded that economic returns are now the most important drivers for reverse logistics and product recovery management. The situation is now changing as economic factors play a pivotal role in pushing more manufacturers to embark on reverse logistics. Previously the legal factor was the main driver.

2.5 Remanufacturing

Remanufacturing is an important subject in research. There have been numerous studies on remanufacturing since the 1980s (Sasikumar et al., 2010; Ferrer, 1997; Aksoy and Gupta, 2005). For instance, Inderfurth et et al. (2001) formulated a periodic review model that could determine the structure of the optimal periodic review policy and address the stochastic remanufacturing problem with multiple reuse options and uncertainties in returns as well as demand. The aim was to select the optimal quantity of returned items that would be remanufactured for selected remanufacturing options/disposal options in a certain time period of a planning horizon that would eventually minimize all relevant costs (stock holding, backordering, remanufacturing and disposal costs etc.).

The incorporation of some inventory issues such as inventory costs, the backordering policy and the stochastic nature of stock replenishment (stock of returned items), made the research by Inderfurth (1997), which was an optimization-based research, different from previous remanufacturing studies. They obtained optimal and near-optimal control rules for a stochastic product recovery problem in which multiple remanufacturing options existed (which yielded different serviceable products that satisfied specific demands). Various situations or assumptions were tested in the paper: single vs. multiple period time planning, linear allocation rules and discounted vs. average cost cases. In general, in the latest research, Inderfurth et al. (2001) dealt with stochastic remanufacturing problems with more focus given to the inventory management issues. Their paper could be improved by considering the impact of the quality categorization of returned products, the incorporation of newly manufactured products into the model (they only considered remanufactured products to serve the demands) and the inclusion of other reuse options such as refurbishment and recycling.

In another study, Inderfurth (2005) analysed the impact of uncertainties (rate of returns, quality level, costs, and demands) on product recovery behaviour in a remanufacturing environment. The purpose of his study was also to determine to what extent profit orientation in product recovery management will stimulate an environmentally conscious behaviour (that will promote a higher recovery level). He then developed a stochastic remanufacturing model focusing on problems and decisions in three main functions: remanufacturing, production and disposal. Other important parameters included in the mathematical models

were inventory (units, holding costs and times), quality of returns, lead times and backordering options. Inderfurth (2005) then identified six types of determinants of product recovery behaviour (uncertainties, return level, quality level, supply chain structure, lead times and costs) and developed a mathematical formula (ratio indicators) for each of the determinants.

His study showed that profit-oriented decision making does not always coincide with environmentally-benign recovery behaviour mainly due to the influence of the returns and quality uncertainties. Based on his computational study, Inderfurth (2005) also found out that during uncertainties, the simple cost superiority of remanufacturing over production will not guarantee a 100% recoverable fraction even if all the returns can be used to satisfy product demands. However, his study was also limited to certain assumptions such as a single product system, limited quality classification (returned products were only classified as either 'good' or 'bad' quality without any further quantification procedures), and the production and remanufacturing lead times were deterministic and equal.

In the meantime, the links between remanufacturing and other operational areas were also highlighted in the previous study. According to Ilgin and Gupta (2010), new methodologies have been developed by researchers to deal with various operational management issues in remanufacturing. These methodologies cover important operational areas linked to remanufacturing such as forecasting, production planning and scheduling, capacity planning and inventory management. The emergence of these new methodologies is attributed to the high

variability of remanufacturing operations that make the use of traditional solution techniques difficult.

2.6   Quality and Product Recovery Management

Quality plays a crucial role in product recovery management. In an uncertain environment, differences in the quality attributes of each returned product may affect decisions in the product recovery strategy (Nikolaidis, 2012). Most importantly, it significantly affects recovery costs depending upon the selected type of recovery options. Robotis, Boyaci and Verter (2012) studied the impact of quality condition uncertainty on investments in product reusability and used product collection. Their study focused on the inspection capabilities of firms dealing with both manufacturing and remanufacturing operations. The impact of reliable and unreliable inspection capabilities on the product recovery environment was examined. The findings showed that reliable inspection capabilities are important in managing the uncertainty in the quality of product returns. Nonetheless, necessary investment costs and the availability of reliable product information should also be carefully analysed before upgrading the inspection capabilities of a firm.

In another study, Zeballos, Gomes, Barbosa-Povoa and Novais (2012) studied the impact of an uncertain quality and quantity of product returns on a closed-loop supply chain planning and decision using a Mixed Integer Linear Programming (MILP) approach. In their study, returned products were graded into five levels (best, better, average, worse and worst). However, the acquisition prices were based on four categories which were raw materials, good, medium and bad graded products. The model was tested using the case study of a

Portuguese glass company. The results showed an increment in the potential risk of product disposal when the amount of product returns increased. However, an improvement in the quality of the returns improved the profitability and performance of the network. Generally, profitability was still on the card for as long as the disposal rate could be kept at a maximum level of 20% or less.

In the meantime, there were also other papers that directly focused on the quality issues of the returned products. Aras, Boyaci and Verter (2004) addressed this issue by assessing the cost effectiveness of a quality-based categorization of the returned products. Via a continuous-time Markov Chain Model of a make-to-stock production system with remanufacturing, the researchers developed two alternative strategies (based on which returned products were categorized into high quality and low quality returns) and incorporated the condition of the returned products into the disposal decisions. Their research also focused on the implementation of a pull-disposal remanufacturing strategy with customer demand and product returns modelled as independent Poisson processes. One of the assumptions in the model (which was also the limitation of this study) was the exclusion of capacity on the remanufacturing processes (no capacity limitation).

An assessment on the cost impact of quality categorization was done by comparing the optimal cost derived from the proposed model with that of a benchmark model (a hybrid remanufacturing – manufacturing system without categorization). Their findings showed that significant cost reductions (cost savings) could be achieved through the categorization of returned products and the implementation of proper remanufacturing and disposal strategies. The

findings also showed that quality-based categorization is the most cost effective when the rate of demand is low (referring to a slow moving product), the return rate is high compared to the demand rate, and the quality difference between the return types is high. However, this paper could be improved by adding the capacity limitation and more recovery options into the model (the paper considered remanufacturing as the only recovery option and assumed no capacity limitations). In practice, there should also be a certain threshold value in categorizing returned products between high and low quality items. The condition of returned products may vary among items and it could be very difficult to determine to what extent the returned products are good enough to be classified as high quality items.

In another study, Guide and van Wassenhove (2001) reviewed the quality management of a third party remanufacturer of mobile phones known as ReCellular Inc. The company inspects incoming returned mobile phones and sorts them into certain quality classes. Due to an extensive amount of sorting and grading activities as well as high labour costs, the company changed their purchasing policy by setting a price for a known level of quality. By doing this, the company also managed to reduce the amount of scrap and minimize the level of variability for inputs to the re-processing system. This scenario shows the importance of quality classification of returned products to product recovery management.

In a more recent study, Lee, Hsu and Tsai (2010) used a Grey Theory in the inverse process of Quality Function Deployment (QFD) to study product reuse

satisfaction based on customer data for reverse logistics. They used the House of Quality (HoQ) to convert the customer's needs into product design requirements. The study also quantified the product reuse value through the mathematical equation for customer satisfaction. The Grey Model developed in this study was also able to find the weights of customer satisfaction and provide a quantitative approach for decision making. However, this study was more towards understanding the customer's satisfaction on product reuse without specific attention to the product recovery activities.

In the meantime, Ferguson, Guide, Daniel, Eylem and Gilvan (2009) examined the impact of a nominal quality grading system on the performance of remanufacturing processes in both capacitated and incapacitated remanufacturing facilities. Three nominal quality grading systems were introduced, which were (1) scrap for materials, (2) harvest for parts, and (3) fit-for-remanufacture. For each quality grade, the firm decided how many returned products to remanufacture. The model proposed in this study used stochastic dynamic programming and it was a maximization problem. According to the findings, it was concluded that the grading system in the remanufacturing industry can increase the profit to an average of at least 4%. It was also concluded that having more quality grades can be beneficial. Nonetheless, a complex grading system involving more than 5 quality grades may generate scant benefit. Overall, this study provided good information on the impact of nominal quality grading on remanufacturing activities. However, the impact of quality grading on other product recovery options was not examined in this study, hence presenting a research opportunity.

Comparable to the above study is a research carried out by Denizel, Ferguson and Souza (2010) examining the influence of quality grading in the remanufacturing industry. They claimed that their research was the first one to consider the stochastic quality of end-of-lease cores (incoming supply of returned products) associated with the capacity and cost implications for production planning in a multi-period setting. The model used stochastic programming with multiple scenarios and time periods being considered. The main decision in the model was to find the optimal amount of cores from each quality grade that should be either remanufactured or salvaged. The model also determined the amount of cores graded at a certain period of time and under a certain scenario. The findings showed that quality grading was indeed affecting the profitability of the remanufacturing activities. Although it was very important to identify the quality class of each core, they pointed out that the grading cost played a huge factor in the profitability costs of remanufacturing activities.

2.7 Production Planning and Product Recovery Management

Production planning is closely related to product recovery management. The output of product recovery processes can not only be sold to the end customers but can also be headed back to the production line as an input. Ilgin and Gupta (2010) emphasized the important links between production planning and recovery management in their survey of product recovery literatures. They concluded that production planning was critical in determining when and how much returned products should be recovered using the respective recovery options. Necessary

and timely orders for materials and parts required to do the rework activities are also parts of the important tasks in the production planning.

Konstantaras and Skouri (2010) studied an inventory system for the production - remanufacturing processes. Their model considered the roles of remanufactured products (recoverable returned products) in helping the production line to cope with the demand (together with the newly manufactured products). In another study, Jayaraman (2006) presented an analytical approach towards production planning and control for closed-loop supply chains with product recovery management. He used a mathematical programming model called Remanufacturing Aggregate Production Planning (RAPP) to solve basic operational planning issues such as calculating expected material recovery rates, expected set of replacement parts and materials, expected costs of the replacement parts and materials, and the expected workloads at resource centres. The aim was to minimize the total cost per remanufactured unit given the incoming distribution of nominal quality. The model was tested using data from a case study of a cellular remanufacturer known as ReCellular, Inc. The outputs of the model were the optimal value for the number of units of cores with a nominal quality level that was disassembled and remanufactured in a period, the number of units of modules remanufactured, and the number of units of cores that remained in the inventory at the end of a time period.

One of the key distinct features of the Jayaraman (2006) paper was the inclusion of nominal quality levels of product returns. Other papers that considered the quality aspect in their study normally offered basic differentiation

such as good/bad quality levels or functional/non-functional returned products but Jayaraman (2006) classified the quality level into six categories (quality grading for mobile telephones). Apart from that, he also suggested further research to build a mathematical optimization model to understand the relationships between acquisition price and incoming quality levels, which was another good point since there were not many studies previously that focused on this aspect. However, his research also left several question marks (gaps) for further analysis such as how to build generic methods for determining the quality rating of used products, the implications between the RAPP model and product return channels, and the inclusion of further recovery options.

Shi, Zhang and Sha (2011) developed an optimal production planning for a multi-product closed loop system with uncertain demand and return, and the parallel system of producing both new products and remanufacturing returned products into as-new ones. The researchers formulated a nonlinear, single-period production planning model that could maximize the profit by jointly determining the optimal quantity of brand new and remanufactured products that needed to be produced, as well as deciding on the optimal acquisition prices of the used products, subject to the capacity constraints. The mathematical model was then solved using a Lagrangian relaxation approach. One of the distinguishing features of the model was that the return horizon was from the beginning of the planning period to the end of remanufacturing. The researchers also claimed that the study represented the first examination in the literature that integrated used product acquisition decisions into the production planning problem for the closed-loop system.

The model also considered returned products with relatively short life cycles, with recycling and remanufacturing being the two selected recovery options. It was then tested using a numerical example (20 problems with varying sizes) based on the data in some previous studies (Kim, Song, Kim and Jeong, 2006; Rouf and Zhang, 2011). The results showed that the solution approach can obtain a near optimal solution to all the problems in a very short time. The result also revealed that the fluctuation of the uncertain demand of a product affects the production and the used product acquisition policies of all other products. Overall, the results showed that the proposed solution using the Lagrangian relaxation approach was highly promising for solving the problems. Nevertheless, this hybrid production system was only tested with two recovery options of recycling and remanufacturing. The capability of the production policies to cope with more product recovery options have yet to be examined.

2.8   Capacity Planning and Product Recovery Management

The importance of capacity planning in product recovery management has been illustrated by many researchers (Ilgin and Gupta, 2010; Kim, Jeong and Jeong, 2005; Guide and Spencer, 1997). In remanufacturing, various researchers have developed capacity planning and rough-cut capacity planning techniques due to the characteristics of the environment (Ilgin and Gupta, 2010). Vlachos, Georgiadis and Iakovou (2007) proposed the development of methodological tools that would assist the decision-making process on the capacity planning of recovery activities for remanufacturing reverse chains. Their study was intended to examine the long-term behaviour of reverse supply chains with

remanufacturing and to further propose efficient remanufacturing and collection capacity expansion policies. The primary modelling and analysis tool used in their study was system dynamics (SD) methodology. The study considered the single product closed-loop supply chain (with relatively low coefficient variation in demand) that included operations of supply, production, distribution, use, collection and inspection, remanufacturing (the only recovery options considered in this study), and disposal.

Three capacity expansion strategies were under consideration: leading, trailing and matching capacity strategy. The firm needed to make decisions over acquiring new capacity for all the options represented by four major decision parameters; (1) remanufacturing and (2) collection capacity expansion decision; (3) remanufacturing and (4) collection capacity review period. Three types of parameters were presented in the analysis: physical, operational and dynamic parameters. The results showed that the leading capacity expansion strategy was the optimal choice for the reverse channel operations. The analysis also involved some important reverse supply chain factors such as the 'green image' effect, take-back obligation and a failure percentage (an average number of reuse cycles of a product).

Georgiadis and Athanasiou (2010) investigated the impact of two-product joint lifecycles on the capacity planning of remanufacturing networks. The focal scope of the study was the expansion and contraction of collection and remanufacturing capacities. The study was based on the previous research by Vlachos et al. (2007). The researchers extended the system's dynamic model in

that study for two product types under two alternative scenarios and different market preferences. In the first scenario, the market showed no preferences, while the second scenario stated that the demand over a product-type could only be satisfied by providing units of the specific type.

The main research aims (which were also the major contributions of the study) were (1) to investigate how different product lifecycles and different patterns of product returns affect the near-optimal expansion and contraction capacity planning policies under two alternative scenarios, and (2) to examine whether and how the entry time of the second product-type into the market affects the near optimal capacity planning policies of the reverse channel. According to the researchers, the model was used not only to evaluate alternative capacity planning policies but also in combination with an appropriate search procedure to identify near-optimal policies that maximize the system's profitability. The results showed that the proposed system performed best when the two product lifecycles formed a certain demand pattern in a particular scenario. Specifically, the system performed best in the first scenario, when the demand was in a trapezoid pattern. In the second scenario, the system was optimal when the demand was in a triangular pattern.

Guide and Spencer (1997) addressed the capacity planning in a remanufacturing environment in which the settings of manufacturing planning and control (MPC) were different from the traditional manufacturing system. They evaluated the performance of rough-cut capacity planning techniques in a job-shop type remanufacturing facility using a simulation model with which five

techniques were evaluated: Bill of Resources (BoR), Capacity Planning using Overall Factors (CPOF), Modified Bill of Resources (MBoR), Bill of Resources with Variance (BoRV) and Modified Bill of Resources with Variance (MBoRV). The simulation model was based on actual data from the Naval Aviation Depot (a military depot) that remanufactures a variety of assets such as aircraft and engine components.

The production planning and control system currently used in the depot is an in-house developed modified MRP system (traditional RCCP techniques). The experimental design was a single factor ANOVA (five levels – representing five types of RCCP) which was later adjusted to the least squares method involving 10 observations for each level. The simulation involved 29 work centres (all five RCCP techniques were implemented) focusing on actual shop utilization rates, and five work centres were then selected, representing a range of values from low to high utilization of resources. The results showed that the MBoRV technique was a good choice compared to the other four RCCP techniques in a remanufacturing environment. The results also showed that the capacity planning technique, that included the variability factors (MBoRV and BoRV), performed better than the standard RCCP techniques (there was high variability in a remanufacturing environment).

2.9   Multiple Product Recovery Options

It was highlighted earlier in this chapter that there are various ways of recovering returned products (Thierry et al., 1995; Teunter, 2006; Sasikumar et al., 2010). There is also another option of simply disposing of the products into

landfills. In Thierry et al. (1995), the study described five categories of recovery options. The practicality of implementing more than one recovery option has been subsequently conducted by Krikke et al. (1998). In a recent study, Li and Tee (2012) examined the usage of multiple recovery options for e-waste using a mixed integer multi-objective linear programming reverse logistics model. The model considered three recovery options, which were (1) the producers' recovery option, (2) the group recovery option, and (3) the third party recovery option. These options were integrated with three recovery decisions (recycling, treatment and disposal).

At the end of the study, Li and Tee (2012) also highlighted that the proposed model was able to generate generalizations of when it would be appropriate to use certain options or certain combination of options. What was also important was their justification of using multiple recovery options. They stated that if the capacity of one recovery option was not enough to meet the treatment requirements or the demand of the producers for the recovered material, then it should be made possible to use other options. Since it was difficult to explore the different possibilities of combining options in reality, a model became necessary.

2.10 Product Return Channels

Product return channels can be defined as avenues or facilities for customers to return used or unwanted products back to the producers, collectors, remanufacturers or recyclers. It is part of the broader network design that may encompass both forward and reverse logistics decisions. Producers or remanufacturers are responsible for designing effective networks (collection

channels) that may also include other non-logistical factors such as monetary incentives or marketing campaigns. The effectiveness of the return channels is normally measured by collection rates and costs. It is one of the important decisions in reverse logistics.

A logistics network design that encompasses decisions such as determining the numbers, locations, quantity of the flow and capacities of the facilities is also one of the most important strategic decisions in the reverse supply chain management (Pishvaee, Kianfar and Karimi, 2010). This network design becomes even more important with the legal implementation of the extended producer responsibility (Alumur et al., 2012). The extended producer responsibility states that manufacturers are responsible for free taking back and recovery of their end-of-life products and must bear all or a significant part of the collection and treatment costs (Mansour and Zarei, 2008). At the same time, the amount of collected used products should at least satisfy the required minimum collection rate. It is also noted that the collection of used products potentially accounts for a significant part of the total costs of any closed-loop supply chain (Dekker, Fleischmann, Inderfurth and van Wassenhove, 2004).

2.11 Collection effectiveness of product return channels

Collection effectiveness depends on the consumers' willingness to return used products at the time of disposal (Wojanowski, Verter and Boyaci, 2007). It has been identified that two important factors which influence the customers' willingness to return their products are accessibility and incentives. Min and Ko (2008) pointed out that customers' convenience when returning their products

should be maximized as it will eventually encourage more returns in the future. There are three initial collection methods that are normally used by manufacturers, namely mail delivery return, pick-up collection and customer drop off. Installing a drop-off facility near residential or commercial areas encourages customers to return their products (easy access). This collection method requires the manufacturer to bear the cost of building or renting as well as operating the drop-off facilities in certain selected areas. Nonetheless, the important decision is to decide how many drop-off facilities are needed and their locations.

According to Wagner (2012), convenience factors play important roles in the collection effort of solid waste. He identified five key convenience factors to increase collection rate: (1) knowledge requirement, (2) proximity to collection site, (3) opportunity to drop off materials, (4) the draw of the collection site, and (5) ease of the process. The researcher also developed a performance matrix based on the abovementioned five convenience factors to help solid waste managers make decisions. The study highlighted that the convenience factors also refer to the availability and ease of the collection process for the customers. In other words, minimizing the customer's time, effort and travelling cost could positively influence product return rates.

Hence, in practice, the facilities need to be located within close proximity to the customers. Some manufacturers use intermediaries such as retailers acting as collection centres to collect returned products from the customers. Previous studies usually group customers based on geographical zones and each zone is served by one particular drop-off facility (Wojanowski et al., 2007; Aras and

Aksen, 2008; Aras, Aksen and Tanugur, 2008). In the meantime, incentives play a significant role in influencing customers' willingness to return their products. According to Aras et al. (2008), some manufacturers have been able to influence the quantity of returns by using buy-back campaigns and offering financial incentives to product holders. Apart from an increment in terms of product return quantities, the amount of incentives offered by the manufacturers influences the quality level of the returned products (Aras and Aksen, 2008). Similar to Wojanowski et al. (2007), these two studies examined how the amount of incentives offered to the customers affects manufacturers' profits and collection strategies.

2.12 The Collection Channels and Decision making

Karakayali, Hulya and Akcali (2007) examined the decentralized collection and processing of end-of-life (EOL) products with the aim of developing models to determine the optimal acquisition and selling price of the EOL products as well as their remanufactured parts. They also addressed problems of how to identify when and why the OEM would prefer a remanufacturer/collector-driven channel (outsource the processing or collection of returned products). The paper also discussed how the decentralized channel could be coordinated to increase the collection rate of the returned products (that could be achieved in the centralized channel). In their model, three channel settings were considered: the centralized channel, the remanufacturer-driven channel (remanufacturer sets the wholesale price and leaves the collectors to maximize their own profits based on this price) and the collector driven channel (collector sets the wholesale price). An analysis

of the decentralized channels (remanufacturer and collector-driven channels) was conducted using the Stackelberg game framework (leader – follower) and mathematical optimization techniques (Continuous Knapsack problem).

The model considered a single type of used product in two different scenarios (homogeneous and heterogeneous used products) that could be categorized into different quality groups according to the age and condition. The findings showed that the collector-driven channel could increase the collection rates and was capable of attaining the same collection rate as the centralized channel due to the pricing behaviour (the most effective strategy). On the other hand, the remanufacturer-driven channel was unable to obtain the same collection rate as the centralized channel (except for a certain condition). This paper offered a comprehensive analysis involving various settings, experiments and different conditions. However, this study only considered a single period model and had limited coverage on the functional aspect of the recovery options as the focus was on the collection methods of the returned products and the role of the pricing behaviour.

In the meantime, an effective product return network is also very critical to product recovery planning and cost minimization. Many researchers have investigated the effectiveness of a product return network. Nonetheless, Qin and Ji (2010) stated that these investigations had largely been in a deterministic environment. They then proposed a logistics network configuration with product recovery in a fuzzy environment. Based on different decision-making criteria, the fuzzy programming approach was employed to formulate three programming

models: the expected value model, the chance constrained programming and the dependent-chance programming. Their work offered an approach for designing a practical product recovery network in an uncertain environment (using fuzzy programming).

In a different study, Savaskan and van Wassenhove (2006) discussed about how to understand when and why a manufacturer would choose to collect returned products directly from consumers or indirectly via the retailers. The decision process involved four types of collection channels/models: (1) decentralized direct collection, (2) decentralized indirect collection, (3) centralized direct collection, and (4) centralized indirect collection. The models involved a manufacturer, two retailers and the central planner. In the decentralized direct model, the manufacturer set the wholesale price of the product and the collection effort while the retailers were free to decide the selling price (while considering competition from the other retailers). The following Figure 2.4 shows the return channel structures as Savaskan and van Wassenhove (2006) differentiated each channel into five categories.

(1) *Model a: No remanufacturing* (2) *Model b: Decentralized direct collection*
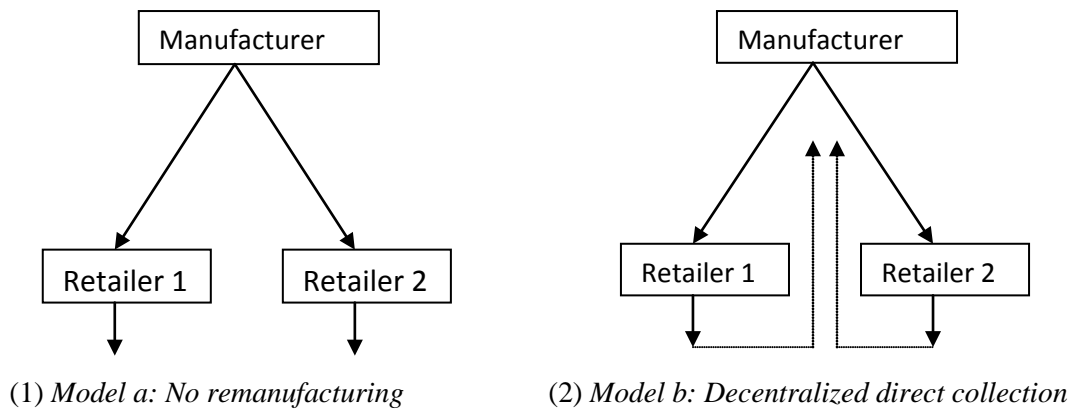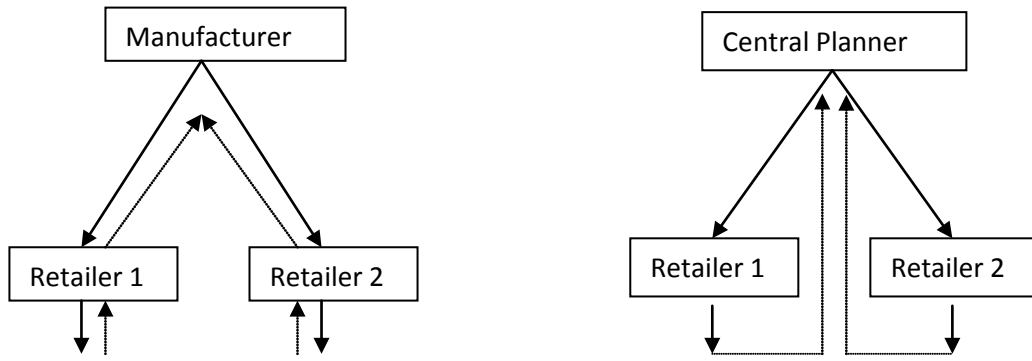
(3) *Model c: Decentralized indirect collection*   (4) *Model d: Centralized direct collection*
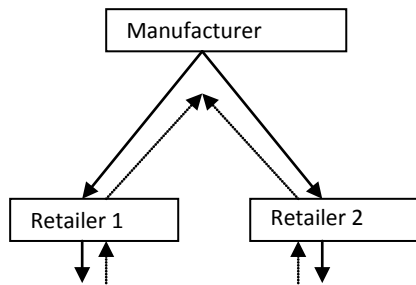
(5) *Model e: Centralized indirect collection*

Figure 2.4: Product Return Channel Structures

Source: Savaskan and van Wassenhove (2006)

In a decentralized indirect model, the retailers are responsible for the collection of returned products (in return of a fixed per unit buy-back payment). The applications of decentralized models were illustrated by Wei, Zhao and Sun (2012). They highlighted the roles of retailers and third-party collectors in helping the manufacturer to gather returned products. In the centralized models, the difference lies upon the role of the central planner, who makes the decisions over pricing and the collection effort (retailers have no power to decide the selling price or the collection effort). However, both the centralized and decentralized models are similar in terms of who collects the returned products

(direct collection = manufacturer; indirect collection = retailers). A comparison between the models was also conducted based upon the total supply chain profit, pricing decisions, collection effort and the allocation of total profits between the manufacturer and the retailers. In the decentralized models, the findings showed that retailers preferred direct collection by the manufacturer (to avoid making an investment in the collection of returned products) while the indirect collection benefitted the manufacturer in terms of saving the investment costs in the collection effort and increasing the sales volume (unless the retailers' products were considered to be direct substitutes).

As for the centralized models, the prices became an important determinant; if the retailers had less impact on the prices, then the manufacturer benefitted from a direct collection system, and vice versa. However, this study could be further improved by incorporating some additional variables such as the transportation costs (collection of returned products), disposal costs, collection costs per unit of returned products, capacity constraints, and examining the impact (and the interactions) of the aforementioned return channels to the selection of product recovery options.

In a more recent study, Shulman, Coughlan and Savaskan (2010) identified three reverse channels, which were (1) the vertically integrated system, (2) the retailer assuming returns responsibility, and (3) the manufacturer assuming returns responsibility. The first is a centralized return channel while the remaining two represent decentralized return structures. The study addressed the relationships between manufacturers and retailers, and how decisions by each

party affect each other. The model also studied the interaction between the reverse channel structure and the contract structure, as well as its impact on the return penalty, retail prices, sales quantity and exchanges.

The results favoured the centralized reverse structure in which the manufacturer had greater control over the flow of returned products from customers. The main reasons for this were the greater profit that could be generated and the neutralization of external negative effects when the retailer handled returns. Overall, the study offered an in-depth analysis on the relationships and interactions between manufacturers and retailers in the reverse channel structure for product returns. What was more intriguing was the analysis of how each decision (wholesale price, penalty charges, fixed fees, retail prices, refund and salvaged values) by each party affected each other's profit making. However, the scope of their study was limited to examining the reverse channel structure for only 'non-defective' returned products (unwanted by the customers as they did not match their preferences but still in a very good condition).

2.13 Latest studies on product return channels

Most of the studies on product return channels continue to focus on the network design. In the broadest sense, this involves the location and routing of problems. The latest studies done by Alumur et al. (2012), Das and Chowdhury (2012), Nikbakhsh, Eskandarpour and Zegordi (2013), Sheriff, Gunasekaran and Nachiappan (2012), Rogers, Melamed and Lembke (2012), Lieckens and Vandaele (2012), Kannan, Diabat, Alrefai, Govindan and Yong (2012), and John and Sridharan

(2013) illustrate discussions on product return channels from the perspective of a network design problem.

In the meantime, the latest study by Wei and Zhao (2013) addressed the problem of collecting returned products using game theory and fuzzy theory. Their research was similar to this study in the sense that the main decision was about selecting the collection modes and their consequences. Wei and Zhao (2013) defined the collection modes into three categories: (1) manufacturer's direct collection, (2) retailer's collection, and (3) third party collection. Under modes (2) and (3), the collection rates and retail prices (buy-back prices) were determined by retailers and third party collectors. It resembled a decentralized collection channel. However, the model did not specify the exact method for collecting the used products from customers.

Touati-Moungla and Jost (2012) reviewed vehicle routing and scheduling literature in environmentally-conscious transportation problems. They highlighted that for pick-up delivery routing problems, most studies used insertion-based algorithms or genetic algorithms. The research also mentioned the growing concerns about environmental issues such as public health, global warming and economic safety.

Wolfer, Sander and Gogoll (2012) stated that pressing global challenges such as climate change and resources depletion demonstrate the need for structural change in our economic approach towards sustainable development. It appears that most of the location models rely on finite solutions and mixed-integer linear programming, which allow for discrete mathematical optimization.

Most location-allocation problems also rely on mixed-integer and linear programming models in which the number, capacities and locations of warehouses are determined.

Jayant, Gupta and Garg (2012) stated that the number of customers supporting environmental protection by delivering their used products to collection points was increasing. In order to minimize the total reverse logistics cost and high utilization rates of the collection points, the selection of appropriate locations for the collection points was a critical issue in reverse logistics. In the meantime, a study on the collection and recycling policies for electronic scraps among countries around the world was conducted by Oliveira, Bernardes and Gerbase (2012). In their study, they compared the policies and collection frameworks of selected European, US, Asian (including Malaysia) and South American countries. Some countries, such as Switzerland and Germany, have better comprehensive collection policies and regulations than other countries. African and South American countries are guilty of lacking a comprehensive e-waste management system. Nevertheless, all the countries share something in common. It can be concluded that albeit there are various strategies and regulations in place, the collection rates are still disappointing and a high percentage of e-waste still ends up in landfills. Hence, the need for an effective drive and strategy to improve the collection rate is still undoubtedly crucial.

2.14 Identification of Research Gaps

Table 2.3 and Table 2.4 summarize the key references of this study for the recovery options and collection channels, respectively. Based on the survey of the literature and the key references, the following research gaps have been identified for the two research focuses of this thesis: (1) product recovery options, and (2) product return channels.

On the product recovery options, a study on multiple recovery options and comprehensive quality classifications remains inadequate. The optimization models allowing flexibility in the recovery assignment are still needed as well. The aims of the product recovery models are varied. Generally, they can be classified as either cost minimization or return maximization. Little work has been focused on return and profit maximization. The situation may be due to previous general views that product return and recovery are more about meeting legal requirements and cost minimization (extended producer responsibility) rather than treating them as a profit-making opportunity. Hence, the proposed model in this study is attempting to fill these gaps by developing a profit maximization model that addresses the abovementioned shortcomings.

On product return channels, the most previous optimization models have treated product returns as a location problem. Hence, it is more towards managing the transportation of returns or finding the best routing strategy rather than looking for an optimal assignment. So far, only a handful of studies have addressed the collection problem comprehensively by incorporating more than one method (pick-up or drop-off). The literature on the mail return method is also very limited, if there

is any at all. Thus, a model for the product return channel selection is proposed in this study in an attempt to fill these gaps by considering multiple collection methods and taking a different viewpoint (assignment of return methods to customer zones).

Table 2.3: Summary of Key References for Product Recovery Options (PRO)

Key Research	Research type	Method used	Recovery options	Recovery Assignment	Key findings	Research contribution
Thierry et al., 1995	Case study	Secondary data and observation	Repair, refurbish, remanufacture, cannibalize and recycling	Fixed assignment	Relates recovery options to manufacturers' operational issues and strategic decisions	Introducing five recovery options and examining their potential practicality using a case study
Krikke et al., 1998	Modelling	Stochastic dynamic programming	Repair, refurbish, remanufacture, cannibalize and recycling	Fixed assignment	A classification scheme and a set of conditional assignment rules for product recovery options	The first research empirically examined the applicability of the 5 types of recovery options proposed by Thierry et al., (1995)
Teunter, 2001	Modelling	Stochastic dynamic programming	Remanufacturing, recycling, disposal & disassembly	Fixed assignment	Multiple and partial disassembly strategy	Focus was on the disassembly strategy
Krikke 2011	Modelling	MIP	Repair, refurbish, remanufacture, cannibalize and recycling	Restricted flexibility	Flexibility assignment depends on 4-types of return quality classes	Recovery decisions for carbon footprints-related industry
Wadhwa, Madaan and Chan (2009)	Modelling	Fuzzy theory	Repair, refurbish, remanufacture, cannibalize and recycling	Restricted flexibility	Flexibility decisions depend on ratings and expert opinions	Explores product recovery decisions using decision support system that may lead to future application of artificial intelligent (AI)
Li and Tee 2012	Modelling	MIP	Recycling, treatment and disposal	Producer, 3rd party and group recovery assignment	Each type of recovery option or a combination of them works for certain scenarios	The research explores recovery decisions for e-waste with special attention to environmental and human health

Table 2.4: Summary of Key References for Product Return Channels (PRC)

Key Research	Research type	Problem domain	Method used	Collection method	Key findings	Research contribution
Wojanowski et al., 2007	Modeling	Location & Incentives problem	Simulation	Drop-off	Identified effective incentives strategy for collection of return products	Addresses collection method from the point of incentives and deposit-refund strategy
Aras and Aksen, 2008	Modeling	Facility-location problem	MINLP & Tabu search	Drop-off	Comparison of incentives strategy under uniform approach against quality dependent approach in a drop-off collection scenario	Among the earliest models addressing drop-off collection method and its linkages to the incentives strategy
Aras et al, 2008	Modeling	Facility-location problem	MINLP & Tabu search	Pick-up	Comparison of incentives strategy under uniform approach against quality dependent approach in a pick-up collection scenario	Among the earliest models addressing pick-up collection method and its linkages to the incentives strategy
Wei and Zhao (2013)	Modeling	Decisions problem	Game theory & Fuzzy theory	Manufacturer, 3rd party and retailers channels	Optimal decisions strategy (expected value model) for each collectors under different environment	Develops decisions model based on fuzzy environment and game theory

2.15 Summary

Product recovery management encompasses various activities within the reverse logistics network. The two important activities are the re-processing activities (product recovery options) and the collection of returned products (product return channels). Numerous studies have been conducted to highlight the importance of the abovementioned activities. In this chapter, a survey of the literature has been carried out to identify gaps and potential research avenues in both product recovery options and return channels.

Studies on product recovery options have been extensively carried out, with most of them focusing on either the remanufacturing or recycling processes, while the recycling of automobiles, electronics and paper are the most common examples of the abovementioned strategy (Srivastava, 2007). It is difficult to integrate all the product recovery options (remanufacturing, recycling, refurbishment, reuse and cannibalization) in a single optimization model. Only Krikke et al. (1998) included almost all of the recovery options in a single study. However, none of these studies offered flexibility in the assignment of product recovery options. This flexibility refers to the relationships between recovery options and quality classification of returned products. For instance, a repairable product can either be remanufactured (upgraded) or recycled (downgraded) and it does not necessarily have to go for the refurbishment option. Hence, the potential benefit of offering flexibility in product recovery assignment is acknowledged and should be further examined.

Another important limitation in previous researches on product recovery options was in terms of the research direction and focus. Previously, most studies treated product recovery as a cost minimization problem. Back then, the main motivation for companies engaged in product recovery operations was due to the legal requirements imposed by government or authorities. For companies, it had more to do with obligations and legal compliance than profit endeavours. Hence, the aim was more on managing cost and improving efficiency. With the latest developments in recovery technology, the consumers' awareness of environmental issues and the growing demand for reused products, the focus is no longer just about cost minimization. Product recovery is now perceived as another significant profit-making opportunity. Thus, it is time that a study is carried out to look in this direction and to embark further.

Most of the researches into product return channels addressed the collection of returned products from a wider perspective; whether the collection should be (1) centralized or decentralized, and whether it should be handled (2) directly or indirectly (Savaskan and van Wassenhove, 2006; Karakayali et al., 2007). Investigations into the activities between consumers and companies, in which the collection of unwanted products occurs, remain wanting. This refers to how products are collected from consumers. The three important collection methods are pick-up, drop-off and mail return. A survey of the literature has shown that there has been a lack of investigation into problems related to the abovementioned collection methods. In particular, research gaps related to product collection methods can be summarized as follows:

a. *Multi-collection methods* – the availability of the three collection methods to companies may increase collection rates. Nonetheless, the relevant investigations remain limited. Prior researches were with regard to problems related to the single collection method, particularly the drop-off or pick-up method. The utilization of multiple methods simultaneously to solve collection problems in product return channels opens up significant research avenues.

b. *Mail return* – Mail return has largely been ignored in previous literature. For small and some medium-sized products, mail return is equally as important as the other two collection methods. It offers a feasible option to companies, particularly in locations where the geographical limitation weakens the other two collection methods. As such, there is a need for a study on mail return as another viable collection option.

c. *Problem focus* – mostly problems related to product return channels have been treated as location problems. It was more concerning transportation management and networking issues. Related problems such as vehicle routing and locations of collection centres were common. The focus on the assignment of collection methods in product return problems remains limited.

This thesis aims to fill in the above identified gaps in previous studies on product recovery options and product return channels. For the product recovery option problem, a new linear programming model will be developed allowing full flexibility in the assignment of returned products to possible recovery options, considering the costs for recovering the products with different qualities and the revenues from the recovered products. The objective of the model is to maximise the total profit. The model will be used to analyse the benefits of flexibility in different demand situations. For the product return channel selection problem, a comprehensive model is built combining the decisions on channel selection, collection centre locations and incentive determination, with the objective of maximising the overall profit of the system. The model is a nonlinear integer programming model, which is very difficult to solve to optimality. A Lagrangian relaxation method is therefore used to get a good heuristic solution in a relatively short time. The next three chapters will present the details of the thesis work with Chapter Three being on product recovery assignment, and Chapters Four and Five on product return channels.

CHAPTER 3
RESEARCH METHODOLOGY

3.1 Introduction

This chapter outlines the methodology adopted for this thesis. As mentioned in chapter one, this study investigates two problems related to product recovery management; product recovery options and product return channels. Although they differ in terms of application and focus, they are on common ground by the fact that both are involved in assignment type of decisions. The challenge posed for product recovery options is to achieve optimal assignment of available recovery methods to returned products. As for product return channels, discerning decisions are required in the selection of product return methods for specific customer zones. This chapter seeks to justify the methods selected for this study. The discussions are limited to methods that were frequently used for relevant types of problems.

3.2 Product Recovery Options

A linear programming model was employed to pave the way for the achievement of optimal assignment of product recovery options and also to determine the effects of flexibility on product recovery allocation. Linear programming (LP) is a widely used mathematical technique designed to assist managers in the areas of planning and decision- making relative to resource allocation (Render and Stair, 1992). Details on the technique can be found in any standard Operations Research textbook. LP models have been proven to be

effective in dealing with product recovery problems. According to Krikke et al. (1998), LP models are appropriate for devising recovery and disposal plans because they are relatively easy to model and solve. Furthermore, these models offer possibilities for sensitivity analysis.

Previous studies on recovery options often do not distinguish the quality of returned products in detail or allow products in each quality class to be recovered using a fixed option or very restricted options. In this research, returned products are separated into five different quality classes which (according to relevant literature) is currently the maximum number ever considered. We also allowed for full flexibility in the assignment of any quality class to any recovery option although the costs for recovering products of different qualities will vary.

The structure of the assignment decisions will be similar to that of a transportation network in which the quality classes are supply nodes, the recovery options are demand nodes, and there is a link between each supply node and each demand node. Clearly, an LP model is suitable for such a problem structure and the model can be solved efficiently. Additionally, the flexibility of recovery options can be altered by the removal of some of the links in the network. The LP model can be solved with different levels of flexibility to examine the effects of flexibility on the performance of the solutions.

3.3   Product Return Channels

For product return channels, the problem understudy involves assignment decisions, the assignment of a collection method for returned products from a

particular customer zone, and the assignment of each zone to a specific collection centre. The problem also involves decisions regarding facility (collection centre) locations. These decisions are discrete and require integer (binary) variables to model.

As the dilemma entails assignment and location decisions, the model will include constraints that are typical for problems concerning assignment, location and allocation. To reflect both economical and legislative factors, we set the objective as maximising profit while taking into consideration the return rate requirement.

The profit from the product return network can be viewed as revenue from the value of returned products minus the cost of running the network. One particular element of the cost is the incentive paid to customers and this is a variable to be determined as part of the problem. The incentive influences the willingness of customers to return their used products and this influence affects the proportion or amount of products returned. If the returned amount is a linear function of the incentive within a certain range, then the cost will be a quadratic function of the variables. Thus, a mixed integer nonlinear programming (MINLP) model is applicable in this situation.

According to Bussieck and Pruessner (2003), MINLP refers to mathematical programming with continuous and discrete variables and non-linearities in the objective function and constraints. The use of MINLP is a natural approach towards formulating problems in situations where it is necessary to simultaneously optimize the system structure (discrete) and parameters (continuous). A MINLP model can be best illustrated by the following general

form (Bussieck and Pruessner, 2003; Tawarmalani and Sahinidis, 2002; Leyffer, 2001):

Minimize f(x, y)

Subject to: $g(x, y) \leq 0$

$x \in X$

$y \in Y$

The function f(x, y) is a nonlinear objective function and g(x, y) is a vector of nonlinear or linear constraint functions. The variables x and y are the decision variables where y is required to be integer (1) valued. X and Y are bounding-box-type restrictions on the variables. MINLP has been applied in a variety of research areas which include logistics, distribution, energy generation, engineering design and chemical sciences. MINLP can be classified as a NP-hard problem and this suggests that a solution will require the utilization of efficient heuristic methods (Melo, Nickel and Saldanha-Da-Gama, 2009).

3.4 Heuristic Solution Methods

There are a variety of heuristic solution methods available for consideration and the selection of the most suitable one is dependent on the structure and characteristics of the problem. Previous studies have applied heuristic methods such as Tabu Search, Lagrangian relaxation, Genetic Algorithm, Simulated Annealing, and Ant Colony in various assignments and location problems. However, heuristic methods vary in terms of effectiveness according to specific kinds of problems. The widely used Tabu Search and Lagrangian relaxation methods have proven to be

among the most efficient when it comes to solving location and assignment problems. The Lagrangian relaxation method is effective in solving non-linear type of integer or mixed integer programming assignment problems (Fisher, 2004; Li and Sun, 2006) as well as large-scale integer problems (Fisher, 1985). These two features (large-scale, mixed integer non-linear model) are significant characteristics of the problem in this study.

A quotation from a book specializing in non-linear integer programming written by Li and Sun (2006) on the effectiveness of the Lagrangian relaxation method is as follows:

"*Without doubt, the Lagrangian dual formulation is one of the most widely used dual formulations in integer optimization, largely due to the associated rich duality theory and its solution elegance in dealing with separable integer optimization problems. The concept of the duality plays an important role in continuous and discrete optimization. Crucially, the duality theory is one of the fundamental tools for the development of efficient algorithms for general non-linear integer programming problems.*"

The following subsections offer brief discussions on the Lagrangian relaxation method and several popular heuristic methods.

3.4.1 Lagrangian Relaxation Method

In brief, the Lagrangian method was first developed by Held and Karp (1970) when they used a Lagrangian problem based on a minimum spanning tree

to develop a successful algorithm for the travelling salesman problem. The name "Lagrangian relaxation" was introduced by Geoffrion (1974). This method is based on the idea that many hard problems can be easily solved if not complicated by a small set of side constraints (Fisher, 2004). Hence, the idea is to reduce the influence of these constraints and ease the way for solutions.

The basic concept of the Lagrangian relaxation method lies in the identification and 'dismantling' of some complicating constraints so that the complexity of the problem is reduced and less computational time is required for a solution. In other words, the method simplifies the problem by 'relaxing' some of the constraints to facilitate a faster solution. According to Darby-Dowman and Lewis (1988), an augmented objective function is formulated which incorporates penalties for violations of the removed constraints. The penalties are controlled by a set of Lagrange multipliers. Different sets of multipliers are used and updated in order to achieve a good feasible solution. The procedure to update the multipliers is normally a version of the subgradient method.

As the solution to the 'relaxed' problem is frequently not applicable for the original problem because it violates some original constraints, an algorithm is needed to generate a feasible solution. Fisher (1985) devised a generic Lagrangian relaxation algorithm comprising three major steps to generate a feasible solution. These steps are (1) the construction of branch and bound tree, (2) the adjustment of multipliers, and finally (3) the solving of the Lagrangian problem. The iteration procedures between step (2) and (3) are vital in efforts to procure a Lagrangian solution. Although a Lagrangian solution is rarely

applicable for the original problem, with some minor modifications the method can still come up with an acceptable solution. A systematic procedure of doing this in step (3) is known as the 'Lagrangian heuristic' (Fisher, 1985).

This method has been widely used in many combinatorial optimization problems encompassing various applications such as production scheduling, assembly system design, hierarchical production planning, vehicle routing, manpower planning, capital budgeting and database condensation (Darby-Dowman and Lewis, 1988). As highlighted earlier, a forte (and key advantage) of this method is its ability to solve large-scale mathematical programming applications that characterize practical industrial problems (Guignard, 2008; Fisher, 1985). This method has also proven to be reliable in solving various mathematical programming problems such as linear, integer, mixed integer and nonlinear programming (Erlenkotter, 1978; Held and Karp, 1970; Fisher, 1985; Beasley, 1993; Mazzola and Neebe, 1999; Fisher, 2004; Tang, Xuan and Liu, 2005; Zhu, Chu and Sun, 2010). Lagrangian relaxation is also recognized as an effective method for solving large scale integer programming models (Fisher, 2004; Fisher, 1985; Shaw, Liu and Kopman, 2008; Tang and Jiang, 2009).

According to Fisher (2004), overwhelming evidence points to the fact that the bounds provided by Lagrangian relaxation are extremely sharp. The method has been successfully applied in the search for solutions to a range of problems which include those related to the travelling salesman, scheduling, general integer programming, location, and generalized assignments. Melo et al., (2009) stated that LR is among

the most popular techniques for solving problems with a high number of discrete variables as well as problems that are complex and large-sized.

3.4.2 Other heuristic methods

There are numerous heuristic solution methods that have been successfully used to solve various combinatorial optimization problems. Specifically, methods such as the Tabu Search (TS), Genetic Algorithm (GA), and Simulated Annealing (SA) have been successfully applied to solve problems involving assignment decisions regardless of whether it is a quadratic, classical or generalized assignment problem. Each method has its own strength that can be utilized to deal with specific problems.

a. Tabu Search (TS)

This method was originally proposed by Glover (1986) and has been successfully applied in a variety of problems such as facility location, vehicle routing, job-shop scheduling, travelling salesman, and quadratic assignment. Briefly, Tabu Search is designed to pursue the search by allowing non-improving moves whenever a local optimum is encountered. TS is a metaheuristic algorithm that guides the local search to prevent it from being trapped in premature local optima or in cycling (Glover and Laguna, 1997). This is achieved by prohibiting the moves that cause it to return to previously visited solutions throughout a certain number of iterations. This method is valued for its simplicity and flexibility, the characteristics that enable this algorithm to provide solutions of a quality high enough to compete with other well-known heuristic methods (Diaz and Fernandez, 2001). However, a major drawback of this method is its inability to

conduct a more comprehensive exploration of its search space. Thus, unless systematic and effective diversified schemes are included in the equation, the search is deemed lacking in breadth (Crainic, Gendreau and Potvin, 2005). Compared to the Lagrangian relaxation method, TS has not been as widely used to solve non-linear integer type of assignment problems.

b. *Genetic Algorithm (GA)*

Genetic Algorithms (GA) are search methods based on the principles of natural selection and genetics. According to Sastry, Goldberg and Kendall (2005), the methods encode the decision variables of a search problem into finite-length strings of alphabets of a specific cardinality. The strings (candidate solutions to the search problem) are referred to as chromosomes, the alphabets as genes, and the values of genes are known as alleles. To summarise, each potential solution is encoded in the form of a string and a population of strings is created which is further processed by three operators: Reproduction, Crossover, and Mutation (Sahu and Tapadar, 2006). Genetic Algorithms provide intelligent heuristics for solving many types of combinatorial problems (Wilson, 1997). However, according to Safaric and Rojko (2006), the methods also have the following limitations:

- Certain optimisation problems (they are called variant problems) cannot be solved by means of genetic algorithms. This is due to poorly known fitness functions which generate bad chromosome blocks in spite of the fact that only good chromosome blocks cross-over.

- There is no absolute assurance that a genetic algorithm will find a global optimum. This is frequently a problem when the population is made up of many subjects.

- Like other artificial intelligence techniques, the genetic algorithm cannot guarantee constant optimisation response times. A further drawback is the fact that the difference between the shortest and longest optimisation response time is much larger with this method than that obtained through conventional gradient methods. This unfortunate genetic algorithm flaw limits the utilization of genetic algorithms in real time applications.

c. Simulated Annealing

Simulated Annealing is another general heuristic method which was originally developed by Kirkpatrick, Gelatt Jr., and Vecchi (1983). This is a stochastic optimization procedure which is widely applicable and has been deemed effective in solving several problems related to computer-aided circuit designs (Kirkpatrick et al., 1983). The simulated annealing procedure replicates the slow-cooling of molten metal process with the objective of arriving at the minimum function value in a minimization problem. It is a point-by-point method. According to Fleischer (1995), along with a few other types of generalized optimization schemes, SA is considered a metaheuristic. Its generality and applicability stems from its foundation in thermodynamics and statistical mechanics. Thus, it can be used to solve many combinatorial optimization problems and some continuous optimization problems (Bonomi and Lutton, 1984). Simulated Annealing has also been successfully utilised to overcome many assignment problems such as the

generalized assignment problem (Osman, 1993), quadratic assignment problem (Wilhem and Ward, 1987), and channel assignment problem (Duque-Anton et al., 1993). According to Elmohamed, Coddington and Fox (1998), some outstanding advantages attributed to SA are: (1) its ability to deal with arbitrary systems and cost functions, (2) it statistically guarantees finding an optimal solution, (3) it is relatively easy to code, even for complex problems, and (4) it generally comes up with a "good" solution. This makes the method an attractive option for optimization problems where heuristic (specialized or problem specific) methods are not available.

However, SA does have its limitations as highlighted by Elmohamed et al., (1998). These limitations are listed as follows:

- For problems where the energy landscape is smooth, or where local minima are few, SA is overkill. Simpler and faster methods (e.g., gradient descent) will work better. Generally, the energy landscape is not associated to any specific problem.
- Although SA is often comparable to heuristics, heuristic methods which are problem-specific or take advantage of extra information about the system will often perform better than general methods.
- The method cannot tell whether it has arrived at an optimal solution. Some other complimentary method (e.g. branch and bound) is required to accomplish this.

3.4.3 Selection of the solution method

Apart from the methods discussed in section 3.4.2, there are also other metaheuristics such as *particle swarm optimisation* and *differential evolution*.

Although metaheuristic methods are flexible and do not rely on specific problem structures, their performance often involves searching a large number of points in the solution space. The selection of product return channels involves complex objective functions and constraints. The generation and evaluation of feasible solutions is far from a straightforward process. As such, it would not be possible to search a large number of solutions within a reasonable computation time. Also, bearing in mind that obtaining optimal solutions is not feasible, evaluating the quality of solutions generated by a metaheuristic method would be a painstaking task.

The Lagrangian relaxation method, on the other hand, takes full advantage of the model structure and guides the search using the bounds found in the process. Due to this, only a few iterations are required by this method to produce a reasonably good solution. Most importantly, the method itself provides lower and upper bounds of the optimal objective value. With these bounds, a duality gap can be calculated to provide an indication of how far at most the heuristic solution is from the optimum.

The Lagrangian relaxation method was selected for this study as it was found to be most appropriate in dealing with the problem of selecting product return channels. The complexity and size of this problem was reduced by the incorporation of some constraints in the objective function. This made it possible for the now relaxed problem to be broken down into smaller portions thus easing the way for solutions. Details of the Lagrangian relaxation algorithm will be presented in Chapter 6.

CHAPTER 4
OPTIMIZATION OF PRODUCT RECOVERY OPTIONS

4.1   Introduction

During this chapter, the focus is on the optimization of product recovery options. A linear programming model was developed to determine optimal allocation of returned products in different quality classes to specific recovery options. The model presented the avenue for an examination on the effects of flexibility in product recovery allocation. A computational example using experimental data was presented to demonstrate the viability of the proposed model. Based on the results, conclusions were drawn at the end of the chapter.

4.2   Product recovery options: overview of current practices

In a product recovery environment, returned products come in various conditions. These include well-preserved ex-displays, faulty products which may or may not be recovered, end-of-life (EOL) products, and good products returned within the warranty period for various reasons. The returned products could come from different sources; directly from the customers, or from independent collectors or brokers. In practice, the time and rate of return is generally uncertain as this is beyond the control of manufacturers. In order to stimulate better product return, manufacturers usually offer a variety of monetary and non-monetary incentives. Examples of monetary incentives are cash refunds for products

returned within the warranty period, buy-back prices for returned products, and cash vouchers that can be used for future purchases.

As for non-monetary incentives, these could be in the form of nearby drop-off facilities, free take-back options and free postage return schemes. There are also different types of return channels such as direct and indirect returns, as well as centralized and decentralized returns. The initial collection stage involves three main methods which are mail delivery return, pick-up and drop-off. Under normal circumstances, it is left to the customers to select their preferred channel for the return of products. It is also up to them to choose the kind of incentive that can encourage them to return their products. Nevertheless, as mentioned earlier, manufacturers can influence the rate of return through monetary and non-monetary incentives.

Upon arrival, all returned products are inspected and sorted into separate quality classes. Quality plays an important role in determining the types of recovery options that will be used for returned products. In brief, products returned in good condition require less rework and can be sold as it is albeit with a decline in quality compared to similar original products. On the other hand, returned products of poor quality may be recovered through extensive repairs if it is still feasible to do so. Returned products that cannot be salvaged are disposed of at a land-fill or incinerated. The quality of the returned product is the decisive factor in the amount of rework required to eliminate its flaws. Unfortunately, there are currently no clear guidelines on quality classification or systematic quality grading of the returned products. Returned products are simply labelled

good or bad quality products. Conversely, some manufacturers may have more complicated or systematic ways of quality grading. For instance, ReCellular Inc. categorizes returned products (used cellular phones) into six quality classes using their own specific measurements (Guide and van Wassenhove, 2001).

Quality identification is followed by the assignment of returned products into various recovery options. During this stage, a decision is required on whether a returned product is generally recoverable or should be disposed of. The returned products deemed recoverable are allocated into separate recovery options. Recovery options include reuse, refurbish, remanufacture, recycling and cannibalization (Thierry et al., 1995). The allocation process is carried out based on the quality of the returned products. However, due to the fact that recycling and cannibalization (dismantling products) require separate recovery facilities, some manufacturers sidestep this dilemma by selling some of the returned products to independent recyclers or dismantlers. In this case, the returned products will be sold as it is and the selling price is normally based on weight and material content. Each recovery option generates outputs with different quality levels. Reuse, refurbishment and remanufacturing deliver recovered products; cannibalization recovers usable parts and components, while recycling recovers the material contents. The remanufacturing process is acknowledged for output of the highest quality followed by refurbishment and reuse with lower levels of output quality.

Although remanufacturing produces the best quality output, this advantage is offset by the high recovery cost as a greater amount of rework is involved. The

remanufacturing output is almost as good as the virgin products or at least recovered up to a specified level. On the other hand, repair requires the least amount of rework and thus, minimum recovery costs. Refurbished products are sandwiched between remanufacturing and repair in terms of recovery costs, amount of rework and selling prices. Recovery costs for the recycling and cannibalization options are essentially based on the principle 'economy of scale'. The more returned products recovered using these options, the more costs can be saved. Whether these two options are employed internally (in-house recovery facility) or outsourced to other parties depends on the strategy of the manufacturer. It is also up to the manufacturer to decide on the preferred recovery options for their returned products. Typically, recovery assignments are based on the quality level of the returned products. For example, if a returned product is still in good condition (minor defaults) and can be easily repaired, this product is classified as a repairable item and is assigned the repair option.

After the recovery processes, the recovered products are released into the market to compete with the virgin products. However, recovered products are usually sold at a lower price to offer customers cheaper options with an acceptable quality level. Recovered products can be sold to 'second hand product' wholesalers or retailers while retrieved parts and components as well as recycled materials can be sold to independent parts brokers and recyclers respectively. If the company decides against cannibalization or recycling due to reasons related to feasibility, then the returned products can be sold to independent dismantlers or recyclers. Alternatively, recovered products, parts and materials can be sold directly to customers.

4.3   Focus of the study

Listed below are various studies conducted in the area of product recovery management: Aras and Aksen, 2008; Aras et al., 2004; Aras et al., 2008; Guide and van Wassenhove, 2001; Fleischmann et al., 1997; Fleischmann, Krikke, Dekker and Flapper, 2000; Georgiadis and Vlachos, 2004; Guide, Kraus and Srivastava, 1997a; Guide, Srivastava and Kraus, 1997b; Guide, Srivastava and Spencer, 1997c; Guide, Souza, van Wassenhove and Blackburn, 2006; Gungor and Gupta, 1999; Gungor and Gupta, 2002; Hervani, Helms and Sarkis, 2005; Inderfurth, 1997; Inderfurth et al., 2001; Inderfurth, 2004; Inderfurth, 2005; Jayaraman, Guide and Srivastava, 1999; Jayaraman, 2006; Kara, Rugrungruang and Kaebernick, 2007; Karakayali et al., 2007; Min and Ko, 2008; Salema et al., 2007; Teunter, 2006; Thierry et al., 1995 and Krikke et al., 1998 . Some of these studies emphasized on recovery assignments while others concentrated on other issues such as capacity planning, production and inventory planning, quality classification, disassembly planning, and the return networks (please refer to the previous chapter).

Some studies focused on recovery options such as remanufacturing, refurbishment and recycling. Only a few researchers considered multiple recovery options in a single model. Studies conducted by Krikke et al., (1998), Teunter (2006) and Mangun and Thurston (2002) investigated this situation. The methods used were Mixed Integer Linear Programming (MILP), stochastic dynamic programming and quadratic programming respectively. The focus of these studies also varied with Krikke et al., 1998 emphasizing on optimization of group

recovery and disposal policy, Teunter, 2006 on disassembly strategy, and Mangun and Thurston on product portfolio design. None of the previous related studies considered flexible assignment involving all product recovery options in a single model. This chapter describes the development of a model that allows for flexible assignment of product recovery options and tests the model for a variety of supply and demand distributions.

4.4   The practice of flexible allocation in product recovery decisions

Currently, there is no record of any study clearly promoting flexible allocation in product recovery decisions. In a broader context, according to Bai and Sarkis (2013), compared to other aspects of the supply chain and reverse logistics, there has virtually been no research on reverse logistics flexibility. Flexibility of the organization and its reverse supply chain/logistics channels is crucial when faced with uncertainty and the greater probabilities of disruption in these channels (Tang and Tomlin, 2008).

Previous research in this area highlighted several significant issues. Firstly, there is more than one recovery option to consider (Thierry et al., 1995; Krikke et al., 1998; Teunter, 2006). Secondly, the condition (quality) of unwanted products returned vary substantially (Guide and van Wassenhove, 2001; Aras et al., 2004), and thirdly, decisions made on product recovery are dependent on the situation in the market. In other words, demand also plays a crucial role in determining recovery decisions (Guide, Teunter and van Wassenhove, 2003). There are indications from earlier research that decisions made on the selection of recovery options may not depend solely on the condition of returned products.

White, Masanet, Rosen and Beckman (2003) studied product recovery practices in the computer industry of the United States. They opined that the recovery process of a desktop computer could take place in various forms. These include reuse, remanufacturing, repair, recycle and demolition (disposal). Although recovery decisions often depend on the condition of the item, some firms preserve their interests on certain processes for their own strategic reasons. For instance, some firms are more interested in recovering the mainframe or CPU of a desktop computer (the most expensive component) which has a better resalable value. In this situation, priority is given to repairing (minor improvement), refurbishing (medium improvement) or remanufacturing (major upgrading) of the CPU instead of simply recycling or disposing providing the options are feasible. This situation indicates that the inclination for flexible allocation of recovery decisions is subject to the strategic reasoning of a firm.

In the field of business, flexible decision-making in reverse logistics was illustrated by Wadhwa et al., (2009). The recovery options in their study are also based on the work of Thierry et al., (1995). They demonstrated the viability of flexible decisions in a reverse logistics system on Original Equipment Manufacturer (OEM), a company producing brown goods. The study employed a fuzzy logic approach using linguistic variables and rating scales with help from experts. However, the flexible decisions using the fuzzy approach require the presence of experts on-site to monitor the system and adjust the fuzzy rule at the beginning of each stage in the recovery system. With this requirement, the cost for the development of the system is substantially increased. The fuzzy model also places more emphasis on rankings based on expert opinions and intervening variables such

as cost, environment, legislature and market factors. As the selections are based on the rankings provided by experts, the tendency for partiality needs to be taken into consideration.

Another practical example of a company implementing multiple recovery options is provided by Krikke (2011). An international document management company known as CopyDoc has been practicing a closed-loop supply chain since 1990. The company's business model categorized returned machines and parts into four different quality classes ranging from very good (A) to poor (D). Under its policy, return quality classes C and D can only be recovered using lower type recovery options such as recycling and cannibalization with disposal as the final option if the returned items are beyond recovery. On the other hand, better return quality products (types A and B) can be recovered using either the repair, refurbishing or remanufacturing options. This scenario establishes the fact that CopyDoc has indeed implemented flexible assignment in product recovery options. Its application though, is limited to two major categories which are 'good to very good' quality items for repair, refurbishing or remanufacturing, and 'moderate to poor' quality items for recycling, cannibalization or disposal. The success of its recovery operations is mainly attributed to the high demand for recovered products among customers in the original market.

In his study, Krikke (2011) also formulated a mixed integer programming model to examine the possibility of minimizing the impact of carbon footprints (emissions) in a full closed-loop supply chain of a copier company. The model includes all the aforementioned recovery options with feasibility and substitution per

recovery option and assumes that the volumes of return flows are known per return class. The constraints also limit certain return quality classes to specific recovery options albeit with some degree of flexibility. The results show that the two different categories of decision-making benefit the company differently under different return situations. The benefit level is raised if volumes for high quality return are also high. The results also suggest that a flexible policy in product recovery assignment is feasible as well as beneficial under certain conditions. However, it should be noted that the results are context-dependent and difficult to generalize. Similar effects of flexible assignment involving actual products remain undisclosed. This study also identifies significant relationships between product recovery and the collection networks.

The business examples mentioned above reveal the potential and practicality of flexible recovery assignment. The quality categorisation of returned products has been practiced by companies such as ReCellular Manufacturing Incorporated and many others. The maximum amount of flexibility that can be allowed in product recovery options without adversely affecting the assignments remain an issue.

4.5   Problem Description

In this study, returned products are graded into five quality classes based on the physical and functionality conditions, $Q = \{1, 2, ..., 5\}$. The five classes from the highest to the lowest quality are:(1) products that can be repaired, (2)products that can be refurbished, (3) products that can be remanufactured, (4) products that can be cannibalized, and (5)products that can be recycled. This type of quality classification is employed by some remanufacturers although their methods may

not be exactly the same. Inspired by the work of Jayaraman (2006), implementation of this classification method can be achieved through professional judgment (quality controller). Following quality classification, returned products ferried to the recovery facility and separated according to specific recovery options. Five recovery options, $R = \{1, 2, \ldots, 5\}$, are considered and these are(1) repair, (2) refurbish, (3) remanufacture, (4) cannibalize and (5) recycle.

It is possible for a returned product of a higher quality to be recovered using a lower option, and vice versa. However, a lower quality returned product that is recovered using a higher recovery option will incur higher recovery costs. Thus, unlike the current practice, each class of returned products should not be restricted to only one designated recovery option. Here, the researcher allows for flexibility in the relationship between the quality of returned products and the recovery options. However, this flexibility is allowed so long as it is technically feasible. In some situations, it is not technically practical to assign certain lower quality returned products to higher recovery options as the cost for doing so would be excessive.

Recovering returned products in the same quality class would involve different recovery costs depending on the recovery option used. It is also clear that if a returned product with a quality level deemed appropriate for cannibalization is recovered through the remanufacturing option (upgrade), then the cost incurred for recovery will be higher. However, the quality of the output

obtained through the remanufacturing option will also be much better and a higher selling price will be in order. This situation is depicted in Figure 4.1.

All the symbols used in Figure 4.1 are defined as follows:

TA_i : Total amount of returned product i

T_{iq} : Total amount of returned product i of quality class q

q_i : Quality class of returned product i

r : Recovery option r (r_1: repair, r_2: refurbish, r_3: remanufacture, r_4: cannibalize and r_5: recycling)

s : Selling prices of product i recovered using option r
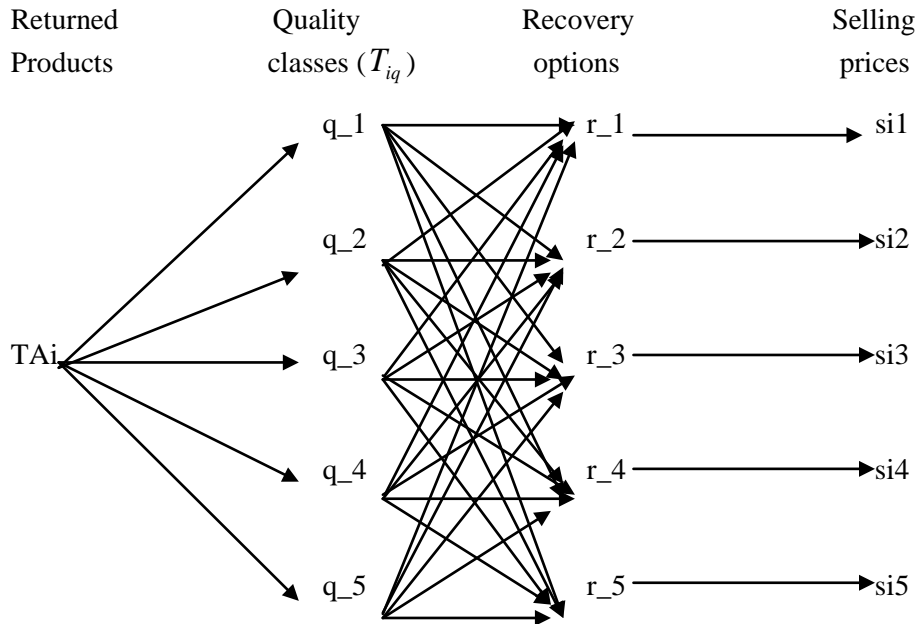
Figure 4.1: The Decision Making Framework for Recovery Options

The relationship between the quality of returned products, recovery options and recovery costs is displayed in Table 4.1. The shaded areas in the table refer to the possibility of a higher recovery cost. This occurs when a lower quality item is upgraded or re-processed to a higher quality output. For instance, a returned product that can be classified as recyclable (suitable for recycling) may also be recovered using other options such as remanufacturing (upgraded). However, as this option may involve a substantial cost due to the amount of rework required, it may or may not be beneficial as this depends on whether the profit margin from the sale of the recovered product can offset the rework cost.

Table 4.1: The Cost for Recovering Item i of Quality q Using Option r

r \ q	1 (repair)	2 (refurbish)	3 (remanufacture)	4 (cannibalize)	5 (recycle)
1	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}
2	C_{21}	C_{22}	C_{23}	C_{24}	C_{25}
3	C_{31}	C_{32}	C_{33}	C_{34}	C_{35}
4	C_{41}	C_{42}	C_{43}	C_{44}	C_{45}
5	C_{51}	C_{52}	C_{53}	C_{54}	C_{55}

Notes: r = recovery option, q = quality class (scale: 1 = good to 5 = bad), C = cost per unit item

As for recovery options, the researcher considers a situation where the company has the necessary facilities to carry out all five recovery methods in-house. It is assumed that the unit processing cost for returned products in each quality class using each recovery option is known (C_{iqr}). The capacity of the facility for each recovery option is limited and known (K_{iqr}). In the analysis, the researcher considers different selling prices for the outputs of different recovery

options (S_{ir}). It is assumed that recovered products from remanufacturing activities have the highest quality followed by refurbished and repaired products. Thus, remanufactured products command the highest selling price followed by refurbished and repaired products. The selling prices for retrieved parts and components are lower than that for repaired products but higher than that of recycled materials. It is also assumed that there is a demand for each recovery output option. The in-house product recovery activities involve processing, collecting and handling costs.

It is also important to consider the impact of market demand and the quality distribution of returned products. Testing a model in variable supply and market environments highlights its potential benefits while exposing its potential limitations. The committed demand (CD_{ir}) and the maximum market demand (MD_{ir}) are presented to illustrate the tightness of market demand. Through quality inspection and classification, the distribution of returns quality is revealed. The use of different quality distributions for testing the model facilitates an evaluation of the potential benefits of the proposed flexible allocation against the fixed allocation of product recovery options in different situations.

Meanwhile, the company is considered to be operating in an environment where product take-back is mandated and the requirement to achieve the minimum recovery target set by the government (G_i) is obligatory. A minimum recovery target is the least proportion of collected used products that must be recovered for reuse, recycling or resale. Upon achieving the recovery target, the next stage involves determining the amount of returned products in each quality

class that should be allocated to each recovery option after taking into consideration all the aforementioned issues.

4.6   Model Formulation

The main purpose for developing the proposed model is to examine the effects of flexibility in the assignment of product recovery options. Flexibility in this situation is with regard to the assignment of returned products to recovery options, while assignment refers to decisions on the amount of returned products of specific types (*i*) from specific quality classes (*q*) to be allocated to specific recovery options (*r*).The introduction of flexibility into the equation allows products from any quality class to be assigned to any recovery option for as long as it is feasible to do soothed proposed model takes into consideration important parameters relevant to the allocation of product recovery options such as the amount of returned products, demands for recovered products, recovery targets, and related capacities. The following are notations for the parameters of the model and decision variables:

Parameters

I = {1, 2, …,*n*} : the set of returned product types;

R = {1, 2, …, 5} : the set of recovery options;

Q = {1, 2, …, 5} : the set of quality classes;

T_{iq} : The amount of returned product *i* in quality class *q*;

TA_i : Total amount of returned product *i*, so, $\sum_{q=1}^{5} T_{iq} = TA_i$;

G_i :Recovery target of item i expressed in terms of proportion of TA_i;

K_{iqr} : Capacity needed to recover item i from quality class q using option r;

TK_r : Maximum capacity of recovery option r;

CD_{ir} : Committed demand for product i recovered using option r;

MD_{ir} : Market demand for product i recovered using option r;

P_{iqr} : Profit (per unit) of item i in quality class q assigned to recovery option r, where $P_{iqr} = S_{ir} - (C_{iqr} + PC_i + CH_i)$. S_{ir} is the selling price (per unit) of item i recovered using option r, C_{iqr} is the direct recovery cost per unit of item i in quality class q recovered using option r, PC_i is the purchasing cost per unit of returned product i, and CH_i is the collection and handling cost per unit of returned product i.

Decision variables

A_{iqr} : the amount of item i in quality class q that should be recovered using option r.

4.7   The Model

The Objective Function:

The decision variable, A_{iqr} , resembles the amount of item i ($i=1,..,n$) of quality class q ($q=1,..,5$) that should be best recovered using option r ($r=1,..,5$). The optimal assignments generate the best combination of possible profit (P_{iqr}) and quantity of recovered returned products. The specific objective of the

proposed model is to maximize the total profit made from the optimal allocation of returned products to the recovery options (profit maximization model).

The Constraints:

1. *Constraints (1) and (2): Committed demand and Market demand*

Demand is separated into two categories; committed demand and market demand. Committed demand refers to all existing demands specifically designated for the manufacturers' own products, while market demand is the total demand of all products including the ones produced by the manufacturer. Committed demand must be satisfied, while the amount of recovered products cannot exceed the total market demand for that particular product. Hence, the equation for constraint (1) is designed to stress that the committed orders for all types of recovered products must be fulfilled. The equation for constraint (2) is formulated to ensure that the amount of each product recovered by each option cannot exceed the total market demand for that type of product.

2. *Constraint (3): Total amount of returned products*

The total amount of returned products for all types and quality classes (T_{iq}) should be greater than, or equal to the amount of recovered returned products (the decision variable). This constraint is designed to ensure that the amount of recovered returned products of type i from quality class q (A_{iqr}) does not exceed the existing amount of returned products in-hand (T_{iq}).

3. *Constraint (4): The capacity constraint*

Each recovery option requires a certain amount of time and resources to be successfully implemented. In other words, each recovery option has its own capacity available for the rework activities. On the other hand, each item that needs to be recovered also has its own individual capacity requirements (K_{iqr}). This constraint is formulated to ensure that the available capacities for each recovery option (TK_r) are not exceeded or violated.

4. *Constraint (5): The recovery target*

One of the distinguishing features of product recovery management is the fulfilment of the recovery target set either by the government or by a specific environmental legislation. In this study, the recovery target (G_i) is based on the proportion of the total amount of returned products (TA_i). Thus, this constraint imposes the requirement of fulfilling the recovery target by ensuring that the decision variable (A_{iqr}) is greater than or at least equal to the $TA_i \times G_i$.

Using the above notion, the problem can now be formulated as the following linear programming model:

Maximize $$\sum_{i=1}^{n}\sum_{q=1}^{5}\sum_{r=1}^{5} P_{iqr}\, A_{iqr}$$

Subject to:

$$\sum_{q=1}^{5} A_{iqr} \geq CD_{ir},\ i \in I,\ r \in R \qquad (1)$$

$$\sum_{q=1}^{5} A_{iqr} \leq MD_{ir}, i \in I, r \in R \qquad (2)$$

$$\sum_{r=1}^{5} A_{iqr} \leq T_{iq}, i \in I, q \in Q \qquad (3)$$

$$\sum_{i=1}^{n} \sum_{q=1}^{5} K_{iqr} \cdot A_{iqr} \leq TK_{r}, r \in R \qquad (4)$$

$$\sum_{q=1}^{5} \sum_{r=1}^{5} A_{iqr} \geq TA_{i}G_{i}, i \in I \qquad (5)$$

$$A_{iqr} \geq 0, i \in I, q \in Q, r \in R \qquad (6)$$

Briefly, the objective of this model is to maximize the total profit made from recovering the returned products. Constraint (1) requires the fulfilment of committed orders for all types of recovered products, constraint (2) states that the amount of each product recovered by each option cannot exceed the total market demand for that type of product, constraint (3) ensures that the sum of the amounts of returned product i in quality class q assigned to different recovery options r does not exceed the total amount of returned product i in quality class q, constraint (4) ensures that the sum of capacities of each recovery option required by all returned products in all quality classes does not exceed the available capacity of this recovery option, constraint (5) guarantees that the amount of all recovered products will meet the recovery target, and constraint (6) requires all variables to be non-negative.

4.8   Computational Experiment

The above model allows for flexibility in the assignment of returned products to recovery options. To portray the potential benefits of flexibility in this

situation, this researcher used this model to demonstrate the effect of flexibility on an example of a problem. In this example, it is assumed that the company collects three different used products (products *1, 2* and *3*) and uses them to produce recovered products. Table 4.2 displays the total amount of each product returned, its recovery target, purchasing cost and handling cost. The selling prices of recovered products are listed in Table 4.3. Tables 4.4 and 4.5 list the unit recovery costs and capacity related parameters respectively.

Utilizing the available data, an investigation on the impact of flexible recovery assignments was conducted under different supply and demand environments (Table 4.6). With regard to supply, three different distributions are considered representing quality classes for each returned product type: the amount of returned products in every quality class equal to $TA_i/5$, from uniform distribution $[0.7*TA_i/5, 1.3*TA_i/5]$, and from uniform distribution $[0.4*TA_i/5, 1.6*TA_i/5]$. These represent three different levels of quality variability of returned products. As for demand, three different levels of demand constraints are considered using different pairs of uniform distributions of CD_{ir} and MD_{ir}. Table 4.6 summarizes these supply and demand distributions.

Table 4.2: Total Return, TA$_i$, Recovery Target, G$_i$, Purchase Cost, PC, and Handling Cost, CH, for Each Product Type

I	TA$_i$	G$_i$	PC	CH
1	100000	0.9	15	10
2	130000	0.85	7	5
3	90000	0.8	8	10

Table 4.3: Unit Selling Price of Recovered Products, S_{ir}

r \ i	1	2	3
1	150	50	180
2	200	70	200
3	250	90	220
4	50	30	45
5	30	20	20

The unit selling prices vary for different recovered products. These differences are due to the variability of the quality level for each recovery output. It has been established that remanufactured products possess the best quality output followed by refurbished, repaired, cannibalize and recycled items. Thus, the quality of a recovered product is defined by its price. A high price denotes a high quality recovered product. As for recycling and cannibalization, prices for outputs from these processes are relatively low due to the unavailability of the final product. These two recovery methods only result in parts and materials for sale.

Table 4.4: Unit Recovery Costs, C_{iqr}

r i, q	1	2	3	4	5
1, 1	20	25	45	20	15
1, 2	20	20	40	20	15
1, 3	55	40	45	20	15
1, 4	160	140	120	20	15
1, 5	100	125	150	40	15
2, 1	10	20	40	8	5
2, 2	20	20	40	8	5
2, 3	45	30	35	8	5
2, 4	80	70	60	8	5
2, 5	50	65	80	25	5
3, 1	20	25	45	20	15
3, 2	20	20	40	20	15
3, 3	65	40	45	20	15
3, 4	120	100	80	20	15
3, 5	140	120	100	30	15

Table 4.5: Capacity Coefficients, K_{iqr}, and Capacities Available, TK_r

r i, q	1	2	3	4	5
1,1	0.25	0.35	0.4	0.3	0.15
1,2	0.3	0.25	0.4	0.2	0.15
1,3	0.35	0.3	0.35	0.2	0.15
1,4	0.35	0.4	0.45	0.2	0.15
1,5	0.4	0.45	0.55	0.25	0.15
2,1	0.25	0.35	0.4	0.3	0.15
2,2	0.3	0.25	0.4	0.2	0.15
2,3	0.35	0.3	0.35	0.2	0.15
2,4	0.35	0.4	0.45	0.2	0.15
2,5	0.4	0.45	0.55	0.25	0.15
3,1	0.25	0.35	0.4	0.3	0.15
3,2	0.3	0.25	0.4	0.2	0.15
3,3	0.35	0.3	0.35	0.2	0.15
3,4	0.35	0.4	0.45	0.2	0.15
3,5	0.4	0.45	0.55	0.25	0.15
TK$_r$	25000	25000	30000	20000	15000

Table 4.6: Supply and Demand Environments

Level	Quality distribution of returned products, T_{iq}	Tightness of demand constraints	
		CD_{ir}	MD_{ir}
1	ta_i^*	[0.8ta_i, 0.9ta_i]	[1.1ta_i, 1.2ta_i]
2	[0.7ta_i, 1.3ta_i]	[0.6ta_i, 0.8ta_i]	[1.2ta_i, 1.4ta_i]
3	[0.4ta_i, 1.6ta_i]	[0.4ta_i, 0.7ta_i]	[1.3ta_i, 1.6ta_i]

* $ta_i = TA_i/5$

For each supply level and demand supply combination, 50 problem instances are generated using the corresponding distributions. The allocation of returned products to recovery options are then carried out for each problem instance in two different ways; **flexible** allocation using the model in Section 3.5, and the conventional **fixed** allocation. All the linear programming models are solved with the utilization of Xpress-MP.

With the fixed allocation, products of a quality class must be assigned to the corresponding recovery option, i.e. A_{iqr} takes non-zero values only when $q = r$. When the quality distribution of returned products did not match the demand requirements for some problem instances, fixed allocation was deemed unworkable. On the other hand, in all tests on the problem instances, the flexible allocation method never failed to provide a feasible solution.

For each instance where both methods generate feasible solutions, let *Flex* be the total profit achieved by the flexible allocation and *Fix* be the total profit achieved by the fixed allocation. The benefit of flexible allocation can be represented using the relative difference between the two total profits:

$$\frac{Flex - Fix}{Fix} \times 100\%$$

For each group of problem instances (each combination of supply level and demand level), the researcher calculated the average benefit for the feasible instances in the group. Table 4.7 reveals the results.

4.9   The Result

The calculated overall average benefit is 9.56%. This demonstrates that for the problems tested, allowing for flexibility in allocation can increase profits by an average of close to 10%. From the results displayed in Table 4.7, it is evident that when the demand constraint is tight, the benefit is inclined to be relatively small. This can be attributed to the fact that the allowance for flexibility here was very limited. When the level of tightness of demand constraint is at 1 (high) and the variability level of supply quality is also at 1 (low variability), the average benefit of flexible allocation is only 4.45%. This figure increased slightly to 4.50% as the variability level of supply rose.

Table 4.7 also shows that when the demand constraint is relaxed and the level of tightness of demand constraint increased to level 2, the average benefit of flexible allocation improved significantly from 4.45% to 8.83%. The benefit from flexible allocation is even greater when the variability level of supply quality went up to level 3 (8.89%). The benefit increased significantly with the relaxation of the demand constraint. When the level of tightness of the demand constraint reached level 3, the benefit increased to between 12.86% and 12.98%. This finding verifies that the relaxation of the demand constraint and a rise in the variability level of supply quality enhances the benefit gained from the flexible allocation method.

Table 4.7: Average Benefit of Flexible Allocation in Different Supply and Demand Environments

Level of variability on supply quality	Level of tightness of demand constraints		
	1	**2**	**3**
1	4.45%	8.83%	12.86%
2	4.50%	8.83%	12.93%
3	$-^{*}$	8.89%	12.98%

* Fixed allocation is infeasible for all the instances in this group

Table 4.8: Number of Infeasible Instances for Fixed Allocation in Different Supply and Demand Environments

Level of variability on supply quality	Level of tightness of demand constraints		
	1	**2**	**3**
1	0	0	0
2	17	0	0
3	50	40	1

Presumably, if the variability in the quality distribution of returned product increases, the benefit from flexible allocation would rise in tandem as higher variability would render the fixed allocation difficult. However, from an observation of the results displayed in Table 4.7, this researcher noted that the difference in the average benefit when the variability of supply quality changed was negligible. This could partially be attributed to the fact that calculations were only carried out for instances where the fixed allocation was deemed feasible.

Considering the detailed results, this researcher is of the opinion that as the variability of supply quality increases, so does the number of unfeasible instances in the group. Table 4.8 portrays the number of unfeasible instances in each group and also shows that when the level of variability of supply quality (quality distribution of incoming returned products) increased to level 3, the number of unfeasible instances rose in tandem to 50 and 40 (level of tightness of demand constraints are 1 and 2 respectively). However, the number of unfeasible instances reduced significantly when the demand constraint was further relaxed (level 3). If penalties are considered for not satisfying demand constraints, then the benefit of flexible allocation will be more significant when the variability of supply quality is large. Nevertheless, the ability to obtain feasible solutions to difficult situations is already a huge accomplishment attributed to the flexible allocation method.

4.10 Summary

This study examines the process of selecting recovery options for returned products. A linear programming model was formulated to determine the optimal amount of recoverable returned products in different quality classes to be assigned to recovery options in order to realize maximum profits. The model was used to demonstrate the potential impact of flexibility in the assignment of returned products to recovery options. The results revealed that the introduction of flexibility into recovery allocation proved to be more beneficial when compared to the fixed allocation approach as the application of flexible allocation can increase profits by an average of almost 10%. Another significant advantage attributed to flexible allocation is its ability to uncover feasible recovery plans under difficult supply and

demand conditions, conditions under which the fixed allocation method would be hard-pressed for a solution. It should be noted that flexible allocation is possible only when returned products are separated into very specific quality categories so that the possible options for each quality class is clear. A simple quality classification for returned products would not suffice for the application of flexible allocation. With increasing awareness on the need for a healthy environment and tighter regulations, companies are obliged to be more diligent in their inspection and classification processes for returned products.

In practice, complete flexibility in the allocation of returned products to recovery options may not be technically practical. Future research may involve the incorporation of other relevant factors such as outsourcing, indirect recovery costs and multiple planning periods.

CHAPTER5
AN INTEGRATED LOCATION-ALLOCATION MODEL FOR PRODUCT RETURNS

5.1 Introduction

This chapter presents an analysis of the location-allocation strategy for product return channels. A mixed integer nonlinear programming model is developed to find the optimal assignment of collection methods for returned products. A novel idea of integrating three different collection methods for product returns in a single model is highlighted. An illustrative example is presented to demonstrate the usability of the model. A conclusion is drawn at the end of this chapter.

5.2 Overview of the problem

Installing a drop-off facility near residential areas or offices encourages customers to return their products (easy access). This collection strategy requires the manufacturer to bear the cost of building or renting the drop-off facilities in a certain specific area. Some drop-off facilities are staffed while others use self-service machines (unmanned). Hence, manufacturers need to bear the fixed setup and operational costs of installing and operating a drop-off facility. Nonetheless, the more important decisions are the number of drop-off facilities needed and their locations. In practice, the facilities need to be located within close proximity to the customers. However, manufacturers also need to consider the distance

between the drop-off facilities and their factories. If the transportation cost is too high, the manufacturer would normally consider using intermediaries, such as retailers, to act as collection centres to collect returned products from the drop-off facilities. Previous studies usually categorized customers based on certain zones and each zone was served by one particular drop-off facility (Wojanowski et al., 2007; Aras and Aksen, 2008; Aras et al., 2008). It is also assumed that customers always choose the nearest drop-off facility. Thus, the function of each drop-off facility does not overlap.

Meanwhile, the willingness to pick up returned products directly from customers' houses improves return rates (convenience) even better, especially for bulky or big products such as household appliances. Again, the distance between the customer's house and the manufacturer's repair facilities or between the customer's house and the retailer's collection centre needs to be taken into account. This collection strategy is feasible for the manufacturers, as long as the transportation cost is not excessive or does not exceed a certain maximum limit. Manufacturers also need to decide on the number of vehicles required (based on their capacity) to cater to a potential amount of returned products. The potential consolidation of the pick-up in terms of either collection time or quantity needs must also be considered.

The abovementioned methods provide easy accessibility and are convenient for the customers. From a practical point of view, the pick-up strategy is much more convenient for the customers than the drop-off strategy. However, this assumption may change if manufacturers offer additional incentives such as an

acquisition fee, a special rebate or a discount voucher in exchange for a returned product. For instance, Tesco offers its customers a Club Card point for every two unused bottles returned via its drop-off facilities. The accumulated points enable Tesco's customers to earn cash vouchers that can be used for shopping. In this case, the supermarket giant is acting as a collection centre.

In the meantime, there are also customers who are willing to make greater efforts to return their products via the mail delivery method. The reasons for this could be due to the higher incentives offered by the manufacturers or because of the unavailability of other collection methods. In practice, customers using this method return their products directly to the manufacturers. The incentives offered are normally in the form of financial refunds (within the warranty period of the product), rebates, vouchers or certain fees. Nonetheless, not all products are suitable for this type of return method. Examples of products returned using this method include books (amazon.com) and refillable ink cartridges. A critical decision for manufacturers implementing this type of collection strategy is to decide on the optimal amount and the type of incentives that should be given to the customers in exchange for their efforts and willingness to return their unused/unwanted products.

Incentives play a significant role in influencing the customers' willingness to return their products. According to Aras et al. (2008), some manufacturers have been able to influence the quantity of returns by using buy-back campaigns and offering financial incentives to product holders. Apart from an increment in terms of product return quantities, the amount of incentives offered by the

manufacturers influences the quality level of the returned products (Aras and Aksen, 2008). Similarly, Wojanowski et al. (2008) also investigated the influences of incentives. These two studies examined to what extent the amount of incentives offered to the customers affects the manufacturers' profits and collection strategies.

There are several differences between the aforementioned studies and this study. In this study, the researcher examines a situation where a manufacturer is adopting the three collection strategies simultaneously while in Wojanowski et al. (2008), Aras et al. (2008) and Aras and Aksen (2008) the models were only focusing on one particular collection strategy at a time. Adopting only the pick-up or the drop-off strategy at a time means the manufacturer can only obtain returned products from the reachable area. It also means that these two options are not always feasible in terms of distance and the transportation cost. Concurrently, adopting only the mail return delivery strategy means that some products are not feasible to be returned using this option. The researcher also considers the element of pressure that manufacturers are facing in terms of government regulations. Government pressure through the predetermined recovery target is incorporated into the model. Hence, in practice a manufacturer would have better chances of achieving the recovery target by adopting more than one collection strategy at a time. This study is motivated by the need for analytical approaches that foster an in-depth understanding on this simultaneous implementation of the collection strategies.

5.3   Problem Definition

This study examines a manufacturer-operated product recovery network design. This type of collection network is practised by many companies (Savaskan and van Wassenhove, 2006). Specific attention is given to the collection stage of product returns. At this stage, customers have several options of returning used products via a drop-off facility, a mail delivery return or a pick-up collection method provided by the manufacturer. It is up to the manufacturer to influence the customers' preference and to assign them to certain collection methods using the incentives offered. As it is technically possible and economically viable, it is assumed that the customers' decision to return their unwanted products as well as their preference over a particular collection method is heavily influenced by the amount of incentives offered. It is also assumed that customers have no other option to return their products. The network structure is depicted in the following diagram.
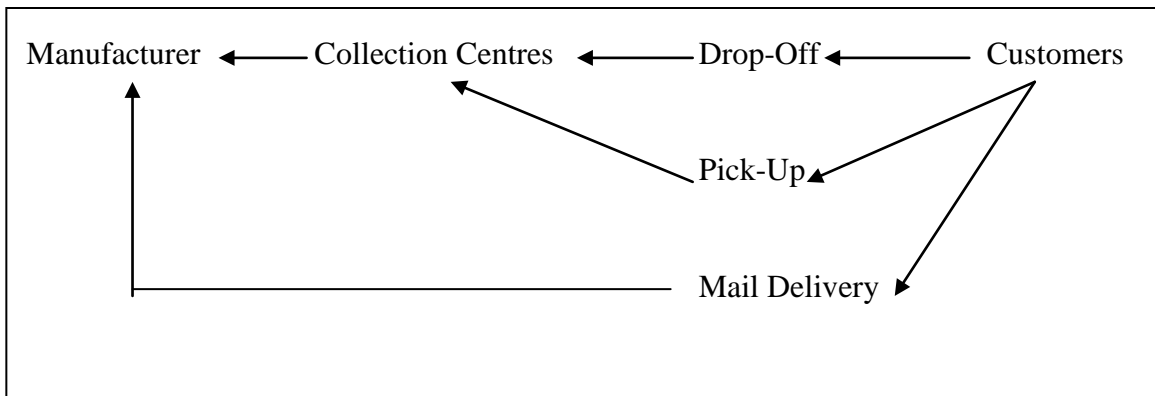
Figure 5.1: Collection Methods in Product Recovery Network Design

In this study, the manufacturer is assumed to implement a centralized collection policy within a single period timeframe consisting of both direct (mail

delivery return) and indirect (drop-off and pick- up methods) collection channels. For this study, the manufacturer is assumed to use his forward distribution networks to collect returned products. In particular, the manufacturer may select and appoint certain retailers as collection centres/drop-off points. Similar to what was done in previous studies, the customers are grouped into certain zones instead of being considered as individuals in order to reduce complexity. In terms of the return flow, if the drop-off option is chosen for a customer zone, the customers in the zone will have to travel to a collection centre to drop-off their products and only one collection centre can be chosen for the customers in each zone. Hence, the function of different collection centres will not be overlapping. If a customer zone is assigned for the pick-up collection method, the returned products will be picked up and then transported to the selected collection centre.

Meanwhile, the cost of operating a collection centre and implementing the pick-up method consists of fixed operating costs and variable costs. The operating costs may include setup/rental costs and handling costs. It is assumed that the operating cost for every collection centre is the same and that all the facilities are homogeneous. The operating cost for the pick-up operation may comprise the rental and maintenance of the vehicles, and the drivers' wages. The vehicles used are also assumed to be homogeneous. The variable cost of a pick-up trip is defined by the cost per unit distance and the distance travelled from the collection centre to the customer zone and back. The amount of incentives offered is assumed to affect the customers' decision to return their products. This study uses an acquisition price per unit of returned product as an incentive based on the quality condition. Apart from that, the values of the incentives (acquisition

prices) vary between the collection methods in order to compensate the customers for their efforts and their travelling costs to return their products. It is also assumed that all the collected products are recoverable and hence, still have remaining values to be recaptured. In terms of the customers' willingness to return their products, if the incentive offered is less than what the customers expect, then the probability of the customer returning the product is zero. On the other hand, if the amount of incentives offered is equal to or higher than the maximum amount of incentives that the customers expect for a particular product, then all the customers will return their products.

The amount of return will not change further if the amount of incentives increases above the maximum incentive that customers expect. This situation can be illustrated by Figure 5.2 (following *Aras and Aksen, 2008*). Figure 5.2(a) shows the proportion of product i of quality q returned as a function of the incentive offered for the drop-off collection method. The minimum incentive value is denoted by "LD_{iq}", while the maximum incentive is represented by "HD_{iq}". The cost of travelling to return the used product from customer zone b to the collection (drop-off) centre k is depicted by "CD_{bk}". Figure 5.2(b) shows a similar function for the pick-up collection method. The minimum incentive is LP_{iq} while the maximum incentive is represented by HP_{iq}. The minimum incentive value for the mail return delivery in Figure 5.2(c) is denoted by "LM_{iq}", while the maximum incentive is represented by "HM_{iq}". The mailing cost to return used products is depicted by "CS_i".

It can also be assumed that $HM_{iq} > HD_{iq} > HP_{iq}$, considering the conveniences for customers to return their products using different methods. A similar assumption may be made for the minimum amount of incentives offered for each type of collection method. In the meantime, the requirement by government regulations can be reflected in the form of minimum recovery rates. In this study, a manufacturer is assumed to be producing multiple products that can be returned by customers using either one of the collection methods. Products such as ink cartridges, rechargeable batteries, disposable cameras, mobile phones and books fit the bill.
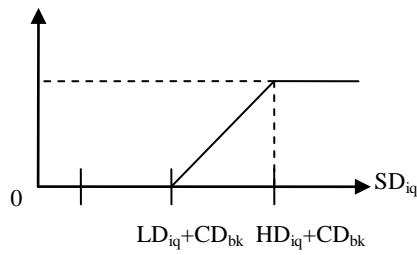
(a) For drop-off method
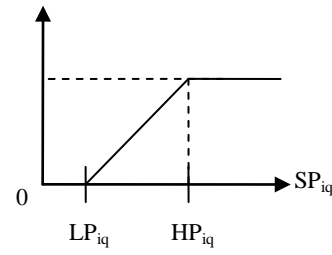
(b) For pick-up method
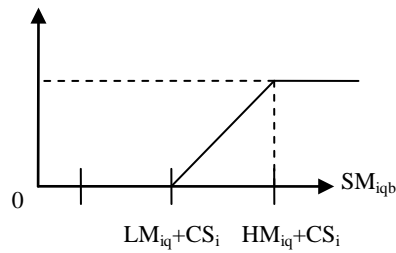
(c) For mail return method

Figure 5.2: Proportion of Products Returned as a Function of Incentives Offered

5.4   Model Formulation

The researcher develops an integrated generic model for the manufacturer to decide on the locations of collection (drop-off) centres in its reverse logistics network, the collection method for each customer zone and the incentives offered for returning products. The objective of the model is to maximize the total profit, which is the value of the collected products minus the collection costs. It is assumed that customers have no other return options except the aforementioned collection methods. The estimated amount of products of each type and each quality class available to return in each zone is assumed to be known. The model formulation of the drop-off collection method is based on the work of Aras and Aksen (2008) and extensions have been made to incorporate other collection methods.

Parameters

n = Number of product types

n_b = Number of customer zones

n_q = Number of product quality classes

n_k = Number of potential collection centres

TA_i = Total amount of used product type, i

T_{iqb} = Total amount of used product type, i of quality, q in customer's zone, b

CD_{bk}= Travelling cost per unit distance for drop off from customer zone, *b* to collection centre, *k*

D_{bk}= Distance between potential collection centre, *k* and customer zone, *b*

cv= Fixed cost of operating a vehicle

CV = Pick-up vehicle's travel cost per unit distance

C_k= Fixed cost of operating a drop-off facility, *k*

CM_i = Cost of receiving and handling a unit of product, *i* returned via mail

CS_i = Customers' shipping/post cost to return a unit of product, *i* via mail

KV= Maximum load (capacity) of a vehicle

KD_k= Maximum capacity of a collection

HP_{iq} = Maximum incentive of product, *i* of quality, *q* (pick-up method)

HD_{iq}= Maximum incentive of product, *i* of (drop-off method)

HM_{iq}= Maximum incentive of product, *i* of (mail delivery method)

LP_{iq} = Minimum incentive of product, *i* of (pick-up method)

LD_{iq}= Minimum incentive of product, *i* of (drop-off method)

LM_{iq}= Minimum incentive of product, *i* of (mail delivery method)

R_{iq}= Expected value per unit of product, *i* in quality class, *q*

XR_i = Required minimum collection rate for product, i

W = A large number

Decision variables

SP_{iq} = Incentive offered for product, i of quality (pick-up method)

SD_{iq} = Incentive offered for product, i of quality (drop-off method)

SM_{iq} = Incentive offered for product, i of quality (mail delivery method)

P_{iqb} = Proportion of product, i of quality collected from customer zone b

D_{iqb} = Proportion of product, i of dropped off by customers in zone b

M_{iqb} = Proportion of product, i of quality mail returned from customer zone b

V_{bk} = Number of vehicles needed to collect and transport returned products from customer zone b to collection centre k

Y_k = 1, if a drop-off facility (collection centre) is setup at site k;0, otherwise

XD_{bk} =   1, if product owners in zone b are assigned to drop-off their products at collection centre k; 0, otherwise

XP_{bk} =   1, if product owners in zone b are assigned for pick-up collection to collection centre k; 0, otherwise

XM_b=1, if product owners in zone b are assigned for mail delivery method; 0, otherwise

α_{iqb} = 1, if product owners in zone b do not drop off their products; 0, otherwise

δ_{iqb} = 1, if all product owners in zone b drop off their products; 0, otherwise

β_{iqb} = 1, if product owners in zone b do not return their products (pick-up); 0, otherwise

ρ_{iqb} = 1, if all product owners in zone b return their products (pick-up); 0, otherwise

χ_{iqb} = 1, if product owners in zone b do not return their products (mail delivery return); 0, otherwise

μ_{iqb} = 1, if all product owners in zone b return their products (mail delivery return); 0, otherwise

The model:

Maximize $\quad Z_1 + Z_2 + Z_3$

where Z_1, Z_2 and Z_3 are profits from the pick-up (not counting the operating costs of the collection/drop-off centres), drop-off (counting all the operating costs of the collection/drop-off centres) and mail return methods, respectively.

$$Z_1 = \sum_{i=1}^{n}\sum_{q=1}^{n_q}\sum_{b=1}^{n_b} T_{iqb}P_{iqb}(R_{iq} - SP_{iq}) - \sum_{b=1}^{n_b}\sum_{k=1}^{n_k}[cv + 2CVD_{bk}]V_{bk},$$

$$Z_2 = \sum_{i=1}^{n}\sum_{q=1}^{n_q}\sum_{b=1}^{n_b} T_{iqb}D_{iqb}(R_{iq} - SD_{iq}) - \sum_{k=1}^{n_k}C_kY_k,$$

$$Z_3 = \sum_{i=1}^{n}\sum_{q=1}^{n_q}\sum_{b=1}^{n_b} T_{iqb}M_{iqb}(R_{iq} - SM_{iq} - CM_i)$$

Subject to the following constraints:

A collection centre, *k*, can receive collected products from more than one customer's zones, *b*, but each zone is assigned to only one collection method, and if it is assigned to the pick-up or drop-off method, it can only be assigned to one collection/drop-off centre:

$$\sum_{k=1}^{n_k} XP_{bk} + \sum_{k=1}^{n_k} XD_{bk} + XM_b = 1, \qquad b=1,...,nb \qquad (1)$$

Returned products of all types and qualities collected via the pick-up and drop-off methods can only be delivered to a collection centre that is set up:

$$XP_{bk} + XD_{bk} \leq Y_k, \qquad\qquad b=1,...,nb, \; k=1,..., nk \qquad (2)$$

The incentive values represent the customers' willingness to return their products. In terms of the drop-off method, the relationships between the incentives and the proportion of products returned are as follows:

$$SD_{iq} \leq (\sum_{k=1}^{n_k} CD_{bk} XD_{bk}) + LD_{iq} + W(1 - \alpha_{iqb}),$$

$$i=1,...,n, \; q=1,...,n_q, \; b=1,...,n_b \qquad (3)$$

$$SD_{iq} \geq (\sum_{k=1}^{n_k} CD_{bk} XD_{bk}) + LD_{iq} - W\alpha_{iqb},$$

$$i=1,...,n, \quad q=1,...,n_q, \quad b=1,...,n_b \tag{4}$$

$$SD_{iq} \leq (\sum_{k=1}^{n_k} CD_{bk} XD_{bk}) + HD_{iq} + W\delta_{iqb},$$

$$i=1,...,n, \quad q=1,...,n_q, \quad b=1,...,n_b \tag{5}$$

$$SD_{iq} \geq (\sum_{k=1}^{n_k} CD_{bk} XD_{bk}) + HD_{iq} - W(1-\delta_{iqb}),$$

$$i=1,...,n, \quad q=1,...,n_q, \quad b=1,...,n_b \tag{6}$$

$$D_{iqb} \leq 1 - \alpha_{iqb}, \qquad i=1,...,n, \quad q=1,...,n_q, \quad b=1,...,n_b \tag{7}$$

$$D_{iqb} \geq \delta_{iqb}, \qquad i=1,...,n, \quad q=1,...,n_q, \quad b=1,...,n_b \tag{8}$$

The above constraints (3) – (8) are formulated in order to relate the proportion, D_{iqb} to the incentive amount SD_{iq}. Table 5.1 summarizes this relationship for each of the four possible combinations of α_{iqb} and δ_{iqb} values.

Table 5.1: Possible α_{iqb} and δ_{iqb} assignments for D_{iqb} and SD_{iq}

α_{iqb}	δ_{iqb}	SD_{iq}		D_{iqb} Const.7	D_{iqb} Const.8	Outcomes
1	0	Constraint 3	Constraint 5	≤ 0	≥ 0	$D_{iqb}=0$
0	1	Constraint 4	Constraint 6	≤ 1	≥ 1	$D_{iqb}=1$
0	0	Constraint 4	Constraint 5	≤ 1	≥ 0	$0 \leq D_{iqb} \leq 1$
1	1	Constraint 3	Constraint 6	≤ 0	≥ 1	Infeasible

In the meantime, constraints (9) and (10) are active only when $\alpha_{iqb}=0$ and δ_{iqb} =0, which indicates that $D_{iqb} = [SD_{iq} - (\sum_{k=1}^{n_k} CD_{bk} XD_{bk}) - LD_{iq}]/[HD_{iq} - LD_{iq}]$. The constraints are redundant when either $\alpha_{iqb}=1$ or $\delta_{iqb}=1$.

$$D_{iqb} \leq [SD_{iq} - (\sum_{k=1}^{n_k} CD_{bk} XD_{bk}) - LD_{iq}]/[HD_{iq} - LD_{iq}] + W(\alpha_{iqb} + \delta_{iqb}),$$

$$i=1,...,n, \quad q=1,...,n_q, \quad b=1,...,n_b \tag{9}$$

$$D_{iqb} \geq [SD_{iq} - (\sum_{k=1}^{n_k} CD_{bk} XD_{bk}) - LD_{iq}]/[HD_{iq} - LD_{iq}] - W(\alpha_{iqb} + \delta_{iqb}),$$

$$i=1,...,n, \quad q=1,...,n_q, \quad b=1,...,n_b \tag{10}$$

As for the pick-up collection method, the relationships are as follows:

$$SP_{iq} \leq LP_{iq} + W(1 - \beta_{iqb}), \qquad i=1,...,n, \quad q=1,...,n_q, \quad b=1,...,n_b \tag{11}$$

$$SP_{iq} \geq LP_{iq} - W\beta_{iqb}, \qquad i=1,...,n, \quad q=1,...,n_q, \quad b=1,...,n_b \tag{12}$$

$$SP_{iq} \leq HP_{iq} + W\rho_{iqb}, \qquad i=1,...,n, \quad q=1,...,n_q, \quad b=1,...,n_b \tag{13}$$

$$SP_{iq} \geq HP_{iq} - W(1 - \rho_{iqb}), \qquad i=1,...,n, \quad q=1,...,n_q, \quad b=1,...,n_b \tag{14}$$

$$P_{iqb} \leq 1 - \beta_{iqb}, \qquad i=1,...,n, \quad q=1,...,n_q, \quad b=1,...,n_b \tag{15}$$

$$P_{iqb} \geq \rho_{iqb}, \qquad i=1,...,n, \quad q=1,...,n_q, \quad b=1,...,n_b \tag{16}$$

The above constraints (11) – (16) are formulated in order to relate the proportion, P_{iqb} to the incentive amount SP_{iq}. Table 5.2 summarizes this relationship for each of the four possible combinations of ρ_{iqb} and β_{iqb} values.

Table 5.2: Possible ρ_{iqb} and β_{iqb} assignments for P_{iqb} and SP_{iq}

β_{iqb}	ρ_{iqb}	SP_{iq}		P_{iqb}		Outcomes
				Const.15	Const.16	
1	0	Constraint 11	Constraint 13	≤ 0	≥ 0	$P_{iqb}=0$
0	1	Constraint 12	Constraint 14	≤ 1	≥ 1	$P_{iqb}=1$
0	0	Constraint 12	Constraint 13	≤ 1	≥ 0	$0 \leq P_{iqb} \leq 1$
1	1	Constraint 11	Constraint 14	≤ 0	≥ 1	Infeasible

In the meantime, constraints (17) and (18) are active only when $\beta_{iqb}=0$ and $\rho_{iqb}=0$, which indicates that $P_{iqb} = [SP_{iq} - LP_{iq}]/[HP_{iq} - LP_{iq}]$. The constraints are redundant when either $\beta_{iqb}=1$ or $\rho_{iqb}=1$.

$$P_{iqb} \leq [SP_{iq} - LP_{iq}]/[HP_{iq} - LP_{iq}] + W(\beta_{iqb} + \rho_{iqb}),$$

$$i=1,...,n,\ q=1,...,n_q,\ b=1,...,n_b \qquad (17)$$

$$P_{iqb} \geq [SP_{iq} - LP_{iq}]/[HP_{iq} - LP_{iq}] - W(\beta_{iqb} + \rho_{iqb}),$$

$$i=1,...,n,\ q=1,...,n_q,\ b=1,...,n_b \qquad (18)$$

The relationships between the incentives and the proportion of products returned from zone b via mail are illustrated in the following equations:

$$SM_{iq} \leq (CS_i XM_b) + LM_{iq} + W(1 - \chi_{iqb}), \quad i=1,\ldots,n, \; q=1,\ldots,n_q, \; b=1,\ldots,n_b \quad (19)$$

$$SM_{iq} \geq (CS_i XM_b) + LM_{iq} - W\chi_{iqb}, \quad i=1,\ldots,n, \; q=1,\ldots,n_q, \; b=1,\ldots,n_b \quad (20)$$

$$SM_{iq} \leq (CS_i XM_b) + HM_{iq} + W\mu_{iqb}, \quad i=1,\ldots,n, \; q=1,\ldots,n_q, \; b=1,\ldots,n_b \quad (21)$$

$$SM_{iq} \geq (CS_i XM_b) + HM_{iq} - W(1 - \mu_{iqb}), \quad i=1,\ldots,n, \; q=1,\ldots,n_q, \; b=1,\ldots,n_b \quad (22)$$

$$M_{iqb} \leq 1 - \chi_{iqb}, \qquad i=1,\ldots,n, \; q=1,\ldots,n_q, \; b=1,\ldots,n_b \quad (23)$$

$$M_{iqb} \geq \mu_{iqb}, \qquad i=1,\ldots,n, \; q=1,\ldots,n_q, \; b=1,\ldots,n_b \quad (24)$$

The above constraints (19) – (24) are formulated in order to relate the proportion, M_{iqb} to the incentive amount SM_{iq}. Table 5.3 summarizes this relationship for each of the four possible combinations of χ_{iqb} and μ_{iqb} values.

Table 5.3: Possible χ_{iqb} and μ_{iqb} assignments for M_{iqb} and SM_{iq}

χ_{iqb}	μ_{iqb}	SM_{iq}		M_{iqb}		Outcomes
				Const.23	Const.24	
1	0	Constraint 19	Constraint 21	≤ 0	≥ 0	$M_{iqb}=0$
0	1	Constraint 20	Constraint 22	≤ 1	≥ 1	$M_{iqb}=1$
0	0	Constraint 20	Constraint 21	≤ 1	≥ 0	$0 \leq M_{iqb} \leq 1$

| 1 | 1 | Constraint 19 | Constraint 22 | ≤ 0 | ≥ 1 | Infeasible |

In the meantime, constraints (25) and (26) are active only when $\chi_{iqb} = 0$ and

$\mu_{iqb} = 0$, which indicates that $M_{iqb} = [SM_{iq} - (CS_i XM_b) - LM_{iq}]/[HM_{iq} - LM_{iq}]$.

The constraints are redundant when either $\alpha_{iqb}=1$ or $\delta_{iqb}=1$.

$$M_{iqb} \leq [SM_{iq} - (CS_i XM_b) - LM_{iq}]/[HM_{iq} - LM_{iq}] + W(\chi_{iqb} + \mu_{iqb}),$$

$$i=1,...,n, \ q=1,...,n_q, \ b=1,...,n_b \qquad (25)$$

$$M_{iqb} \geq [SM_{iq} - (CS_i XM_b) - LM_{iq}]/[HM_{iq} - LM_{iq}] - W(\chi_{iqb} + \mu_{iqb}),$$

$$i=1,...,n, \ q=1,...,n_q, \ b=1,...,n_b \qquad (26)$$

Constraints (27 – 29) imply that no product can be returned using a particular

collection method if the method is not chosen:

$$D_{iqb} \leq \sum_{k=1}^{n_k} XD_{bk}, \qquad i=1,...,n, \ q=1,...,n_q, \ b=1,...,n_b \qquad (27)$$

$$P_{iqb} \leq \sum_{k=1}^{n_k} XP_{bk}, \qquad i=1,...,n, \ q=1,...,n_q, \ b=1,...,n_b \qquad (28)$$

$$M_{iqb} \leq XM_b, \qquad i=1,...,n, \ q=1,...,n_q, \ b=1,...,n_b \qquad (29)$$

Constraint (30) indicates that collections of returned products using either the

drop-off or pick-up method cannot exceed the available capacity of each selected

collection centre.

$$\sum_{i=1}^{n}\sum_{q=1}^{n_q}\sum_{b=1}^{n_b}(T_{iqb}D_{iqb}XD_{bk} + T_{iqb}P_{iqb}XP_{bk}) \le KD_k \ , \ k=1,...,n_k \tag{30}$$

Constraint (31) determines the number of vehicles that will be needed if the pick-up method is chosen as the collection method for a certain amount of returned products.

$$(\sum_{i=1}^{n}\sum_{q=1}^{n_q}T_{iqb}P_{iqb}XP_{bk}) / KV = V_{bk} \ ,b=1,...,n_b, \ k=1,...,n_k \tag{31}$$

Constraint (32) implies that the total amount of each type of product collected using the pick-up, drop-off and mail return methods must satisfy the minimum collection rate requirement for the product.

$$\sum_{q=1}^{n_q}\sum_{b=1}^{n_b}[T_{iqb}(P_{iqb} + D_{iqb} + M_{iqb})]/TA_i \ge XR_i, \ i=1,...,n \tag{32}$$

Constraint (33) is a non-negativity constraint for the number of vehicles to transport returned products.

$$V_{bk} \ge 0 \ , \quad b=1,...,n_b, \ k=1,...,n_k \tag{33}$$

Constraint (34) sets the non-negativity requirement for the incentives and product return proportions, and the upper limit for the product return proportions.

$$P_{iqb}, D_{iqb}, M_{iqb}, SP_{iq}, SD_{iq}, SM_{iq} \ge 0 \text{, and } P_{iqb}, D_{iqb}, M_{iqb} \le 1$$

$$i=1,...,n, \ q=1,...,n_q, \ b=1,...,n_b \tag{34}$$

Constraint (35) specifies the binary variables.

$$Y_k, XP_{bk}, XD_{bk}, XM_b, \alpha_{iqb}, \delta_{iqb}, \beta_{iqb}, \rho_{iqb}, \chi_{iqb}, \mu_{iqb} \in \{0,1\},$$

$$i=1,...,n, \quad q=1,...,n_q, \quad b=1,...,n_b \ k=1,...,n_k \tag{35}$$

5.5 Computational test

The proposed model is tested using a set of 10 small experimental problem instances. The parameters in these instances are $n = 2, n_q = 2, n_b = 4, n_k = 2$. The other main data of these instances are presented in Table 6.1 in the next chapter. The model was coded using C++ programming language and solved using the nonlinear programming software, LINGO10. The experiment was carried out on a PC with an Intel Core i5 3.2GHz CPU and 4 GB RAM.

The results for the instances are shown in Table 5.4.

Table 5.4: Results for Small Problem Instances

Problem instance	*Optimal objective values*	*Computation times (in seconds)*
1	194263.09	412.34
2	169450.59	765.54
3	111735.90	217.84
4	245368.90	480.00
5	193123.41	118.36
6	189470.30	78.33
7	236195.90	378.51
8	212202.09	2080.81
9	212171.80	2649.25
10	211388.00	394.60

The results shown in Table 5.4 indicate that for problems with this size (4 customer zones), the model can be solved to optimum in about 12 minutes on average. This shows that the model is useful to find optimal solutions for small problem instances. We also tried to solve the model for larger problem instances. However, it was difficult to find solutions for medium and large problem instances in a relatively shorter time. The difficulty to solve the problems is obvious particularly for medium and large instances. This is due to the

characteristic and size of the proposed model. The model is not only large but also contains integer variables. For small problem instances, it contains 60 integer variables. In addition, the model is a nonlinear model which is much difficult to solve than linear models. That is why it takes more than 10 minutes on average to solve the model for even the small instances, and for some instance it is more than 40 minutes. For medium instances, the number of integer variables increases to 313, and the model for larger problem instances contains 705 integer variables. Integer programming models, even the linear ones, are NP-hard problems which are well known for its difficulty to solve. As the number of integer variables increases, the computation time required increases exponentially. The substantial increment in the number of integer variables has made the medium and large problem instances difficult to solve. This indicates the need for a heuristic approach to enhance the practicality of the model and increase chances of solving medium and large problem instances quickly.

5.6   Summary

This chapter presented analysis on product return channels with further specification on the collection methods namely drop-off, pick-up and mail delivery return. A mixed integer nonlinear programming model is developed and tested to find optimal allocation of the collection methods that will eventually generate maximum profit. The model was also purposely designed to illustrate the potential integration of the three collection methods in a single model, which is one of the novel contributions of this study. The model was also addressing mail

return which had hardly been examined in previous studies on product return channels. To demonstrate the model's potential and usability, the proposed model was then tested using experimental data.

The result shows that the integration of the abovementioned collection methods was possible. This could be beneficial particularly for organizations that are capable of offering all three collection methods. Having a possibility of offering all collection methods to the customers also means a higher probability of getting better product return rates. Subsequently, generating maximum profit from the recovery activities would be attainable as well. However, the problem is an NP-hard problem and contains substantial number of integer variables. As the problem size increases, the computation time needed to solve the model would increase exponentially. Therefore, the exact method was unable to solve medium and large problem instances in reasonable times. Hence, the need for heuristics approach is evident. The next chapter will elaborate a heuristic algorithm to find solutions to the problems. Nevertheless, the proposed model depicted in this chapter has shown significant promises and its potential contribution has also been highlighted.

CHAPTER 6
HEURISTIC SOLUTION: A LAGRANGIAN RELAXATION METHOD

6.1   Introduction

This chapter discusses the development of a heuristic algorithm to solve the problem that was addressed in the previous chapter. Specifically, this chapter discusses the use of the Lagrangian relaxation algorithm to solve the problem of assigning collection methods to customer zones. The algorithm is proposed in order to find good, feasible solutions to larger problem instances. The failure of the exact method to obtain an optimal solution for larger problem instances is one of the motivations to employ the algorithm. The algorithm is tested on different sized problem instances. The results are discussed and subsequent concluding remarks are presented at the end of this chapter.

6.2   Overview of the method

In this study, the Lagrangian relaxation method is used because the problem is difficult to solve (NP-hard) and involves a substantial amount of computation time when tested using large scale data. The problem size is considerably large involving many complicating constraints. As discussed in Chapter 3, the Lagrangian relaxation method is already a proven and effective method for solving location-allocation problems. Most of the previous researches dealt with

mixed integer linear programming problems, whereas this study deals with a mixed integer non-linear programming problem.

6.3   Relaxation of the problem

In order to relax the problem, complicating constraints need to be removed and incorporated into the objective function. The selected constraints for relaxation are the capacity constraints and the minimum collection rate constraints. By dualizing the capacity constraints, the problem becomes an uncapacitated facility location-allocation problem. This situation enables each collection centre to receive as many returned products as possible without restriction as to its capacity. Relaxing this constraint would make the problem less complicated and more solvable. In previous location-allocation problems in which the Lagrangian Relaxation method had been used, the capacity constraint was always the one that was selected for relaxation purposes (Erlenkotter, 1978; Klincewicz and Luss, 1986; Mazzola and Neebe, 1999; Fisher, 2004).

Recall that the initial objective function, (P$_1$), was as follows:

$$\text{Maximize } Z_{P_1} = \sum_{i=1}^{n} \sum_{q=1}^{n_q} \sum_{b=1}^{n_b} T_{iqb} P_{iqb} (R_{iq} - SP_{iq}) - \sum_{b=1}^{n_b} \sum_{k=1}^{n_k} [cv + 2CVD_{bk}]V_{bk} \; +$$

$$\sum_{i=1}^{n} \sum_{q=1}^{n_q} \sum_{b=1}^{n_b} T_{iqb} D_{iqb} (R_{iq} - SD_{iq}) - \sum_{k=1}^{n_k} C_k Y_k \; + \; \sum_{i=1}^{n} \sum_{q=1}^{n_q} \sum_{b=1}^{n_b} T_{iqb} M_{iqb} (R_{iq} - SM_{iq} - CM_i)$$

Referring back to the previous chapter, the capacity constraints were as follows:

$$\sum_{i=1}^{n}\sum_{q=1}^{n_q}\sum_{b=1}^{n_b}(T_{iqb}D_{iqb}XD_{bk}+T_{iqb}P_{iqb}XP_{bk}) \leq KD_k \quad , \quad k=1,\ldots,n_k$$

The above constraint stated that the amount of all the returned products collected via the drop-off and pick-up methods could not exceed the capacity of the opened collection centres. Let v_k be the Lagrangian multiplier, a non-negative variable, for the constraint related to centre k. With the constraints being relaxed, the term to be added to the objective function will be as follows:

$$\sum_{k=1}^{n_k}v_k[KD_k-\sum_{i=1}^{n}\sum_{q=1}^{n_q}\sum_{b=1}^{n_b}(T_{iqb}D_{iqb}XD_{bk}+T_{iqb}P_{iqb}XP_{bk})]$$

or

$$\sum_{k=1}^{n_k}KD_kv_k-\sum_{i=1}^{n}\sum_{q=1}^{n_q}\sum_{b=1}^{n_b}\sum_{k=1}^{n_k}T_{iqb}D_{iqb}XD_{bk}v_k+\sum_{i=1}^{n}\sum_{q=1}^{n_q}\sum_{b=1}^{n_b}\sum_{k=1}^{n_k}T_{iqb}P_{iqb}XP_{bk}v_k$$

The second constraint to be relaxed is the minimum collection rate constraint. This constraint requires the total amount of collected returned products via drop-off, pick-up and mail return to be greater than or equal to the minimum collection rates.

Earlier, the minimum collection rate constraint had been formulated as follows:

$$\sum_{q=1}^{n_q}\sum_{b=1}^{n_b}[T_{iqb}(P_{iqb}+D_{iqb}+M_{iqb})]/TA_i \geq XR_i, \quad i=1,\ldots,n$$

Let w_i be the multiplier for the constraint related to the product type i. With the constraints being relaxed, the term to be added to the objective function will be as follows:

$$\sum_{i=1}^{n} w_i (\sum_{q=1}^{n_q} \sum_{b=1}^{n_b} [T_{iqb}(P_{iqb} + D_{iqb} + M_{iqb})]/TA_i - XR_i)$$

Hence, the Lagrangian relaxed problem (LR_p) will become:

$$\textbf{\textit{Maximize }} Z_{LR} = \sum_{i=1}^{n} \sum_{q=1}^{n_q} \sum_{b=1}^{n_b} T_{iqb} P_{iqb} (R_{iq} - SP_{iq}) - \sum_{b=1}^{n_b} \sum_{k=1}^{n_k} [cv + 2CVD_{bk}]V_{bk} \quad +$$

$$\sum_{i=1}^{n} \sum_{q=1}^{n_q} \sum_{b=1}^{n_b} T_{iqb} D_{iqb} (R_{iq} - SD_{iq}) - \sum_{k=1}^{n_k} C_k Y_k \quad + \quad \sum_{i=1}^{n} \sum_{q=1}^{n_q} \sum_{b=1}^{n_b} T_{iqb} M_{iqb} (R_{iq} - SM_{iq} - CM_i) \quad +$$

$$\sum_{k=1}^{n_k} v_k [KD_k - \sum_{i=1}^{n} \sum_{q=1}^{n_q} \sum_{b=1}^{n_b} (T_{iqb} D_{iqb} XD_{bk} + T_{iqb} P_{iqb} XP_{bk})] +$$

$$\sum_{i=1}^{n} w_i (\sum_{q=1}^{n_q} \sum_{b=1}^{n_b} [T_{iqb}(P_{iqb} + D_{iqb} + M_{iqb})]/TA_i - XR_i)$$

subject to constraints (1 – 29), (31), (33– 34).

The remaining constraints in the related problem can be completely separated into different groups, one for each customer zone b. Most items in the objective function can also be separated according to b. Therefore, the relaxed problem can be decomposed into small sub-problems, one for each customer zone. The items related only to k are not associated to any b. To make sure the sum of the objective values of the sub-problems is an upper bound of the original

problem, all the items related to b and the items that are not related to any b but with a positive sign are included in the objective function of each sub-problem b. The sub-problems are much smaller and can be solved more efficiently.

The related problem LR_p is a relaxation of P$_1$. For any non-negative values of the Lagrangian multipliers, the optimal objective value of LR_p provides an upper bound to the optimal objective value of P$_1$. On the other hand, any feasible solution of P$_1$ gives a lower bound for the objective value of the optimal solution. An iterative procedure can therefore be developed to search for the best (minimum) upper bound and the best (maximum) lower bound so as to close the gap between them by updating the value of the Lagrangian multipliers. Once the gap is very small, the lower bound represents the solution that is very close to optimality. The process of updating the multipliers should be guided by bounds so that the relaxed solution becomes closer and closer to being feasible.

The calculation (and updating rules) of the multiplier values is based on the general rule of (Fisher, 2004):

$$u^{h+1} = u^h + t_h(Ax^h - b), \text{ where } h \text{ is the iteration number.}$$

Considering the constraints that have been selected to be relaxed, the multipliers are updated as follows.

$$v_k^{h+1} = v_k^h + ss[\ KD_k - \sum_{i=1}^{n} \sum_{q=1}^{n_q} (T_{iqb} D_{iqb} XD_{bk} + T_{iqb} P_{iqb} XP_{bk})]$$

and

$$w_i^{h+1} = w_i^h + ss[\sum_{q=1}^{n_q}\sum_{b=1}^{n_b}[T_{iqb}(P_{iqb} + D_{iqb} + M_{iqb})]/TA_i - XR_i]$$

where *ss* is a positive scalar step size and *h* is the iteration number. The calculation on the step size value is as follows:

$$ss = \frac{\lambda(Z_{LR}(v) - Z_{LB})}{\sum_{k=1}^{n_k}[KD_k - \sum_{i=1}^{n}\sum_{q=1}^{n_q}(T_{iqb}D_{iqb}XD_{bk} + T_{iqb}P_{iqb}XP_{bk})]^2 + \sum_{i=1}^{n}[\sum_{q=1}^{n_q}\sum_{b=1}^{n_b}[T_{iqb}(P_{iqb} + D_{iqb} + M_{iqb})]/TA_i - XR_i]^2}$$

Here $Z_{LR}(v)$ represents the objective value for the current solution of the relaxed model, LR_p with Lagrangian multipliers, v_k and w_i, Z_{LB} represents the best lower bound up to the current iteration; and λ is a scalar satisfying $0 < \lambda < 2$ (Held et al., 1974). Having determined the method for calculating the multipliers and the step size, the following section illustrates the complete algorithm.

6.4 Lagrangian Relaxation Algorithm

P_1 produces the optimal solution to the original problem. As it is a maximization problem, the objective value of the optimal solution, $Z_{P_1}^*$ is the maximum objective value among all the feasible solutions to the problem. Removing certain constraints, such as the capacity limitation for each collection centre, generates a higher objective value for the relaxed-problem (LR_p). Nonetheless, LR_p does not necessarily guarantee feasible solutions. So a heuristic needs to be developed to generate a feasible solution based on the

solution of LR_p. The objective value of the feasible solutions, (Z_{LB}), will be a lower bound for the optimal objective value $Z_{P_1}^*$. The gap between the lower and upper bounds will be used to direct the updating of the values of the multipliers with the aim of reducing the gap. As the multipliers are updated through iterations, both the lower and upper bounds will be improved towards the optimal objective value, and thus the gap between them will be minimized. The objective value of the best feasible solution in the process will be taken as the heuristic solution of the original problem. Overall, the algorithm is designed to minimize the gap between the upper and lower bounds. Graphically, this can be depicted by Figure 6.1.
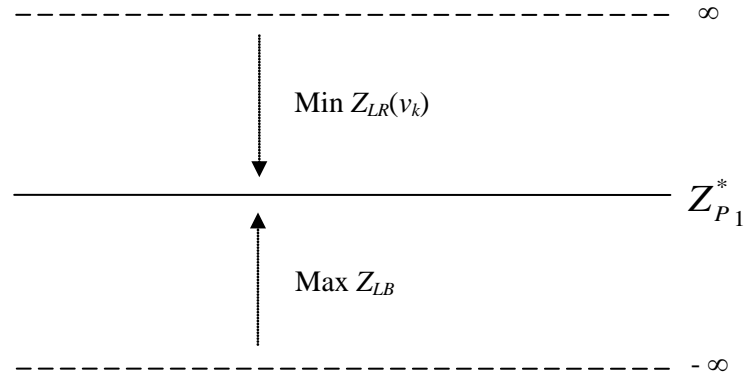
Figure 6.1: The convergence of lower and upper bounds to the optimal value

As shown in Figure 6.1, the initial value of Z_{LR} should be set to a very high value, while the initial value of Z_{LB} should be set to a very low value. The current value of Z_{LB} remains the best known objective value of the feasible solution, until a better feasible solution is found and becomes the new current

solution. The procedure of the Lagrangian relaxation algorithm for the problem understudy is presented below.

1. Initialize:

    a. Set the initial upper and lower bounds for the optimal objective value, $Z_{UB} = +\infty$, $Z_{LB} = -\infty$.

    b. Set the maximum number of iterations, N_{max}, and the target duality gap, ε.

    c. Set the initial iteration number h=0, and the initial Lagrangian multipliers, $v_k^h = 0$ for all k and $w_i^h = 0$ for all i.

2. Solve the Lagrangian relaxation problem and denote the resulting objective value as Z_{LR}. If $Z_{LR} < Z_{UB}$, let $Z_{UB} = Z_{LR}$.

3. Test the feasibility of the Lagrangian relaxed solution for both constraints. If it is not feasible, generate a feasible solution based on the relaxed solution (details will be presented in the next subsection). Denote the objective value of the feasible solution as Z_{feas}. If $Z_{feas} > Z_{LB}$, let $Z_{LB} = Z_{feas}$.

4. If $h >= N_{max}$ (the iteration limit is reached) or $(Z_{UB}-Z_{LB})/|Z_{LB}| <= \varepsilon$ (the target gap between the best UB and LB is reached), go to Step 6. Otherwise, update the multipliers:

$$v_k^{h+1} = v_k^h + ss[\, K_k Y_k - \sum_{i=1}^{n} \sum_{q=1}^{n_q} (T_i \, P_i \, X_{bb} + TD \, P_i \, X_{bb})$$

and

$$w_i^{h+1} = w_i^h + ss[\sum_{q=1}^{n_q}\sum_{b=1}^{n_b}[T_{iqb}(P_{iqb}+D_{iqb}+M_{iqb})]/TA_i - XR_i]$$

where

ss= *stepsize*, calculated using the following formula:

$$ss = \frac{\lambda(Z_{LR}(v)-Z_{LB})}{\sum_{k=1}^{n_k}[KD_k - \sum_{i=1}^{n}\sum_{q=1}^{n_q}(T_{iqb}D_{iqb}XD_{bk}+T_{iqb}P_{iqb}XP_{bk})]^2 + \sum_{i=1}^{n}[\sum_{q=1}^{n_q}\sum_{b=1}^{n_b}[T_{iqb}(P_{iqb}+D_{iqb}+M_{iqb})]/TA_i - XR_i]^2}$$

With λ being a scalar satisfying $0 < \lambda < 2$

5. Let h=h+1, go to Step 2.

6. Stop. The best feasible solution found is taken as the problem solution and its objective value is Z_{LB}. Z_{UB} is the best upper bound of the optimal objective value.

6.5   Generating feasible solutions

In Step 3 of the above Lagrangian relaxation algorithm, a feasible solution needs to be generated based on the solution of the relaxed problem. The following are the details for doing this.

First, check the collection rate constraints for each product *i*. If the constraint is not satisfied, increase the incentives for this product of all quality classes. Based on the new incentives, calculate the new proportion and amount of returns from all customer zones. With the new collection amount, check the

constraint again. If it is still not satisfied, increase the incentives again. Continue the process until the constraint is satisfied.

In the above process, the assignment of the collection method for each *b* is not changed. As the collection amount increases, more capacity constraints may be violated. The following steps further modify the solution to satisfy the capacity constraints. The basic idea is that if a collection centre is overloaded, choose the customer zone assigned to it which has the highest cost, and re-assign the customer zone to the mail return method. Repeat this until the capacity constraints are all satisfied.

1. Let k=1.

2. Test the feasibility of the capacity constraint for collection at centre *k*:

   If $\sum_{i=1}^{n}\sum_{q=1}^{n_q}\sum_{b=1}^{n_b}(T_{iqb}D_{iqb}XD_{bk}+T_{iqb}P_{iqb}XP_{bk}) \le KD_k$, go to step 6; otherwise proceed to step 3.

3. For each customer zone *b* :

   If XP_{bk}=1, let $Cost_{bk}=\sum_{i=1}^{n}\sum_{q=1}^{n_q}T_{iqb}P_{iqb}SP_{iq}+cv+2CVD_{bk}$;

   If XD_{bk}=1, let $Cost_{bk}=\sum_{i=1}^{n}\sum_{q=1}^{n_q}T_{iqb}D_{iqb}SD_{iq}$;

   If XM_{bk}=1, let $Cost_{bk}$=0.

4. Identify the *b* with the highest $Cost_{bk}$, and denote the corresponding *b* as *b'*.

5. Let $XP_{b'k}=0$, $XD_{b'k}=0$, $XM_{b'k}=1$; go to step 2.

6. If $k<n_k$, let $k=k+1$, then go to step 2; otherwise, a feasible solution has been found, and the objective function value of the feasible solution can be calculated as follows:

$Z_{\text{feas}}= Z_1 + Z_2 + Z_3$, with

$$Z_1= \sum_{i=1}^{n}\sum_{q=1}^{n_q}\sum_{b=1}^{n_b}T_{iqb}P_{iqb}XP_{bk}(R_{iq}-SP_{iq})-\sum_{b=1}^{n_b}\sum_{k=1}^{n_k}[cv+2CVD_{bk}]V_{bk}XP_{bk} ,$$

$$Z_2= \sum_{i=1}^{n}\sum_{q=1}^{n_q}\sum_{b=1}^{n_b}T_{iqb}D_{iqb}(R_{iq}-SD_{iq})XD_{bk}-\sum_{k=1}^{n_k}C_kY_k ,$$

$$Z_3 = \sum_{i=1}^{n}\sum_{q=1}^{n_q}\sum_{b=1}^{n_b}T_{iqb}M_{iqb}XM_{bk}(R_{iq}-SM_{iq}-CM_i)$$

6.6 Computational experiment settings

To test the Lagrangian relaxation algorithm, it was applied to solve 3 sets of problem instances representing small, medium and relatively large problem sizes. Each set consisted of 10 instances. In each small, medium and large problem, there were 4, 10 and 20 customer zones, respectively. The experiments were conducted on a PC with Intel Core i5 3.2GHz CPU and 4GB RAM. The algorithm was programmed using Microsoft Visual C++, and the software package, LINGO10, was used as a solver. To obtain a solution in a reasonable time, the maximum number of iterations was set as 10 in the experiments. The computation time taken to complete the whole algorithm was in seconds. As a maximization

problem, the upper bound (UB) referred to the objective function value of the relaxed solution, while the lower bound (LB) represented the best feasible solution. The relative gap between UB and LB was calculated as follows:

$$\text{Relative Gap} = \frac{UB - LB}{LB}$$

6.7   Small Problem Instances

Although all small problem instances are similar in terms of the number of customer zones, collection centres, quality classes and type of items, other parameters are different in values. For example, the total amount of returned products, the minimum recovery rate and the collection centre capacity vary from instance to instance in order to test the robustness of the proposed method under different circumstances. Table 6.1 shows three main types of problem data for all ten small instances. These are the amount of used products (TA_i), the capacity of each collection centre (KD_k), and the minimum collection rate for each type of product (XR_i). They are parameters in the relaxed constraints in the Lagrangian relaxation algorithm.

Table 6-1: Selected parameter values for small problem instances

	Data 1	Data 2	Data 3	Data 4	Data 5	Data 6	Data 7	Data 8	Data 9	Data 10
	$n = 2, n_q = 2, n_b = 4, n_k = 2$									
TA_i	4211 3639	4576 3854	4571 3401	3986 4232	3827 4768	4730 3975	4910 4507	4220 4588	5030 3706	4910 4507
KD_k	4317 3964	5353 5521	4464.3 5421	4355.5 4437.7	5500.8 6274.4	5048.9 5353.6	6450.6 5085.2	5637.1 5813.3	4979.5 5634.7	6450.6 5085.2
XR_i	0.59 0.59	0.75 0.55	0.63 0.67	0.82 0.60	0.70 0.68	0.88 0.55	0.66 0.87	0.80 0.64	0.84 0.60	0.66 0.87

Table 6.2 shows the results for these problem instances. The method generated fairly good solutions with an average relative gap of 0.309 or 30.9%. The average solution time was about 2 minutes.

Table 6-2: Lagrangian heuristic results for small problem instances and comparison with the optimal solutions

HEURISTIC SOLUTIONS					ORIGINAL MODEL		
Problem Number	Objective in solution	Upper Bound	Relative Gap	Computation time (seconds)	Optimal Solutions	Relative Gap	Computation time (seconds)
1	146220.75	203542.31	0.392	159.14	194263.09	0.247	412.34
2	123152.72	179167.2	0.455	125.06	169450.59	0.273	765.54
3	84534.34	117587	0.391	104.91	111735.9	0.243	217.84
4	206015.25	245437.31	0.191	140.16	245368.9	0.160	480
5	166590.22	221786.53	0.331	88.34	193123.41	0.137	118.36
6	184047.58	216575.44	0.177	98.09	189470.3	0.029	78.33
7	195426.02	238442.44	0.22	156.05	236195.9	0.173	378.51
8	201894.75	233874.61	0.158	135.23	212202.09	0.049	2080.81
9	133962.16	218383.59	0.63	156.66	212171.8	0.369	2649.25
10	196947.75	224771.09	0.141	112.69	211388	0.068	394.6
Average			0.309	**127.63**		**0.175**	**757.56**

These small problem instances were solved optimally in Chapter 5 using the original model. It took 12.6 minutes to solve an instance. So the heuristic was much faster than that. Note that the relative gap for the heuristic solution was between the lower and upper bounds, using the lower bound as a base. The optimal solution was between the lower and upper bounds. The heuristic results can be compared with the optimal solution. Using the optimal solution as a base, the heuristics solution is 17.5% away from the optimal. Some of the heuristic solutions were also very close to the optimal solutions. So the actual performance of the heuristic solution was better than the relative gap suggested.

6.8   Medium-sized Problem Instances

After testing with small-sized problem instances, the proposed algorithm was then examined using the medium-sized instances containing ten customer zones and three collection centres. The number of product types and the number of quality classes remained the same. Table 6.3 illustrates the main parameter values (TA_i, KD_k and XR_i) for all ten medium instances.

Table 6-3: Selected parameter values for medium problem instances

	Data 1	Data 2	Data 3	Data 4	Data 5	Data 6	Data 7	Data 8	Data 9	Data 10
	$n = 2, n_q = 2, n_b = 10, n_k = 3$									
TA_i	8510	11508	9527.0	9614.0	9403.0	8992.0	9435.0	10507.0	11133.0	10438.0
	9946	10853	9531.0	10018.0	9590.0	8830.0	9876.0	10639.0	8971.0	10621.0
KD_k	8059.1	10658.7	7813.8	9488.8	7217.3	7722.9	8175.0	10220.6	9515.9	10248.7
	6828.7	10807.8	6797.4	7263.8	9053.3	8376.3	7853.1	7260.1	7706.5	8634.2
	7197.8	7528.2	8766.7	7329.3	9306.6	8673.4	9462.4	9092.8	9113.8	9336.2
XR_i	0.73	0.68	0.81	0.72	0.56	0.66	0.85	0.77	0.79	0.77
	0.82	0.83	0.61	0.87	0.71	0.64	0.55	0.71	0.65	0.51

The solution results are shown in Table 6.4. The results show that the proposed algorithm was capable of generating solutions with an average computation time of less than 11 minutes. This is a short time, considering that the original model could not get a solution in hours. On average, the relative gap for the medium instances was 0.437 or 43.7%. This looks quite large. But as was seen from the results of the small problems, the heuristic solution could be much closer to the optimum than this gap because the upper bound may not be tight. Recall that the maximum iteration was set to 10. In practice, if we are facing one problem, we can afford more time to solve it. By setting a larger iteration limit, we should be able to obtain better solutions.

Table 6-4: Lagrangian relaxation: results for medium problem instances

Problem Number	Objective in solution	Upper Bound	Relative Gap	Computation time (seconds)
1	434747.38	579389.63	0.333	577.96
2	352572.25	416372.44	0.181	653.31
3	302032.00	553059.56	0.831	472.20
4	277539.34	367424.25	0.324	559.45
5	591994.19	648105.69	0.095	415.64
6	306221.41	393897.06	0.286	750.55
7	418249.88	527827.44	0.262	570.37
8	388068.44	502217.81	0.294	561.51
9	372708.00	528377.81	0.418	661.55
10	110973.67	260934.19	1.351	1280.98
Average			0.437	650.35

6.9   Large Problem Instances

The Lagrangian relaxation algorithm was further tested on large problem instances, which have a number of customer zones that are twice as many as those in the medium instances. The problem was thus bigger and even more complicated. The following Table 6.5 lists the main parameter values (TA_i, KD_k and XR_i) for all ten medium instances.

Table 6-5: Selected parameter values for large problem instances

	Data 1	Data 2	Data 3	Data 4	Data 5	Data 6	Data 7	Data 8	Data 9	Data 10
	$n = 2, n_q = 2, n_b = 20, n_k = 5$									
TA_i	20570.0	18731	19694.0	19253.0	18648.0	20886.0	19150.0	21310.0	19468.0	18830.0
	20156.0	18012	19976.0	18859.0	17981.0	18434.0	18377.0	21192.0	20459.0	18185.0
KD_k	8633.9	9259.2	11186.9	9528.0	10256.1	11009.6	8706.3	11985.6	8225.0	7773.1
	9041.2	8083.5	8251.4	8689.5	9889.8	8886.3	9606.9	9350.4	8624.2	8883.6
	11321.8	9553.2	8965.4	10900.0	8497.9	8965.0	10582.6	8840.4	10940.0	9846.0
	9529.9	9773.6	7934.0	10900.0	8424.7	11324.2	7505.4	11815.6	9662.3	10216.1
	10425.9	7936.5	9124.1	9375.6	10695.7	11166.9	9757.0	10455.5	8065.3	10512.3
XR_i	0.87	0.81	0.58	0.82	0.71	0.81	0.62	0.78	0.59	0.78
	0.62	0.61	0.75	0.80	0.58	0.51	0.84	0.68	0.67	0.78

Table 6.6 presents the solution results. The results show again that the algorithm could generate reasonably good solutions with an average computation time of about 20 minutes. The relative gap on average was 0.449 or 44.9%. Considering that the size of the problem was much larger than the medium problems and that the iteration limit was still 10, it was very encouraging to observe that the relative gap remained similar and that the computation time had not increased very much. This indicated that the performance of the heuristic method was not affected much by the problem size, and that the method could be used to solve even larger problems. Again, the solution could be much closer to the optimum than the gap because the upper bound may not be tight. If time permitted, better solutions could have been obtained by setting a larger iteration limit.

Table 6.6: Lagrangian relaxation: results for large problem instances

Problem number	Objective in solution	Upper Bound	Relative gap	Computation time (seconds)
1	839327.63	1043003.44	0.243	1162.08
2	675431.88	878991.56	0.301	1194.66
3	669028.44	1181626.38	0.766	1034.83
4	634506.19	1058359.25	0.668	946.32
5	517666.09	708200.38	0.368	1160.82
6	618763.00	777284.31	0.256	1237.92
7	455850.19	621258.00	0.363	1582.50
8	462926.06	724827.06	0.566	1535.21
9	814666.13	1332931.13	0.636	880.86
10	554066.56	734467.63	0.326	1285.29
Average			0.449	1205.05

6.10 Summary

This chapter discussed the potential application and performance of the proposed Lagrangian relaxation method. Based on the model built in the previous chapter, a Lagrangian relaxation heuristic algorithm was proposed and then tested on three sets of problem instances in order to examine its applicability and performance. The instances represented three different problem sizes. Based on the results, it can be concluded that the proposed heuristic algorithm is capable of generating reasonably good solutions and bounds within a relatively short computational time. Although for larger instances the relative gaps were quite large, the solution should

be closer to the optimal solution. The relatively short computational time suggests that better solutions could be obtained by setting a larger limit on the number of iterations.

CHAPTER 7
DISCUSSIONS AND FUTURE WORK

7.1 Introduction

This chapter presents the discussion part of the dissertation. The discussions are divided into two main sections, which are (1) product recovery options, and (2) product return channels. Discussions on the Lagrangian relaxation findings are also presented. The discussions address mainly the managerial implications of the results as well as the benefits and the strengths of each model. Nonetheless, the weaknesses and the potential area of improvement for each model are also highlighted.

7.2 Product Recovery Options

In Chapter Four, the goal was to optimize the selection of the product recovery options. A linear programming model was developed to achieve the aforementioned goal. Important factors such as demand uncertainty and variable supply distribution were also considered in the equation. The returned products were graded into five quality classes prior to the assignment. Once graded, each returned product would then be assigned to any one of the five recovery options. In contrast with the standard allocation, the model presented in this study promotes a flexible assignment of returned products. Each graded returned product may be assigned to any recovery option that is available and which is feasible for it.

In a standard fixed allocation, the assignment is based on "$q = r$" in which 'q' represents the quality class of an item, and 'r' refers to the type of recovery option. This assignment is very simple and straightforward. If a returned product is suitable for the recycling option (graded as recyclable product after inspection), then it must go for that recovery option. Similarly, a repair option should be selected if a returned product is graded as repairable (minor cosmetic defects). Hence, that product will undergo minor repair jobs and the final output is a repaired item with no quality enhancement or improvement. It is not only that the standard fixed allocation may give an infeasible solution when the variability of the supply distribution is high and the demand constraint is tight, but the policy also lacks flexibility to manoeuvre and improve the firm's production strategy to meet an unexpected surge of demand over certain recoverable items or to satisfy emerging patterns among consumers.

The problem deepens if the amount of returns is imbalanced among the quality classes. For instance, if the post-inspection period identifies that almost 80% of the returns in the first quarter of the year are recyclable items and the rest of the pack is a mixture of other quality classes, then for that time frame most of the firm's output is recycled materials (80%). The firm may lose substantial opportunities to gather more profit if the demand for better second hand products (remanufacturable or refurbishable products) increases during the corresponding period. The amount of potential profit from this situation may well surpass the incremental cost of upgrading the items.

Another pressing issue is the uncertainty over product returns in terms of both quantity and quality distribution. At the same time, the demand for recoverable items is also ambiguous. Hence, it is not easy to predict the customers' demand pattern and determine what type of recoverable items they prefer. In terms of quality categorization, no one can forecast accurately the actual quality (as well as quantity) of the incoming supply distribution. In some periods, the firm may receive more recycle-type of product returns. In some other timeframe, most of the returns may well be the repairable-type or remanufacturing-type of products. Hence, a flexibility policy is paramount, especially when the firm is dealing with higher uncertainty over supply and demand distributions. The best place to implement the standard fixed allocation policy is when the variability of demand and supply distributions are low and the firm possesses adequate necessary information over the two mentioned distributions.

In the meantime, a comparison of the fixed and flexible allocation was carried out to demonstrate the potential contribution of the latter policy. Based on the results in Chapter Four, it has been shown that a flexible allocation generates an average benefit of almost 10% on all tested problem instances. The average benefit is only between 4.45 – 4.50% when the demand constraint is very tight. The benefit increases dramatically to almost 13% when the demand constraint is relaxed at level 3 (please refer to Table 4.6). The difficulty in generating a feasible solution when the variability in the quality distribution of the returned products is high also shows the limitation of the fixed allocation policy. The findings conclude that the more relaxed the demand constraint is and the more

varied the quality of the supply distribution is, the better the flexible allocation policy.

The potential contribution of the flexible allocation policy is very promising. Yet most of the previous studies focused on the standard fixed allocation policy (Krikke et al., 1998; Krikke et al., 1999; Inderfurth et al., 2001; Mangun and Thurston, 2002; Teunter, 2006). Other researches related to the selection of product recovery options narrowed their scope either into 'end-of-life' items only (Bufardi, Gheorghe, Kiritsis and Xirouchakis, 2004; Staikos and Rahimifard, 2007a; Staikos and Rahimifard, 2007b, Chan, 2008; Iakovou, Moussiopoulos, Xanthopoulos, Achilllas, Michailidis, Chatzipanagioti, Koroneos, Bouzakis and Kikis, 2009) or 'end-of-life' items with limited recovery options (Jorjani, Leu and Scott, 2004; Tan and Kumar, 2008; Xanthopoulos and Iakovou, 2009).

However, the importance of a flexible recovery assignment has recently been acknowledged in some recent studies. Wadhwa, Madaan and Chan (2009), Krikke (2011) and, Li and Tee (2012) highlighted the benefit of flexible decisions in a reverse logistics system, particularly with regard to the assignment of recovery options. As for this study, the proposed model is very much capable of generating a beneficial and useful solution for both academicians and practitioners, especially as a stepping stone for a much more comprehensive model. However, it has to be admitted that more work can be done to strengthen and improve the model.

First, the model excludes disposal as one of the available options. The assumption that all returned products are recoverable may not be entirely practical due to the inconsistency of the supply distribution. In some cases, some of the returns may not be feasible to be recovered using any of the recovery options due to the severe condition of the items. In other words, the cost to recover such items may be too high and infeasible. Hence, disposing such items may be the best option albeit the last resort. This option not only saves costs but also preserves the resources capacity for other items with much better quality conditions. From the modelling point of view, this variable (disposal option) can be easily incorporated into the model, if necessary. Nevertheless, changes will be made to the relevant costs, and the one that should be considered in this situation is a 'regret cost' or 'loss of opportunity cost'. If an item is allocated to the disposal option, then no profit can be attained as no corresponding item has been recovered. Hence, a 'loss of opportunity cost' represents both penalty charges and a firm's inability to generate potential revenue from a supposedly recovered item. However, a mechanism is required to systematically determine and quantify such a cost.

Secondly, although the model allows each graded item to be allocated into any recovery options (flexible allocation), it is only applicable if the allocation is feasible. In other words, there may be some instances where a flexible allocation generates an infeasible solution. For example, an item with a very poor quality condition that may only be best recycled or even disposed of, may not be feasible to be recovered using refurbishment or remanufacturing options. The question is, how can we determine how flexible an item is to be recovered and to what extent

can an infeasibility allocation be determined accurately when the demand for recovered items varies (for each quality classes and recovery options)? To what extent can an item be upgraded as much as the firm wants? Likewise, how can it be determined quantitatively whether a good quality item can be downgraded as far as the firm wants? The abovementioned issues present a challenge and further consideration is needed on how to incorporate them into the model. From the modelling point of view, a set of feasible recovery methods can be defined for each category of returned products, or an infinite cost can be assigned to the infeasible options. The challenge is to determine the feasibility of the recovery options for each quality class before using the model.

Third, the availability of the five recovery options depicts the firm's ability to carry out all the options in-house. In practice, not all firms are capable of doing this nor do they have sufficient facilities to implement it. Hence, some firms 'outsource' selected recovery options to other firms specializing in particular methods such as recycling (independent recyclers), cannibalization (independent dismantlers) and remanufacturing (independent remanufacturers). Some firms even use third party logistics providers, brokers or agents to not only collect returned products but also to sell them to the end users. The reasons why the firm uses such intermediaries or other external firms are (1) to minimize the re-processing costs and (2) to concentrate resources towards their core business processes. Certain recovery options, such as recycling, need a huge initial investment to setup all the necessary facilities. Thus, only a substantial amount of product returns can compensate the huge outlay which is not guaranteed, given the inconsistent nature of the supply distributions. Further research should be

carried out to examine the impact of the abovementioned external parties on the performance of the flexible allocation policy. The inclusion of these external parties may strengthen the practical aspects of the proposed model. Hitherto, the flexible policy has not been scrutinized in a situation where not all the recovery options are available in-house, and where the firm is forced to use external services or outsourcing options.

Nevertheless, the proposed linear programming model in Chapter Four represents a practical solution approach in product recovery strategy. The strength of the model lies in its ability to find feasible solutions in difficult supply and demand situations in a very short computational time. It can also be summarized that the flexible assignment contributes significantly to the increment in profit as compared to the fixed allocation policy. The benefit of the flexible assignment is even greater when the demand constraint is relaxed and the variability in the quality distribution of the returned products increases. If penalty charges were imposed for not satisfying demand constraints, then the benefit of flexible allocation will be more momentous, especially when the variability of the supply quality is large. However, the model proposes a more comprehensive quality classification scheme as returned products are graded into five classes.

Classifying returned products into five quality grades (exclusive of the disposable grade) requires significant investment in labour, time and inspection costs. Uncertainty over the quality level of returned products makes this task even more difficult, particularly when dealing with larger return volumes. Apparently, the uncertainty in the quality of returned products translates into variabilities in

remanufacturing costs and lead times (Aras et al., 2004). Nevertheless, a rigorous quality classification scheme is needed to further utilize the benefits of a flexible allocation policy. As pointed out by Aras et al. (2004), incorporating the quality of returned products in the decision process enables the firm to develop more intelligent product recovery and disposal policies as well as to achieve larger cost savings.

7.3   Product Return Channels

In Chapter Five, the examination was around three collection methods and how to optimally use them to collect returned products from customer zones. Previous research on product return channels focused more on other 'general' return networks such as centralized and decentralized, and direct or indirect return networks (Savaskan and van Wassenhove, 2006; Karakayali et al., 2007; Shulman, Coughlan and Savaskan, 2010). Only several researches studied the abovementioned collection methods albeit focusing on a different scope and approach than this study (Wojanowski et al., 2007; Aras and Aksen, 2008; Aras et al., 2008; Min and Ko, 2008; Sasikumar et al., 2010; Wei and Zhao, 2013).

In this study, three collection methods, namely drop-off, pick-up and mail return delivery, were used to collect returned products from the customer zones. The primary goal was to find the optimal way of allocating the collection methods to a particular customer zone so as to maximize returns and profit. The model also determined the amount of incentives for each selected allocation in order to encourage better product returns from the customers. The location of the collection centres and the proportion of product returns were addressed in the

model. The novel idea of the proposed model in this study is the integration of the three collection methods and the empirical investigation of the mail return method. To the best of the researcher's knowledge, this study pioneers the incorporation of the three collection methods in a single model. The lack of study on the mail return method is also another pressing factor.

Nevertheless, not many firms may be able to facilitate three collection methods simultaneously. The costs of offering these facilities such as the handling and setup costs (drop-off) of the collection centre, and the related transportation costs (pick-up), are relatively high. Hence, many firms prefer to outsource some, if not all, of the collection jobs to third party collectors (Sohail and Sohal, 2003; Karakayali et al., 2007). In some cases, the firm prefers intermediaries, such as retailers, to collect the returned products for them (Savaskan and Van Wassenhove, 2006; Shulman, Coughlan and Savaskan, 2010). These retailers offer drop-off facilities at their premises to the consumers to return their products. However, as more countries around the globe legally implement the extended producer responsibility (Mansour and Zarei, 2008), more firms are beginning to realize that product recovery is no longer a burden, but an opportunity to make profits from a new avenue. Hence, some firms prefer to have direct control over the collection of returned products to better manage and improve the collection rates. Subsequently, having the three collection methods simultaneously is a good option as long as it is feasible.

In the meantime, the generic nature and the usability of the proposed model are also under scrutiny, particularly in terms of the returned products'

applicability. Since the model combines three collection methods together, it should be equally applicable for all of them. The problem occurs when some products are only suitable to be collected using one or two methods. For instance, bulky items, such as large freezers and used cars, are not feasible for mail return delivery. So, the applicability of the model is therefore limited to the returned products that can be collected using any of the three methods. Otherwise, the model should be modified to cater for returned products with different 'preferences' over the collection methods. In this case, it is suggested that different weights or a special grouping system be used to differentiate between the sizes of the returned products. Then constraints can be set to limit the choices for each sized group.

In terms of the allocation rules, the first constraint declares that each customer zone can be assigned with only one collection method. In practice, it is difficult to actually dictate customers' preferences over which collection method is the best for them. Within the same zone, some customers may prefer to mail their returns, while others may opt for a different collection method. As in the model, the only thing that a firm can do is to influence the return preferences via different incentive schemes as well as to provide nearby collection facilities at the selected customer zones. The fruitfulness of this approach is not practically guaranteed. In the meantime, it is mathematically complicating to offer flexible collection methods for customers in the same zone. A mechanism allowing a certain degree of mixed collection methods within the same zone requires further investigation. For instance, for customer zones assigned with the drop-off method, customers are also allowed to mail their returns (if they wish to).

In the meantime, the model allows customers to go to the collection / drop-off centre to return their products (drop-off method) or the firm to collect the returned products from the customers' premises and put them temporarily at nearby collection or drop-off centres. Then, all the returned products (in a certain time frame) are sent to the main recovery facility. However, it is still ambiguous as to whether the collection or drop-off centre should best belong to the firm. In practice, some collection or drop-off centres are operated by independent organizations such as municipal councils or retailers, such as Tesco. These organizations offer drop-off facilities and charge the firm for every returned item. There are no setup and handling costs for the firm, but there are higher buyback fees. On the other hand, privately owned collection or drop-off centres cost the firm both setup and handling expenses. However, this facility offers no buy-back fees or direct control over the collection jobs. As for the proposed model, the collection or drop-off centres are assumed to be operated by the firm. All collection jobs as well as the transportation vehicles are also operated by the firm. Further investigation should be carried out to determine the impact of the former approach (collection or drop-off centres and the transportation vehicles operated by independent organizations). Comparatively, the economical values and efficiencies of both approaches should be evaluated.

The model was tested using a set of experimental data. The results show that the proposed model is beneficial. Nevertheless, it is also understandable that the mail return method is only suitable for small or medium-sized items. In such situations, the model can be revised by fixing some variables to prevent the mail return channel from being considered for some product types.

7.4 The Lagrangian Relaxation Method

In Chapter Six, the Lagrangian relaxation method was used to obtain feasible solutions to the original problem that had been solved earlier using a software package. The aim was to generate good bounds and good feasible solutions in fairly short computational times. By relaxing some constraints, the relaxed model could be decomposed into smaller sub-problems which could be solved more easily. The method enables decision makers to find feasible solutions for larger problems within reasonable computation times.

Based on the test of three sets of problem instances with different sizes, the proposed Lagrangian relaxation approach did produce reasonably good solutions in a short time. As expected, the average computation times were increasing as the size of problem instances were getting bigger. Nevertheless, the feasible solutions for all the large instances were successfully obtained in about 20 minutes on average. On the contrary, the exact method failed to generate an optimal solution for even the medium-sized instances in hours. For small instances with a known optimal solution, the proposed algorithm generated feasible solutions which were not far from the optimum in approximately just 2 minutes.

The Lagrangian relaxation method has proven to be effective in enhancing the practicality of the proposed model, particularly in situations where the exact method fails to deliver. The significant benefit of the Lagrangian method has been more obvious with an increasing problem size.

Nevertheless, there are some limitations that may affect the solutions generated from the proposed method.

1. The examination of the proposed Lagrangian relaxation method would also have been more comprehensive had it included other heuristic methods for further comparison, such as the Tabu search and the genetic algorithm.

2. The usage of real data from the industry would have further enhanced the credibility of the solution. However, this research opportunity will be left to be done in the future.

7.5   Summary

This chapter presented discussions on the findings of each of the previous three chapters. Each model and problem was analysed, highlighting the strength and limitations of each of the proposed models and solutions. In the product recovery options, the huge potential and the novel idea of flexible allocation was highlighted. The contributions and benefits of the MINLP model and the Lagrangian solution approach were also addressed for the product return channel selections.

CHAPTER 8
CONCLUSIONS

8.1   Introduction

This chapter presents the overall conclusions of the dissertation by revisiting the previous chapters and the research findings. The conclusions are based on the three research objectives that were presented in the first chapter. The linkages between the research objectives and the research findings are also discussed. The strengths and contributions of the study are also pointed out in order to reinforce the potential of the research.

8.2   Product recovery options

In the first chapter, it was highlighted that two of the most important components within the reverse logistics network are product return channels and product recovery options (re-processing activities). The two components are inter-related and are significantly important for those players actively involved in the reverse logistics business. Nevertheless, it was also evident that there is a need for further investigation into both components. Hence, three research objectives were drawn to investigate the matter.

On the product recovery options, the aim is to examine the potential benefit of allowing flexibility in the allocation of product recovery options. In line with the corresponding research objective, a linear programming model was developed to address the problem of assigning returned products of various quality

conditions to multiple recovery options under the aforementioned flexibility policy. The model was then tested using a set of experimental data.

The results show that the model is capable of generating an optimal solution under various supply and demand distributions. The strength of the model lies in its ability to obtain optimal feasible solutions under difficult supply and demand conditions in a very short computational time. The proposed model managed to demonstrate the benefit of a flexible allocation approach. Different scenarios of demand and supply quality have been presented to reiterate the benefit. In a scenario where the variability of the supply quality is higher, and the demand constraint is tighter, the benefit of allowing flexibility in product recovery decisions is greater. If a penalty is imposed for failing to satisfy certain demands, then the benefit of the flexible allocation approach is even more appealing. In all, the model has illustrated its potential for use in industry and has proven to be a valuable addition to the existing body of knowledge.

Nevertheless, there is a need to include other relevant parameters and variables, considering the 'limited coverage' of the model on certain issues such as the processing capacity, forecasting and related inventory management of the plant. The model can also be easily modified to accommodate disposal as another addition to the existing recovery options. However, a penalty cost should be imposed for choosing the disposal option in order to encourage more recovery activities. In a scenario where the demand is tight, a penalty charge can also be incorporated to further illustrate the benefit of allowing flexibility in product recovery options.

8.3 Product return channels

As depicted earlier, product return channels form another important component within the reverse logistics network. As the function of this component is about collecting returned products, its performance is crucial for other components within the network, such as the recovery activities. In Chapter One, it was highlighted that the empirical evidence on the three collection methods (drop-off, pick-up and mail return) remains limited. Investigations into mail return are even more wanting. It was also acknowledged that some countries have already regulated minimum collection rates and mandated collection activities to the manufacturers. This scenario has put more pressure on the manufacturer and the collection component. Hence, the availability of any kind of collection method will be embraced and considered in order to enhance the performance of the collection activities. This is where the potential incorporation of the three collection methods should be investigated and validated.

The second objective of this research was to develop an optimal assignment of the collection method for the returned products for each customer zone. The allocation was based on the three collection methods and was formulated as a mixed integer, non-linear programming model. The proposed model has successfully generated an optimal solution for small problem instances. Nonetheless, the model requires longer computation times to generate solutions for larger instances. In general, the results demonstrate the usability of the model. It also shows the benefit of the possible incorporation of the three collection methods.

However, the model is also complex and is classified as an NP-hard problem. For medium and large instances, the model could not find a solution within a reasonable time. Hence, a Lagrangian relaxation algorithm was employed to produce good feasible solutions in shorter computational times. In Chapter Six, the employment of the Lagrangian relaxation approach was elaborated and justified. Based on the results, the heuristic approach managed to produce reasonable feasible solutions in a fairly short reasonable time. The model and solution method allows more return choices to the customers, which may lead to a better return rate.

However, the importance of further examining the model and the quality of the solutions in order to incorporate more realism is acknowledged. The proposed algorithm still lacks examination, particularly in the use of real industrial data, and some areas of improvement have been identified for future research. Overall, the proposed model has incorporated all three collection methods in a single model successfully and has highlighted its potential benefits. The inclusion of the mail return method has enhanced the significance of the proposed model. Apart from that, the model opens up a new direction in research about product return channels. As mentioned earlier, the problem understudy has been treated as an assignment decision rather than the usual location and allocation problem. This may be beneficial to the management team in planning an appropriate collection strategy for product returns.

8.4   Research limitations and further works

The research limitations have been explained in the previous sections encompassing both product recovery and the return channels (refer to Sections 7.2 – 7.4, and Sections 8.2 – 8.3). For the product recovery options, the proposed model has limitations and it can be modified to address the shortcomings. In particular, the model can be adjusted to include disposal options or to consider redefining the set of recovery options for each quality category of returned products. This refers to the feasibility issues in which a returned product may not be practical to be recovered using a particular recovery option. In other words, total flexibility in product recovery assignment may not be feasible in certain conditions. Apart from that, there may not be many firms that have in-house facilities to carry out all the recovery and disposal options. The proposed model also requires a comprehensive quality grading system that can separate returned products into five or six (including disposable) quality classes. This may challenge the practicality of the proposed model. Hence, further works can be done on the abovementioned issues pertaining to the product recovery options. Specifically, studies on the impact of imbalanced or unfavourable returns quality towards a flexible recovery assignment are needed to further validate the practicality of the proposed model in difficult situations. In the meantime, a flexible allocation policy should also be examined in a situation where the company has to use outsourcing services for certain recovery options. This may happen when certain recovery options are not available in-house, thus force the company to outsource some of the recovery options. A study on the impact of intermediaries, such as independent recyclers or remanufacturers, on a company's flexible allocation policy may also open up other research avenues, particularly those related to the

issues of cost efficiency, buy-back strategy and incentives, or minimum recovery rates for certain types of recovered items.

For product return channels, the proposed model is a mixed integer nonlinear programming model and the problem is formulated as an NP-hard problem. Hence, the problem is difficult to solve. It is also a large and complicated model that incorporates three different collection methods together. The model struggled to find solutions for medium and larger problem instances in shorter computation times. Hence, a heuristics approach was employed to solve the problems within a reasonable time. Nevertheless, the study only considered the Lagrangian relaxation method. Although it proved to be effective, a comparison with other heuristic methods has not been carried out. It may be good to look into this in future work, especially the use of other heuristic methods such as the Tabu Search, Genetic Algorithm or Simulated Annealing.

In the meantime, the model can also be modified because some products may not be practical for certain collection methods due to their size or geographical limitations. Under such circumstances, some variables can be fixed to prevent a particular collection method from being considered for certain product types. This applies to the mail return method, which may not be suitable for all kinds of products. Apart from that, it may be more practical and beneficial to use real data in future studies. The impact of third party logistics providers or independent collectors (intermediaries) on the proposed model is another significant research avenue. This is due to the steady growth of recycling as well as the logistics and transportation industries. Meanwhile, future research can also be carried out to examine the roles of

government or regulatory bodies in product return channels via subsidy mechanisms or other incentives. Investigations should be on the impact of subsidies or other related government incentives on multiple collection methods. The government incentives may have a different effect on the collection rates as compared to incentives offered by companies.

8.5   Conclusion

In summary, the study has achieved its intended research objectives and managed to demonstrate the usability and benefits of each model. In both topics of the study (product recovery options and product return channels), the proposed models have effectively found solutions to the respective problems albeit with some limitations. The gaps in the literature in both areas have also been identified and filled. Nevertheless, the practicality of both models may still require further examination, particularly by using real industrial data. Some modifications on the constraints may also be needed for both models to enhance their practicality. However, being able to promote flexibility in product recovery options and to incorporate mail return together with drop-off and the pick-up methods in the production return network design under a variety of problem settings is already a huge benefit. Both models have shown significant potential and have also opened up more possibilities for future research in the area. As an overall conclusion, the product recovery options and return channels are inter-related, and effective solutions to these problems have proven to be very important and hugely beneficial to the relevant industries, logistics providers and policymakers.

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