Reverse Logistics:
A Multicriteria Decision Model With Uncertainty

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This is to certify that I have examined this copy of a doctoral dissertation by

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Abstract

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Waste reduction is critical in today's manufacturing climate. Producers are being compelled to incorporate reverse logistics into their supply chain by government legislation, the potential for recovering economic value, and consumer demand for "green" practices. Complicating network design for reverse logistics is the need to incorporate existing supply chain networks and higher levels of uncertainty in quantity, frequency and quality of return product.

Even though facility location models have been developed for reverse logistics network design, the producer is confronted with a number of high-level decisions before detailed decisions can be made. For instance, how will the product be collected? Will testing be done centrally or near the collection site? Where will processing be performed? In order to answer these questions, decision makers need a means to quantify and analyze tradeoffs inherent in the network design.

This work presents a flexible, generalized decision model that integrates high-level and detailed design decisions and that incorporates uncertainty. The first part of the work is a conceptual framework for the high-level decisions identifying eight possible network configurations based on more than thirty-five case studies. The second part extends the framework into a multicriteria decision making model using Analytical Hierarchy Process (AHP), which quantifies tradeoffs and provides insights through sensitivity analysis. The third part of the

work presents a suite of mixed-integer linear programming (MILP) models that integrates the high-level and detailed decisions, and that addresses uncertainty using three methods: chance-constrained programming, stochastic programming, and robust optimization. The deterministic and chance-constrained models provide a comparatively inexpensive way to determine the optimal network configuration, while the stochastic programming and robust optimization models require more computation but better address sensitivity to detailed site locations through recourse variables.

The AHP decision making model is demonstrated on three case studies with different characteristics. The findings show that the AHP preference ranking of network configurations is sensitive to the producer's goals and values, and sensitivity analysis explores the impact of the relationships of those goals and values. For instance, the collection decision is sensitive to the preference for business relations vs. cost savings, the sort-test decision is sensitive to potential cost savings from reducing testing costs and identifying scrap early, and the processing decision is sensitive to the need to protect proprietary knowledge and the availability of original facility processing capacity.

The suite of MILPs with uncertainty is demonstrated on a numerical study from the literature and a fourth case study involving consumer electronics recycling. The research found that the choice of network configuration is relatively insensitive to uncertainty, but that there is sensitivity to site location decisions. The findings indicate that the combination of the AHP decision making model and the detailed MILP models provides a strategic approach for decision makers facing the challenge of designing a reverse logistics network into their supply chain.

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TJB

DEDICATION

To my husband Jim Thomas,
who unfailingly encouraged me in accomplishing my dreams,
and who happens to be a wizard in Excel.

Chapter 1
INTRODUCTION

1.1 Motivation

Experts tell us that we are facing an impending scarcity of natural resources. According to a number of sources, there is an enormous amount of waste in today's manufacturing world. As William McDonough and Michael Braungart, authors of *Cradle to Cradle: Remaking the Way We Make Things*, state:

> Cradle-to-grave designs dominate manufacturing. According to some accounts more than 90 percent of materials extracted to make durable goods in the United States become waste almost immediately (McDonough and Braungart, 2002, p. 27).

Kirstie McIntyre of Hewlett Packard puts it another way:

> The primary output of today's production processes is waste. Across all industries, less than 10 percent of everything that is extracted from the earth (by weight) becomes usable products. The remaining 90 percent becomes waste from production ... (McIntyre, 2007, p. 243).

Producers are increasingly aware that they can no longer afford to produce a product that is tossed into a landfill in a few years. From single-use cameras to printer ink cartridges to outdated cell phones, products are being recycled, reused and remanufactured more then ever before. Manufacturers are incorporating product recovery into their supply chains, and while there are many reasons for doing so, three primary drivers are at work. First, there may be governmental legislation mandating that the producer be responsible for disposal of the product. Nineteen states in the U.S. have already passed laws requiring manufacturers of consumer electronic products to pay for the disposal of those products safely. In Europe where there is a paucity of landfill space, laws have been passed not only for electronic products, but for carpet as well. Second, there may be significant economic value residing in the product even after being used by a consumer. Scrap metal, automobile engines, and power tools are among such products. Third, consumers are demanding "earth-friendly" practices by manufacturers, and they are choosing to buy from producers who can demonstrate "green" practices.

Yet producers need to be thoughtful when incorporating product recovery into their supply chain. Supply chains are acutely optimized for efficiency and cost-effectiveness when distributing new product to customers; going the reverse direction can be costly and inefficient, cutting into profits. Compounding the problem is the fact that reverse logistics does not seek to merely maximize profit or minimize costs, as with conventional supply chain models. Instead, multiple objectives are involved, such as protecting specialized product knowledge from falling into competitive hands, maintaining a reliable supply of older model replacement parts to retain established customers, or identifying scrap early in the return process that can be sent directly to disposal to reduce transportation costs.

Reverse logistics is further complicated by higher levels of uncertainty in volume, frequency and quality of return product than in new product. Producers often have little control over when and how much product is returned, and the quality can vary from nearly new to completely worn-out, depending on the product and the market.

While much work has been done to develop facility location models, there are a number of high-level decisions that a producer needs to consider before settling on a set of candidate facility locations. Among these decisions are how to collect the product, whether testing will be done at the collection site or at a central facility, and if processing could be performed more effectively by a third-party logistics provider (3PL). These high-level decisions involve tradeoffs: for example, collecting directly from a customer is likely to be more costly than a shared collection system among similar manufacturers, but the cost may would be necessary if the producer needs to protect its proprietary knowledge. Yet before making such a decision the producer needs to know the difference between the cost of implementing customer-only collection and the cost of implementing an industry-wide collection system.

In addition, the challenge of higher variability in return flows must be met. Would the network layout be different if volumes are significantly higher or significantly lower than expected? The impact of uncertainty needs to be assessed before making critical design decisions – the network design should perform well under uncertain conditions.

There is a need for a flexible, generalized decision model that integrates high-level and detailed design decisions, and that incorporates uncertainty. The model needs to quantify tradeoffs in high-level decisions, and it should have the capability for sensitivity analysis relative to the high-level decisions. The model should be informed by real-world applications, and it should be tested using those applications so that manufacturers can see the benefits of the model, and so that they can understand how the model is implemented. This is the direction of the research in this work.

1.2 Overview of research contribution

The primary contribution of the research is in developing a set of decision making models to analyze the tradeoffs inherent in reverse logistics network design and to evaluate the impacts of uncertainty on network design. The first part of the work consists of developing a conceptual framework that encompasses the high-level decisions with eight possible network configurations, derived from an analysis of forty case studies: 37 published case studies and three additional case studies developed through this research. The second part quantifies the framework using Analytical Hierarchy Process (AHP), taking into account multiple criteria of cost savings and business relationships. The AHP model was applied to the three case studies to demonstrate the high-level decision model and to explore sensitivity of the high-level decisions to changing business conditions. The third part of the research provides a suite of mixed-integer linear programming (MILP) models that integrates the high-level and detailed design decisions and addresses uncertainty using three probabilistic methods: chance-constrained programming (CCP), stochastic programming (SP), and robust optimization. The MILP models are demonstrated with a numerical study and a real-world application involving consumer electronics recycling.

Integrating the conceptual framework and the AHP model in a suite of MILP models with uncertainty provides a methodology for network design. Through this work, the producer can evaluate the cost of an AHP-preferred solution relative to the lowest-cost solution. The AHP model also provides sensitivity analysis to explicate inherent tradeoffs in the high-level decisions. Sensitivity analysis on the case studies shows: 1) that the collection decision is largely determined by producer ranking of business relations relative to cost savings, 2) that the sort-test decision is governed by the potential for cost savings of reducing test costs or the need to eliminate scrap early in the return process, and 3) the processing decision is reliant on the availability of original facility processing capacity. Processing is also sensitive to a higher desire to protect proprietary or intellectual knowledge by the producer. In addition, both collection and processing choices are affected by whether the product is to be recycled, because a recycling operation favors industry-wide collection and secondary processing facilities to reduce costs as much as possible. The interaction among competing producer preferences is handled well by the AHP model and sensitivity analysis.

With regard to uncertainty, the findings from the numerical study indicate that the high-level decisions are relatively insensitive to variability in return volumes, although the site location decisions are sensitive to uncertainty. Because the deterministic and CCP models are comparatively inexpensive and quick to run, a producer can use them to determine an optimal network configuration. Through recourse variables, the SP and robust optimization models are better prepared to handle uncertainty and may be an alternative for determining detailed site location decisions. The CCP model allows the producer to balance increased costs against the probability of meeting return volume demand.

The industry study on consumer electronics recycling demonstrates the value of the AHP model as well as the MILP models in understanding the cost and benefits related to high-level and detailed reverse logistics decisions.

1.3 Organization of the dissertation

The rest of this disseration is organized as follows. Chapter 2 describes the background and literature survey for the problem. Chapter 3 develops the conceptual framework and quantifies it into a multicriteria decision model using AHP. The AHP model is demonstrated on three new case studies, using sensitivity analysis to provide insights into the critical aspects of the high-level decisions. Section 3.1 and portions of 3.4 appear in a paper published by *The International Journal of Sustainable Engineering* (Barker and Zabinsky, 2008), and Sections 3.2, 3.3, and portions of Section 3.4 appear in a paper that has been submitted to *Omega: The International Journal of Management Science* and is currently under revision (Barker and Zabinsky, 2009).

Chapter 4 presents the suite of optimization models incorporating uncertainty and a numerical study to analyze the sensitivity of high-level decisions and the impacts of uncertainty on network design. The work in Chapter 4 has been submitted in a paper to a special issue of *IEEE Transactions on Engineering Management* entitled *"Engineering Management and Sustainability"* and is in review (Barker and Zabinsky, 2010).

Chapter 5 presents a demonstration of the methodology on an industrial study for consumer electronics recycling. Chapter 6 is a summary of the research and a description of future research in the field.

Chapter 2

BACKGROUND AND LITERATURE SURVEY

Over the past two decades, traditional supply chains in which product is shipped from producer to consumer are giving way to supply chains which incorporate reverse logistics. Because traditional supply chains are designed to provide a certain quantity of product to the customer at a certain time, they are typically not designed to accommodate reverse logistics efficiently.

Reverse logistics is the process of recovering value from end-of-life products, and it has been defined 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. (de Brito and Dekker, 2004, p. 5)

A number of facility location mixed-integer linear programming models exist for detailed network design for reverse logistics (Kroon and Vrijens, 1995; Wang et al., 1995; Bloemhof-Ruwaard et al., 1996; Spengler et al., 1997; Del Castillo and Cochran, 1996; Barros et al., 1998; Louwers et al., 1999; Jayaraman et al., 2003; Sahyouni et al., 2007; Aras and Aksen, 2008; Tan and Kumar, 2008). These MILP facility location models assume certain high-level decisions have already been made, e.g., that a set of candidate sites have been identified, and that certain reverse logistics activities have been assigned to specific candidate sites. However, there are key considerations that need to be taken into account before these MILP models can be implemented. For instance, how will the producer collect the return products? Will the product be shipped to a central site for sorting and testing, or will the necessary testing be done at the time of collection? Does the product need to be processed at the original factory? Could the return products be processed by a third party processor?

Addressing these considerations through high-level conceptual decisions are a critical part of an effective reverse logistics network design.

Another key consideration for reverse logistics is addressing uncertainty. The literature has established that there is higher uncertainty in volume, quantity and condition of return product than in new product production (Fleischmann et al., 1997). Some MILP models have used stochastic programming (Listeş and Dekker, 2005; Fleischmann et al., 2004; Salema et al., 2007; Chouinard et al., 2008) or robust optimization (Realff et al., 2004; Fleischmann et al., 2004; Hong et al., 2006) to model inherent uncertainties.

A related consideration is assessing the impact of uncertainty. Even though uncertainty is a recognized consideration, the impact of uncertainty may or may not be significant in a particular problem, as noted by (Wallace, 2000):

> ... it is important to remember that although all decisions can be viewed as being made under uncertainty, this does not imply that uncertainty is an important aspect of all problems. If, for example, the same decision is the unique optimum for absolutely all possible values of the uncertain parameters, although the objective function value may be very dependent, the true optimal decision can be found simply by solving one single problem, normally the one where all parameters are set at their mostly likely value. In such a case it is fair to claim that uncertainty is unimportant for making decisions.

The two major challenges confronting a motivated producer are: 1) incorporating conceptual decisions into detailed network design, and 2) assessing the degree to which uncertainty affects network design.

2.1 Previous frameworks

A number of frameworks have been presented in the literature, describing critical high-level decisions and the considerations for network design.

An early framework proposed by Flapper (1996) provides an overview of the logistics of reuse, in which the author categorized reuse activities into collection, processing, and distribution, and discussed various aspects of each activity. Flapper described a number of tradeoff considerations, including whether to collect directly from customers or at depots, whether the network should be geographically wide-spread or localized, whether different items should be collected together or separately, whether to transport return product back to a processing plant or to reuse or recycle the product locally, and whether inspection and sorting should be done immediately on collection or at the point of processing.

Fleischmann et al. (1997) presented a comprehensive review of quantitative models for reverse logistics, in which they enumerated considerations for these network design questions. These network design questions were the basis for later conceptual models. They described the entities performing reverse logistics (e.g., collectors, reprocessors, etc.), which functions need to be carried out and where, and whether the forward and reverse flows should be integrated or separate.

In 2000, Fleischmann et al. (2000) proposed a conceptual model based on the network design questions in Fleischmann et al. (1997). Using common characteristics of several case studies, they classified product recovery networks into three types: (i) bulk recycling networks, (ii) assembly product remanufacturing networks, and (iii) re-usable item networks. Each type of network was identified by a specific set of characteristics, including degree of centralization, integration with existing supply chain operations, and whether products would be returned to the manufacturer for reprocessing or to an outside entity. The result was a descriptive conceptual model that distinguishes among network types based on product function – recycling, remanufacturing, or reusing – and then proposed specific network design considerations for each network type.

DeBrito et al. (2003) presented a descriptive framework for reverse logistics, which discussed structures for re-use, remanufacturing, and recycling networks in 24 case studies. Their work was informed by two previous works: Thierry et al. (1995), and Goggin and Browne (2000). Thierry et al. (1995) categorized networks by type of product recovery options: (i) direct re-use and re-sale, (ii) repair, refurbishing, remanufacturing, cannibalization and recycling, and (iii) waste disposal. Goggin and Browne (2000) developed a generic typology of resource recovery as a basis for problem-solving to help original equipment manufacturers (OEMs) determine whether to implement recovery and how to operate it. Their typology defined the complexity of types of recovery and provided insights into the requirements for material reclamation, component reclamation, and remanufacturing product recovery.

The framework in DeBrito et al. (2003) encompassed the following observations: (i) successful re-use networks rely on matching supply and demand of returned items at the same time; (ii) optimal remanufacturing depends on the location of the remanufacturing facility, ensuring a steady return product volume and minimizing the impact of uncertainty in return supply, and (iii) recycling is primarily done through public government-sponsored networks, driven by environmental objectives, and is likely to be centralized due to expense of facilities.

These frameworks presented important information on conceptual decisions. They identified many characteristics of reverse logistics networks and described implications of those decisions. Although not quantitative, the frameworks provide understanding of the principles of reverse logistics within the supply chain system.

Other frameworks in the literature approached this topic from a business analysis point of view. (Carter and Ellram, 1998) developed a decision framework predicated on the relationship between drivers (Regulations, Customers, Policy Entrepreneurs, and Uncertainty) and constraints (Stakeholder Commitment, Top Management Support, Incentive Systems, Quality of Inputs, and Vertical Coordination). The framework also explicated internal and external drivers. Their work suggested, for instance, that the principal internal driver is having at least one policy entrepreneur, and that top management support, stakeholder commitment, and appropriate incentive systems are necessary for successful implementation of reverse logistics.

Krumwiede and Sheu (2002) proposed a decision-making model for third-party logistics providers (3PLs), using interviews of 3PLs and analyzing related research articles. They identified a three-stage flow: retrieval (collection), transportation (including storage), and disposition (two types: on-site and off-site). The authors then developed a marketing-oriented model for decision making that included researching existing issues and identifying current customers, building marketing channels using those customers, identifying a specific niche, and performing a feasibility study.

Meade et al. (2007) analyzed an large number of articles from the literature to determine the definition, functions and mechanisms of reverse logistics, and presented a framework composed of two categories of driving forces: 1) environmental factors (e.g., regulation and environmental friendliness), and 2) business factors (e.g., liberal customer returns and customer satisfaction).

The work by previous researchers has explored various aspects of high-level reverse logistics decisions. Yet existing frameworks do not bridge the gap between conceptual decisions and quantitative models. The need for generalized models was observed by Meade et al. (2007). In a similar vein, Rubio et al. (2008) confirmed the need for new research into strategic aspects and organizational frameworks for reverse logistics, despite existing quantitative models and case studies.

2.2 Analytical Hierarchy Process decision methodology

One method of quantifying decision models is Analytical Hierarchy Process (AHP). AHP is a multicriteria decision methodology introduced by Saaty (1982) that encompasses both quantitative and non-quantitative objectives. AHP is a flexible approach that defines the problem and derives the desired solution, and the sensitivity of the solution can be tested to changes in information (Saaty, 1982, 2001). It has been used for business decisions, public policy and economic policy decisions, and representing systems networks.

In reverse logistics, AHP has been used by Staikos and Rahimifard (2007) to develop an AHP decision model for product recovery of shoes. Their model consists of criteria in three areas: environmental factors based on Life Cycle Analysis (LCA), economic factors from cost-benefit analysis, and qualitative technical factors from a secondary AHP analysis.

AHP was also used by Fernández et al. (2008), who proposed a conceptual model using Delphi and AHP as an illustration of model-building under multiple conflicting priorities. The Delphi method was used to develop concensus among reverse logistics practitioners to determine which variables caused reverse logistics success and what cause-and-effect sequences impacted these successes. AHP was then applied to determine the relationships among the variables and their relationships to the recovery options.

Kannan et al. (2008) created a multicriteria decision making model using AHP and Fuzzy

Analytical Hierarchy Process (FAHP) to evaluate collection centers for product recovery in the tire manufacturing industry in India.

The ability to synthesize multiple criteria into a desired solution and evaluate the sensitivity of the solution to changing conditions makes AHP a good choice to quantify a decision framework.

2.3 Evaluating the impact of uncertainty

Probabilistic optimization models have been developed for reverse logistics using stochastic programming and robust optimization. Stochastic programming approaches have been presented by Fleischmann et al. (2004), Listeş and Dekker (2005), Salema et al. (2007), and Chouinard et al. (2008), while robust optimization was applied by Realff et al. (2000, 2004), Fleischmann et al. (2004), and Hong et al. (2006). Both methods implemented scenarios to represent probabilistic demand and return volumes.

Stochastic programming (SP) strives to account for varying conditions by minimizing expected costs over a set of scenarios. On the other hand, robust optimization determines the solution with the best performance by minimizing the maximum cost across all scenarios, without an associated probability for each scenario. SP and robust optimization models employ recourse variables in a second stage to capture the ability of the system to adapt to uncertain information. It is worth noting that scenario-based approaches require expert situational knowledge to choose meaningful scenarios. In addition, while more scenarios can more accurately reflect the uncertainty, the computational cost increases significantly as the number of scenarios increases.

In another probabilistic method, chance-constrained programming (CCP) represents the uncertain parameters as random variables with a probability distribution (Charnes and Cooper, 1959; Prékopa, 1995; Growe, 1997). In an optimization formulation, the constraints involving the uncertain parameters are formulated as probabilistic statements, in which the probability of satisfying a constraint is greater than or equal to a given satisfaction level ε (Mayer, 1997).

An MILP model using CCP for a vendor selection problem was presented by Li and Zabinsky (2009), and CCP has been used recently in widely varying fields (Campos et al., 2006; Bhattacharya, 2009; Laslo et al., 2009; Ostrovsky et al., 2010). CCP avoids the computational complexity of SP and robust optimization, although it also lacks the flexibility of including recourse variables as in SP and robust optimization. Additionally, the satisfaction level of the probability constraints ε can be varied in CCP to explore the balance between costs and an acceptable satisfaction level.

2.4 Producer responsibility for end-of-life disposal

The drive to reduce waste and to protect the natural environment is introducing new paradigms in manufacturing. Some sources predict that manufacturing will begin to provide the service of a product rather than selling the product itself to a customer:

> ... recent decades have witnessed a shift in business thinking from selling products to providing service solutions to customer needs. (Mont et al., 2006)

> In industrialized countries sustainable development has to start with a considerable reduction of the consumption of resources. ... This then defines a new management task, to unlink economic success from resource consumption, i.e. to produce the same sales turnover and profits with a substantially reduced resource throughput throughout the economy. In many cases, this will only be feasible by redefining corporate strategies, orienting them towards selling performance rather than goods. (Stahel, 1998)

This shifts the focus of manufacturing away from products that end up in a landfill and toward higher quality products that are reusable or repairable. Producer responsibility is becoming a focus, according to several industry experts interviewed for this research (Linnell, 2010; O'Brien, 2010; Spille, 2010; Trotti, 2010). Legislation is increasingly a factor in compelling manufacturers to provide funding for the disposal of products that are considered especially prevalent or costly to dispose of. For governments facing increasing budget shortages and an atmosphere of "no new taxes," putting the financial responsibility for product disposal on the producer is a fiscal reality (Spille, 2010).

Although manufacturers are generally responding to government mandates, the need to provide for end-of-life disposal is also beginning to translate into designing the product with efficient disposal in mind, such as reduced packaging and reuse options. An expert with twenty years' experience in the solid waste management industry believes that increased producer responsibility will change materials and construction techniques to be more efficient. Consumers are bringing more awareness of the demand for responsible disposal as well (Trotti, 2010).

From a producer point of view, reverse logistics is evolving from having to pay for disposal of products to being able to reclaim some value from end-of-life products. Increasing environmental standards for manufacturing are also motivating manufacturing to become more focused on improving product disposal options. Further, remanufacturing and product recovery can have the added benefit of increasing revenue through product resales and extended customer service contracts (Aanenson, 2010).

In summary, producer responsibility for end-of-life disposal is predicted to increase, according to industry experts. However, in the words of one expert, the problem is not simple: "people need to know the cost implications" (O'Brien, 2010). It is clear that the efficient use of materials in manufacturing and the environmentally productive disposal of used materials is becoming a focus in today's consumer arena.

2.5 Summary

Producer responsibility for end-of-life product disposal is a key issue confronting manufacturers. The literature contains conceptual frameworks describing the high-level decisions and considerations for reverse logistics network design, yet existing frameworks do not quantify important tradeoffs. Many quantitative MILP models have been developed to determine detailed network layouts. However, previous models do not conjoin the high-level and detailed design decisions. As well, probabilistic models using stochastic programming and robust optimization are presented in the literature. Chance-constrained programming is an alternative to these approaches that has not yet been developed, and that can provide an assessment of a cost-satisfaction level balance and reduced computational complexity.

The suite of MILPs in this research incorporates conceptual and detailed decisions into a network design model, and addresses the impact of uncertainty on the network design using three probabilistic methods. The next chapter develops the high-level conceptual model with AHP.

Chapter 3

HIGH-LEVEL CONCEPTUAL FRAMEWORK AND AHP DECISION MODEL

This chapter describes a conceptual framework for evaluating tradeoffs in network design decisions, and the model is quantified using AHP, a multi-criteria decision-making (MCDM) method. The model provides an optimal network configuration with respect to a preference ranking among the eight possible configurations identified in the conceptual framework. This work explores the dependencies of network configuration decisions on various cost and business relations factors, including the strength of customer relationships and the degree of cost savings that can be achieved to evaluate the sensitivity of the solution. The AHP model and sensitivity analysis is demonstrated with three case studies for real-world applications: medical device remanufacturing, residential carpet recycling, and commercial carpet recycling.

3.1 Conceptual framework

In reverse logistics, it has been established that there are three fundamental stages of flow: 1) collection, 2) sort-test and 3) processing (Flapper, 1996; DeBrito et al., 2003; Fleischmann et al., 2004). As Fleischmann et al. (2004) observes:

> In particular, companies need to choose how to collect recoverable products from their former users, where to inspect collected products in order to separate recoverable resources from worthless scrap, where to re-process collected products to render them remarketable, and how to distribute recovered products to future customers.

A product recovery flow diagram showing the three stages is shown in Figure 3.1. After the collection stage and the sort-test stage, the product is sent to processing, which may include

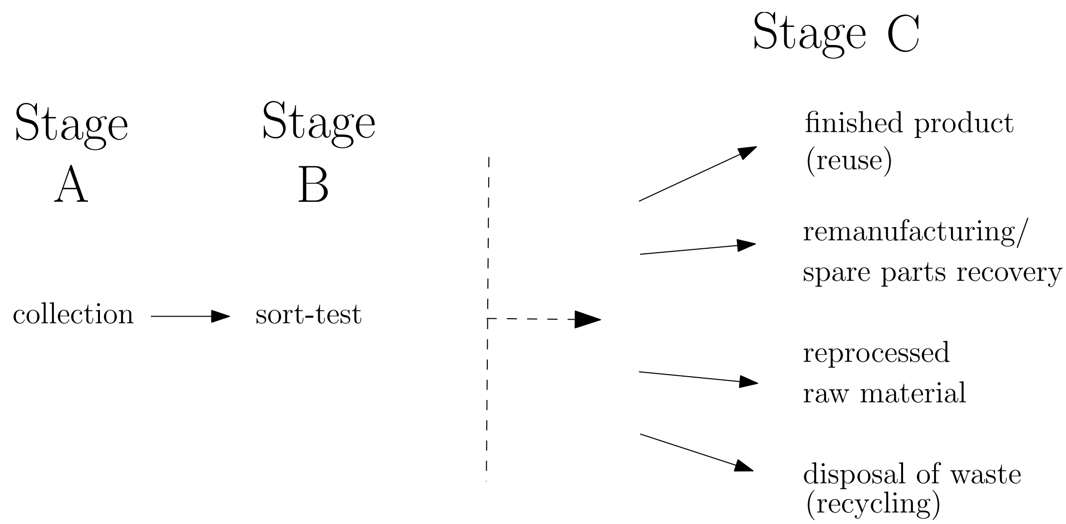


Figure 3.1: Flow of reverse logistics activities.

include finished product reuse, remanufacturing and spare parts recovery, reprocessed raw material and disposal of waste.

The conceptual framework with the design decisions and associated tradeoff considerations is shown in Figure 3.2. The framework consists of the three stages of reverse logistics, with each stage having two decision options, resulting in eight possible configurations. The eight configurations and their corresponding notations are shown in Table 3.2. The decision options for each stage are:

1) Collection: *Proprietary collection*, in which the producer collects only their own products ("P"), or *Industry-wide collection*, in which multiple producer's products are collected in a single return stream ("I").

2) Sort-Test: *Centralized sort-test sites*, in which products are taken to a centralized location for sorting and testing ("C"), or *Distributed sort-test sites*, in which products are sorted and tested at or near the collection site ("D").

3) Processing: *Original facility processing*, in which products are processed at the producer's own facility ("O"), or *Secondary facility processing*, in which products are processed at a secondary facility ("S").

Each stage of flow has a set of network characteristics involving critical tradeoffs, which lead to choices for network design decisions. The decision choices and key tradeoff considerations were developed through case study analysis. Case studies were selected through a literature search to represent diverse products and industries, and 13 published case studies representing a variety of industries were used to develop an initial framework. The framework was further tested using an exhaustive set of case studies in DeBrito and Dekker (2003). Of 67 case studies in DeBrito and Dekker (2003), 31 case studies written in English were examined. Of these 31 case studies, seven were duplicated in the original set of 13, leaving 24 additional case studies to be classified. Table 3.1 classifies the complete set of 37 case studies under the eight possible configurations.

Of the 37 case studies in the analysis, approximately one-third of the case studies (12) had the configuration (P,C,O): *proprietary* collection, *centralized* sort-test and *original facility* processing. Proprietary systems often have this configuration, in which a company retrieves its own products, and processing is done at the original facility. This configuration is consistent with a proprietary remanufacturing system, such as car engines (Seitz and Peattie, 2004) or reusable glass soft drink bottles (Del Castillo and Cochran, 1996).

Four case studies had the configuration (P,C,S): *proprietary* collection, *centralized* sort-test and *secondary facility* processing. This system makes sense for a proprietary collection system using a third-party logistics provider, such as toner cartridges (Bartel, 1995), for a company without space in its original facility, such as business lease-return computers (Fleischmann, 2000; Fleischmann et al., 2004) or where the secondary processing is dramatically different from original manufacturing, such as proprietary battery recycling (Yender, 1998).

Another four had the configuration (P,D,O): *proprietary* collection, *distributed* sort-test and *original facility* processing. Proprietary systems where sorting can be done at the collection site fall into this category. For instance, some reusable container systems perform inspection at distributed depots, before being sent to a new user (Duhaime et al., 2001), or

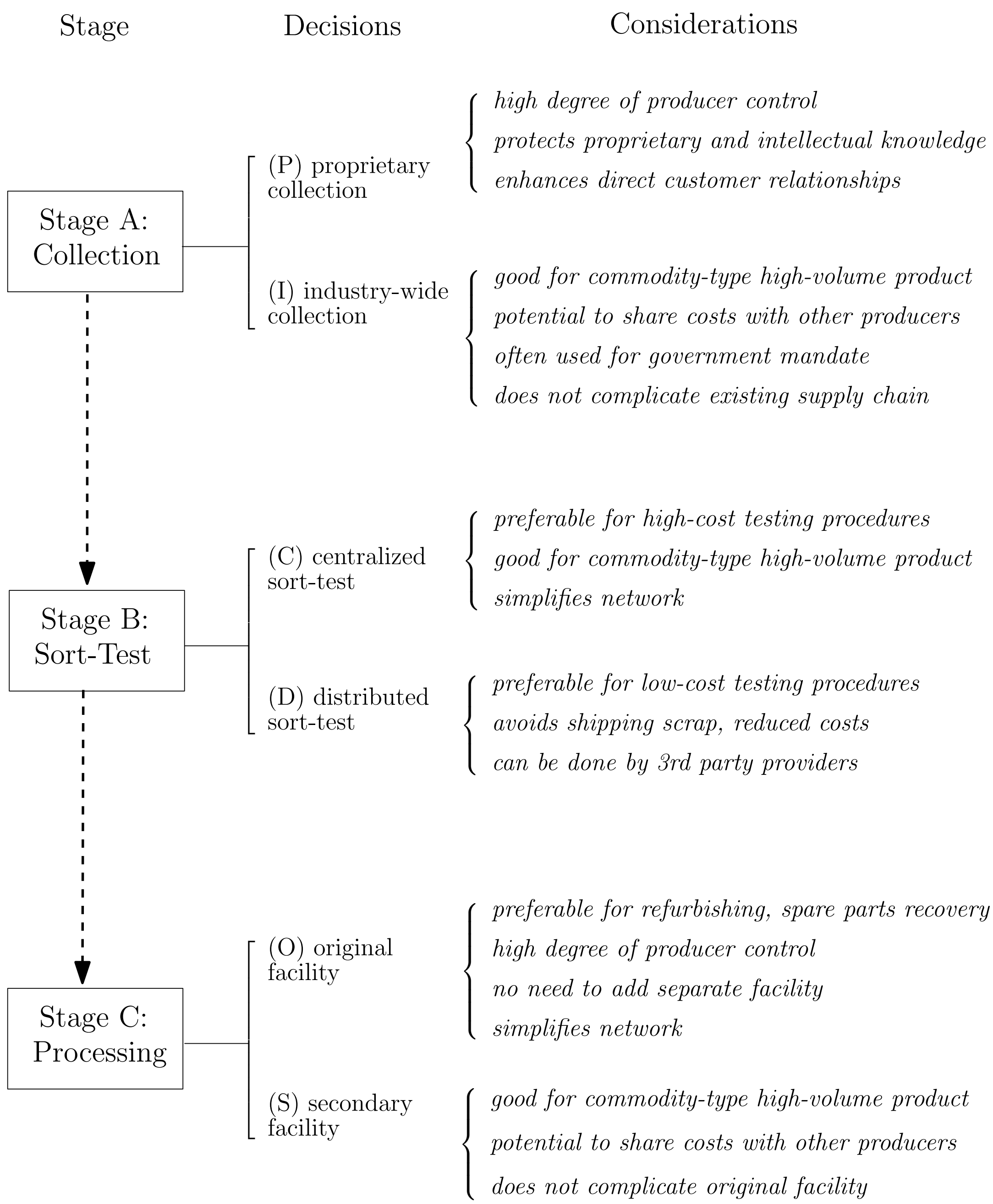


Figure 3.2: Framework for network design decisions.

Table 3.1: Classification of 37 published case studies by network configuration.

1. (P,C,O): 12 of 37 case studies
    - (Del Castillo and Cochran, 1996) Reusable glass soft drink bottles
    - (DeBrito and Dekker, 2003) Lab equipment restocking
    - (DeBrito and Dekker, 2003) Mail order company restocking
    - (DeBrito and Dekker, 2003) Refinery spare parts restocking
    - (Diaz and Fu, 1997) Subway spare parts restocking
    - (Guide Jr. and Van Wassenhove, 1997) Military aircraft remanufacturing
    - (Linton and Johnston, 1999) Circuit board refurbishing
    - (Maslennikova and Foley, 2000) Electronic product remanufacturing
    - (McGavis, 1994) Printer toner cartridge recycling
    - (Meyer, 1999) Cosmetics products restocking
    - (Seitz and Peattie, 2004) Car engine remanufacturing
    - (Toktay et al., 2000) Single-use camera recycling
2. (P,C,S): 4 of 37 case studies
    - (Bartel, 1995) Printer toner cartridge recycling
    - (Fleischmann, 2000) Business computer refurbishing
    - (Thomas Jr., 1997) Aircraft engine remanufacturing
    - (Yender, 1998) Battery recycling
3. (P,D,O): 4 of 37 case studies
    - (Duhaime et al., 2001) Reusable postal containers
    - (Gupta and Chakraborty, 1984) Glass scrap recycling
    - (Krikke et al., 1999a) Copier refurbishing
    - (Rudi et al., 2000) Wheelchair refurbishing
4. (P,D,S): 2 of 37 case studies
    - (Kroon and Vrijens, 1995) Reusable packaging
    - (Thierry et al., 1995) Copier refurbishing
5. (I,C,O): 0 of 37 case studies
    - No published case studies found
6. (I,C,S): 12 of 37 case studies
    - (Barros et al., 1998) Construction sand recycling
    - (Chang and Wei, 2000) Municipal curbside waste
    - (Farrow et al., 2000) Recycled plastic kayaks
    - (Guide Jr. and Van Wassenhove, 2001) Cellular phone remanufacturing
    - (Klausner and Hendrickson, 2000) Power tool remanufacturing
    - (Krikke et al., 1999b) PC monitor recycling
    - (Louwers et al., 1999) Carpet recycling
    - (Nagel and Meyer, 1999) Refrigerator remanufacturing
    - (Realff et al., 2000) Carpet recycling
    - (Spengler et al., 1997) Steel by-products
    - (Staikos and Rahimifard, 2007) Shoe recycling
    - (Wang et al., 1995) Cardboard recycling
7. (I,D,O): 0 of 37 case studies
    - No published case studies found
8. (I,D,S): 3 of 37 case studies
    - (Bloemhof-Ruwaard et al., 1996) Paper recycling
    - (Hong et al., 2006) e-Scrap recycling
    - (Kleineidam et al., 2000) Paper recycling

Table 3.2: Eight network configurations.

Notation	Collection	Sort-Test	Processing
(P,C,O)	Proprietary	Centralized	Original facility
(P,C,S)	Proprietary	Centralized	Secondary facility
(P,D,O)	Proprietary	Distributed	Original facility
(P,D,S)	Proprietary	Distributed	Secondary facility
(I,C,O)	Industry-wide	Centralized	Original facility
(I,C,S)	Industry-wide	Centralized	Secondary facility
(I,D,O)	Industry-wide	Distributed	Original facility
(I,D,S)	Industry-wide	Distributed	Secondary facility

computer manufacturers inspect at disassembly centers before shipping to the refurbishing facility (Krikke et al., 1999a).

Two case studies with the configuration (P,D,S): *proprietary* collection, *distributed* sort-test and *secondary facility* processing. In both studies, return product was sorted and processed by a third party at a decentralized location. One was a reusable container system (Kroon and Vrijens, 1995) and the other was a copier remanufacturing system (Thierry et al., 1995).

Of the case studies with proprietary collection systems, the majority also had original processing facilities. This was primarily due to the desire to protect proprietary product knowledge, often combined with the availability of specialized technical knowledge and labor for processing controlled by the company. However, for a company that may not have a strong value for proprietary knowledge and control, performing processing at a secondary facility may be an appropriate option, possibly by a third party logistics provider.

Another one-third of the case studies (12) had the configuration (I,C,S): *industry-wide* collection, *centralized* sort-test and *secondary facility* processing. In these systems, returned product is collected via an industry-wide system, transported to a central facility for sorting and testing, and then processed at a secondary facility which is not company-specific. This configuration is common for a commodity-type recycling system, such as used construction sand (Barros et al., 1998) or carpet (Realff et al., 2000).

Finally, three case studies had the configuration (I,D,S): *industry-wide* collection, *distributed* sort-test and *secondary facility* processing. These case studies were recycling studies, two recycled paper systems and an electronic waste recycling system, in which the return product was first sorted at the collection site before it was transported to the recycling facility (Bloemhof-Ruwaard et al., 1996; Hong et al., 2006; Kleineidam et al., 2000).

All of the case studies with industry-wide collection systems performed processing at secondary facilities, and none used original facilities. In industry-wide collection systems, processing was highly likely to occur at a secondary facility, because it is relatively inefficient to retrieve a specific manufacturer's products from an industry-wide collection system and then deliver those products to the original manufacturing facility for processing. However, such a configuration may become viable if certain conditions change – for instance, if a specific manufacturer's products were easily identified and separated out from a industry-wide collection stream, then shipped directly from a collection site to the original facility to avoid unnecessary transportation costs. One example of such a system would be the use of RFID tagging for a particular manufacturer's product in an industry-wide collection system; RFID tagging would make tracking and retrieval of that manufacturer's products much simpler. Another example is the specific labeling of a manufacturer's product with a guarantee of end-of-life return by the manufacturer, such as for flooring squares, allowing the collector to contact the manufacturer to return the product.

The tradeoff considerations for each stage are as follows:

3.1.1 Stage A: Collection

Collection systems are either proprietary (company-specific), in which a company collects only its own products for recovery, or industry-wide, in which the same type of product from multiple producers is collected within the system. For proprietary collection systems, producers can use proprietary routing, in which the producer uses its own transportation system for collection, or they can outsource collection to a third-party logistics provider.

A proprietary collection system is particularly beneficial when the company has a strong direct relationship with its customer, such as a lease-return relationship, or when there is high customer trade-in behavior, such as there is in the business computer market (Fleischmann, 2000; Fleischmann et al., 2004). The proprietary collection system tends to strengthen those customer relationships, enhancing marketing and sales efforts. However, transportation costs may be higher than in an industry-wide collection system, because proprietary collection cannot take advantage of economies of scale available to higher volumes that an industry-wide system would handle.

Within a proprietary collection system, the company may either do its own collection using company trucks or freight providers, or it may contract with a third party to pick up its products for processing. Collecting with company trucks or freight is an attractive choice when a company wishes to protect intellectual and proprietary information. It can be desirable for integrating forward and reverse flows, such as for dropoff and pickup of reusable containers (Kroon and Vrijens, 1995). This system is also beneficial when there are relatively few customer sites. One drawback is potentially higher costs, as proprietary routing may be more expensive than outsourcing the collection system.

Contracting with a third-party for collection within a proprietary system may provide some economies of scale, as third-party logistics providers can pool shipping and facilities needs for multiple customers. This type of system may also be preferable for companies with large numbers of customer sites. Nevertheless, a third-party routing system has the drawback of reduced control by an individual company when it comes to intellectual and proprietary information.

Proprietary collection is a common choice for remanufacturing or remanufacturing systems. By contrast, industry-wide collection systems tend to be used for commodity-type products, such as paper recycling (Bloemhof-Ruwaard et al., 1996). These systems are also beginning to be prevalent for computers and electronic products, due to government mandates for industry-wide e-waste collection systems (Hong et al., 2006). A benefit of this type of system is economies of scale, due to higher volumes. It also does not complicate a company's forward supply chain, as an industry-wide system is typically a completely separate product return stream, collected by a third-party entity, as it is for electronic waste (e-scrap). However, an individual company has limited control over this type of collection system, and that includes costs and routing. Also, higher start-up costs may be incurred for an industry-wide collection system, because of the much larger scale and scope of the system.

3.1.2 Stage B: Sort-test

Sorting and testing can be performed either at a centralized site, or at distributed locations. A centralized site is common for a commodity-type product, such as construction sand recycling (Barros et al., 1998) or carpet recycling (Louwers et al., 1999; Realff et al., 2000), owing to efficiencies from higher volumes. But a centralized site is also desirable for high-cost testing procedures, because it minimizes costs of testing equipment and specialized labor. One drawback to centralized sorting and testing is the risk of higher transportation costs for shipping scrap to the testing facility first, rather than directly to waste disposal.

Distributed sort-test sites are often used if low-cost testing procedures are available, such as for paper recycling (Bloemhof-Ruwaard et al., 1996; Kleineidam et al., 2000), machine refurbishing (Thierry et al., 1995; Krikke et al., 1999a), or reusable containers and equipment (Duhaime et al., 2001; Kroon and Vrijens, 1995; Rudi et al., 2000). Scrap can be identified early and shipped to waste disposal, reducing transportation costs. However, testing procedures must be consistent and reliable, and the network may be more complicated because scrap and usable return product are shipped in separate streams.

3.1.3 Stage C: Processing

Once the type of processing is determined (recycling, reprocessing raw material, remanufacturing and spare parts recovery, or reuse), the key decision is whether to reprocess at the original facility, which is the methods for copiers (Krikke et al., 1999a), or at a secondary facility, which is the method for carpet (Realff et al., 2000).

Processing at the original facility provides increased efficiency from use of original facility equipment and processes, and it is often used for machine remanufacturing or spare parts recovery processing. However, there may be a need for increased processing capacity, which would be a drawback.

The benefits of processing at a secondary facility include economies of scale if done across the entire industry rather than for a single manufacturer, which makes this a good choice for a bulk commodity-type product such as construction sand. The drawbacks include the need to establish new, separate facilities with a possible loss of processing efficiency.

3.2 AHP decision making model

This section presents a multicriteria AHP decision model for network design. AHP is a multicriteria decision making (MCDM) method that provides a quantitative evaluation for decisions with both qualitative and quantitative decision factors. The AHP model in this research incorporates the following steps: 1) identify network configurations as alternatives, 2) specify decision criteria and subcriteria drawn from the conceptual framework in the previous section, 3) create pairwise comparison matrices with relative rankings among the criteria and the alternatives, and 4) synthesize them into a solution vector of overall preferences for the network configurations.

3.2.1 Decision factors: criteria and subcriteria

AHP involves identification of criteria and subcriteria and assigning rankings to the alternatives, criteria and subcriteria. The alternatives in the model are the eight network configurations in Table 3.2, while the criteria and subcriteria were derived from the conceptual framework in the previous section.

The decision hierarchy for our model is illustrated in Figure 3.3, comprising an overall goal, two principal criteria, six subcriteria, and eight alternatives. The criteria and subcriteria are described next.

Principal criteria: cost savings and business relations. The principal criteria consist of two categories into which the six subcriteria are assigned. Taken all together, the criteria and subcriteria encompass the set of considerations identified in the conceptual model in the previous section.

The cost savings criterion indicates the potential for cost savings and its relative importance as compared to business relations. On the other hand, the business relations criterion consists of whether strong customer relationships exist and whether proprietary knowledge needs to be protected. There is an implicit balance between cost savings and

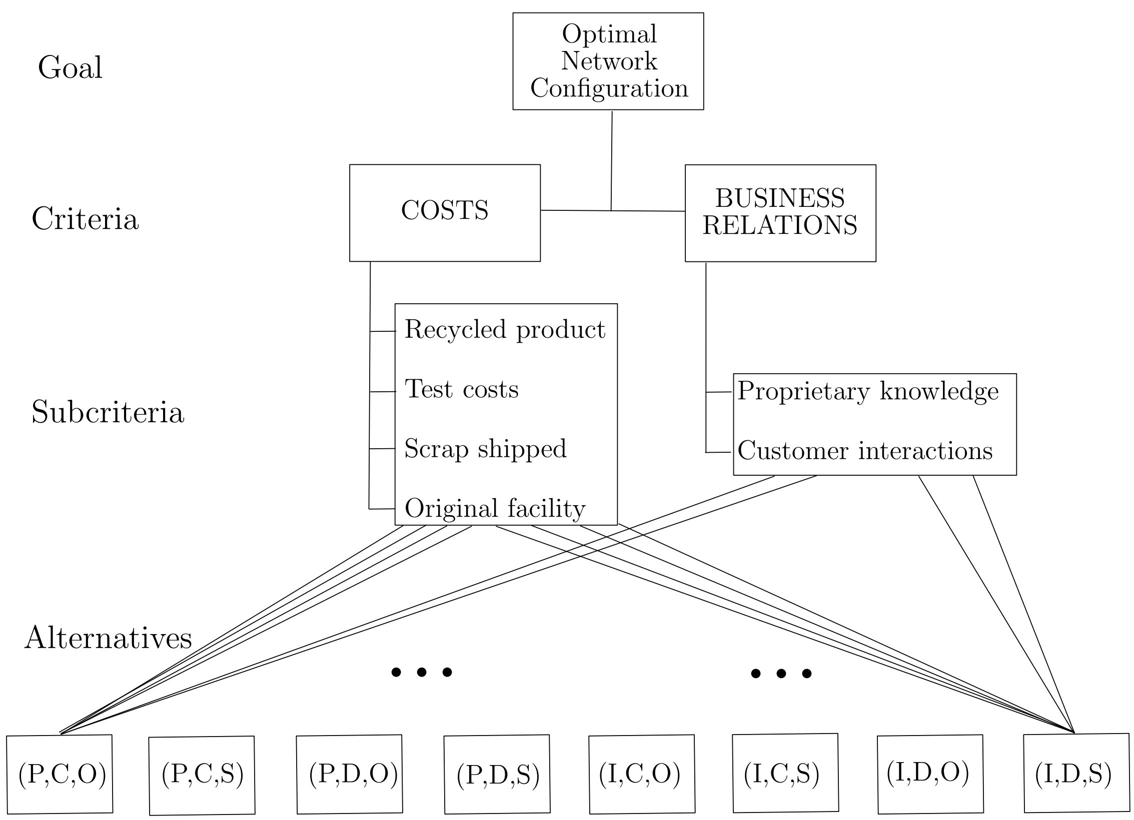


Figure 3.3: AHP hierarchy for network design of reverse logistics.

business relations. If the producer has few customer relationships or does not have a significant investment in product proprietary knowledge, then the cost savings criterion will be assigned a higher ranking relative to the business relations criterion. On the other hand, if the producer has strong customer relationships or may need to control the entire product recovery process due to a proprietary product knowledge investment, then the business relations criterion will be assigned a higher ranking relative to the cost savings criterion.

The six subcriteria, derived from the conceptual framework in Figure 3.2, are grouped under the principal criteria. Four subcriteria relate to the cost savings criterion:

Cost Savings subcriterion 1: Recycled product. Is the return product going to be recycled into raw materials, such as paper, carpet, or end-of-life consumer electronics? Or will the product be reused, remanufactured or refurbished? The recycled product subcriterion will be assigned a high ranking if there is a high potential for cost savings for recycling the product into raw materials. If the product will not be recycled, but instead will be reused or remanufactured, then there is little opportunity for cost savings due to recycling, and hence the ranking for this subcriterion will be assigned a low value. This subcriterion affects the collection stage decision and the processing stage decision.

Cost Savings subcriterion 2: Testing. How will the quality and condition of the return product be determined? Does it require high-cost equipment, specialized labor or materials? Or is the quality decision based on low-cost procedures, like determining model year, batch date or quantity on hand? The testing subcriterion will be assigned a high ranking if the product involves high testing costs with potential for reducing those costs, and it will be assigned a low ranking if it has little or no opportunity to save on testing costs. This subcriterion affects the sort-test stage decision.

Cost Savings subcriterion 3: Scrap shipped. Is there a high proportion of scrap in the return product stream? Does it need to be sent directly to a disposal location? If there is a high proportion of scrap in the product return stream, then transportation costs for scrap will be high, and that allows a high potential for cost savings by considering the location of sorting and testing facilities. Thus the ranking for this subcriterion will be high.

In contrast, if there is very little scrap, then this subcriterion will be assigned a low ranking, because there is a low potential for cost savings. This subcriterion affects the sort-test stage decision.

Cost Savings subcriterion 4: Original facility. Does the producer have capacity in its original plant to reprocess return product? Is it willing to dedicate specialized labor or machines to the reprocessing system? Or would it have to acquire or lease a secondary facility or to contract with a third party logistics provider instead? The original facility subcriterion will be assigned a high ranking if there is a high potential for cost savings, such as when the original facility has capacity for reprocessing, or a low ranking if there is a low potential for cost savings, such as when a secondary facility would need to be obtained. This subcriterion affects the processing stage decision.

Two subcriteria relate to the business relations criterion:

Business Relations subcriterion 1: Proprietary knowledge and control. Is there a notable amount of proprietary knowledge in the product? Does the producer want to keep a return product out of a competitor's hands? To what degree does the producer want to control the entire return product process? If it is important that the producer control the return product process, then this subcriterion will be assigned a high ranking. If there is little proprietary knowledge in the product or no desire to control the return process, then it will be given a low ranking. This subcriterion affects the collection stage decision and the processing stage decision.

Business Relations subcriterion 2: Customer interactions and direct relationships. Are there strong direct customer relationships with the producer? Is the product under warranty or a lifetime guarantee? Does the producer interact frequently with the customer, such as under a service contract? If the producer has a high degree of customer interactions and strong customer relationships, this subcriterion will be given a high ranking. If there are no direct customer relations, it will have a low ranking. This subcriterion affects the collection stage decision.

3.2.2 Pairwise comparisons: assigning priorities to criteria, subcriteria and alternatives

After identifying criteria and subcriteria, pairwise comparison matrices are constructed that contain numerical judgments assigned for each criterion, subcriterion and alternative. The Saaty scale is commonly used to denote the relative importance of one element to another (Saaty, 1982), but this study uses a related method, benchmarking (Saaty, 2001). In benchmarking one element is ranked 1, and the other elements are assigned an integer ranking relative to the benchmark element. With the benchmarking approach it is relatively straightforward for a producer to rank criteria and alternatives by comparing them to a benchmark element.

In this study, the rankings for pairwise comparison matrices were developed from information gathered in expert interviews and from published case studies. Industry knowledge from managers in the three case studies was used for the criteria and subcriteria rankings, because those rankings are dependent on the specific business situation and company values involved. On the other hand, the rankings of alternatives – network configurations – were determined by referring to the information across all case studies analyzed in this research, and those rankings depend only on the characteristics of the network configuration, not on the business situation or company values. Thus, the pairwise comparison matrices for principal criteria and subcriteria will vary from one application to another, while the pairwise comparison matrices for alternatives will not change.

The following is a description of the pairwise comparison matrices. Note that in each matrix, the matrix entries and priority vectors are presented as expressions in terms of each ranking (e.g., g_1, c_1, etc.) to clarify the relationship among rankings, which will lead into the sensitivity analysis that appears later in this section.

Pairwise comparison matrices for principal criteria and subcriteria. The pairwise comparison matrix for the principal criteria level of the decision hierarchy is shown in Table 3.3, in accordance with standard AHP methodology. The rankings of the cost savings and business relations criteria are denoted by g_1 and g_2 respectively. A matrix entry is the ratio of the row element ranking to the column ranking and all diagonal elements

Table 3.3: Pairwise comparison matrix for principal criteria.

Goal	Cost Savings g_1	Business Rel's g_2	Priority Vector V^G
Cost Savings g_1	1	g_1/g_2	$g_1/(g_1+g_2)$
Business Rel's g_2	g_2/g_1	1	$g_2/(g_1+g_2)$
	$\dfrac{g_1+g_2}{g_1}$	$\dfrac{g_1+g_2}{g_2}$	

Table 3.4: Pairwise comparison matrix for cost savings subcriteria.

Cost Savings	Recycled c_1	Testing c_2	Scrap c_3	Facility c_4	Priority Vector V^C
Recycled c_1	1	c_1/c_2	c_1/c_3	c_1/c_4	$c_1/\sum_{i=1}^4 c_i$
Testing c_2	c_2/c_1	1	c_2/c_3	c_2/c_4	$c_2/\sum_{i=1}^4 c_i$
Scrap c_3	c_3/c_1	c_3/c_2	1	c_3/c_4	$c_3/\sum_{i=1}^4 c_i$
Facility c_4	c_4/c_1	c_4/c_2	c_4/c_3	1	$c_4/\sum_{i=1}^4 c_i$
	$\dfrac{\sum_{i=1}^4 c_i}{c_1}$	$\dfrac{\sum_{i=1}^4 c_i}{c_2}$	$\dfrac{\sum_{i=1}^4 c_i}{c_3}$	$\dfrac{\sum_{i=1}^4 c_i}{c_4}$	

are equal to 1. The priority vector V^G in the rightmost column of the pairwise comparison matrix in Table 3.3 is the normalized set of values for the principal criteria level.

Using a similar approach, a pairwise comparison matrix was constructed for the four cost savings subcriteria in Table 3.4, whose rankings are denoted by c_1 through c_4. Table 3.5 shows the matrix for the two business relations subcriteria, with rankings of r_5 and r_6. Priority vectors V^C for the four cost savings subcriteria and V^R for the business relations subcriteria are also shown in Tables 3.4 and 3.5.

Pairwise comparison matrices for alternatives. Six pairwise comparison matrices were constructed, one for each subcriterion, to compare the eight network configuration alternatives, as shown in Table 3.6. The rankings are denoted by a_1^m through a_8^m, where

Table 3.5: Pairwise comparison matrix for business relations subcriteria.

Business Rel's	Propr. Knowl. r_5	Customer Int's r_6	Priority Vector V^R
Propr. Knowl. r_5	1	r_5/r_6	$r_5/(r_5+r_6)$
Customer Int's r_6	r_6/r_5	1	$r_6/(r_5+r_6)$
	$\dfrac{r_5+r_6}{r_5}$	$\dfrac{r_5+r_6}{r_6}$	

Table 3.6: Pairwise comparison matrix for alternatives relative to subcriteria $m = 1, \ldots, 6$.

Subcriteria m	(P,C,O) a_1^m	(P,C,S) a_2^m	$\cdots$	(I,D,S) a_8^m	Priority Vector W^{A^m}
(P,C,O) a_1^m	1	a_1^m/a_2^m	$\cdots$	a_1^m/a_8^m	$a_1^m/\sum_{i=1}^8 a_i^m$
(P,C,S) a_2^m	a_2^m/a_1^m	1	$\cdots$	a_2^m/a_8^m	$a_2^m/\sum_{i=1}^8 a_i^m$
$\vdots$	$\vdots$	$\vdots$	$\cdots$	$\vdots$	$\vdots$
(I,D,S) a_8^m	a_8^m/a_1^m	a_8^m/a_2^m	$\cdots$	1	$a_8^m/\sum_{i=1}^8 a_i^m$
	$\dfrac{\sum_{i=1}^8 a_i^m}{a_1^m}$	$\dfrac{\sum_{i=1}^8 a_i^m}{a_2^m}$	$\dfrac{\sum_{i=1}^8 a_i^m}{a_3^m}$	$\dfrac{\sum_{i=1}^8 a_i^m}{a_4^m}$	

m is an index associated with a specific subcriterion ($m = 1$ is recycled product, $m = 2$ is testing, etc.). The priority vectors are denoted by W^{A^1} through W^{A^6}.

As mentioned previously, the rankings in the matrixes for alternatives were developed from information across all case studies. The rankings reflect specific relationships between network configuration alternatives and the subcriteria, which are described in Table 3.7. For example, the cost savings for recycled product subcriterion impacts both the collection decision and the processing decision. It is probable that costs of collection and processing will be lessened by having an industry-wide collection system and a secondary processing facility, because recycled product networks are part of a waste stream with no cost flexibility to justify a proprietary collection system and would not merit processing in the original manufacturer's facility. The (I,_,_) and (_,_,S) entries in the recycled column indicate that

Table 3.7: Network configuration alternatives and relationships to subcriteria.

i	Config.	Recycled	Testing	Scrap	Facility	Propr. Knowl.	Customer Int.'s
1	(P,C,O)	–	(_,C,_)	–	(_,_,O)	(P,_,O)	(P,_,_)
2	(P,C,S)	(_,_,S)	(_,C,_)	–	–	(P,_,_)	(P,_,_)
3	(P,D,O)	–	–	(_,D,_)	(_,_,O)	(P,_,O)	(P,_,_)
4	(P,D,S)	(_,_,S)	–	(_,D,_)	–	(P,_,_)	(P,_,_)
5	(I,C,O)	(I,_,_)	(_,C,_)	–	(_,_,O)	(_,_,O)	–
6	(I,C,S)	(I,_,S)	(_,C,_)	–	–	–	–
7	(I,D,O)	(I,_,_)	–	(_,D,_)	(_,_,O)	(_,_,O)	–
8	(I,D,S)	(I,_,S)	–	(_,D,_)	–	–	–

if the return product will be recycled to raw material, costs can be reduced in network configurations with an industry-wide collection decision option and a secondary facility processing decision option.

On the other hand, the cost savings for testing subcriterion impacts only the sort-test decision. There is an opportunity to reduce overall testing costs by performing testing at centralized locations rather than at distributed locations. The (_,C,_) in the testing column indicates that high testing costs may be reduced through network configurations with the centralized sort-test decision option.

The cost savings for scrap subcriterion also impacts only the sort-test decision. Costs to ship scrap can be reduced by having distributed testing sites, so that scrap can be identified early and shipped directly to a disposal site. The (_,D,_) in the scrap column denotes that, if there is a high proportion of scrap in the return stream, it is possible to reduce costs by having a distributed sort-test decision option in the network configuration.

The cost savings for original facility subcriterion impacts only the processing decision. Having capacity in the original plant and specialized labor for reprocessing can eliminate costs to obtain a secondary processing facility or outsource processing to a third party processing. The (_,_,O) in the facility column indicates that costs can be reduced in network configurations with a secondary processing decision option when the producer has original facility capacity for reprocessing.

Table 3.8: Relative rankings for eight network configurations.

i	Config.	Recycled a_i^1	Testing a_i^2	Scrap a_i^3	Facility a_i^4	Propr. Knowl. a_i^5	Customer Int.'s a_i^6
1	(P,C,O)	1	4	1	3	6	6
2	(P,C,S)	2	4	1	1	4	6
3	(P,D,O)	1	1	6	3	6	6
4	(P,D,S)	2	1	6	1	4	6
5	(I,C,O)	4	4	1	3	2	1
6	(I,C,S)	6	4	1	1	1	1
7	(I,D,O)	4	1	6	3	2	1
8	(I,D,S)	6	1	6	1	1	1

The business relations for proprietary knowledge subcriterion impacts both the collection decision and the processing decision. Protecting proprietary knowledge can be best accomplished by proprietary collection and original facility processing. The (P,_,_) and (_,_,O) entries in the proprietary knowledge column denote that network configurations with a proprietary collection decision option and an original facility processing decision option enable the producer to maintain full control over their proprietary product investment.

The business relations for customer interactions subcriterion impacts the collection decision only. Strong direct producer-customer relationships make it easier to implement a proprietary collection system, because there are natural opportunities for collection during customer interactions, fostering repeat purchases and potentially increasing business for the producer. The (P,_,_) in the customer interactions column shows that a proprietary collection system is linked with a high degree of customer interactions.

Numerical values were developed for the rankings a_i^m, $i = 1, \ldots, 8$ and $m = 1, \ldots, 6$ in the case studies, and are provided in Table 3.8. As mentioned previously, these rankings among network configurations are independent of specific industries, whereas the subcriteria rankings g_1, g_2, c_1, c_2, c_3, c_4, r_5 and r_6 are dependent on the specific situation in each case study.

3.2.3 Synthesis: solution vector

The solution vector of preferences can be obtained with a straightforward matrix-vector multiplication approach of the priority vectors. The algebraic expressions for the multiplication are provided next as a basis for the sensitivity analysis calculations in the next section.

A matrix with the four network configuration priority vectors W^{A^1} through W^{A^4} that relate alternatives to the four cost savings subcriteria, is multiplied by V^C, the priority vector for the cost savings subcriteria, resulting in an 8 x 1 cost savings priority vector U^C:

$$U^C = [W^{A^1}\ W^{A^2}\ W^{A^3}\ W^{A^4}]\ [V^C]. \tag{3.1}$$

Similarly, a matrix with the two network configuration priority vectors W^{A^5} and W^{A^6} is multiplied by V^R, the priority vector for the two business relations subcriteria, to form an 8 x 1 business relations priority vector U^R:

$$U^R = [W^{A^5}\ W^{A^6}]\ [V^R]. \tag{3.2}$$

A matrix formed with U^C and U^R is then multiplied by the priority vector for the principal criteria, V^G, resulting in the 8 x 1 solution vector, U^G:

$$U^G = [U^C\ U^R]\ [V^G]. \tag{3.3}$$

Using equations (3.1), (3.2), and (3.3), the solution vector U^G can be written in terms of the relative rankings g_1, g_2, c_1, c_2, c_3, c_4, r_5, and r_6. The ith element of the solution vector U^G has the form:

$$\begin{aligned} u_i^G \quad = \quad & \frac{g_1}{g_1+g_2}\left(\frac{1}{\sum_{k=1}^{4} c_k}\right)\left(\frac{c_1 a_i^1}{\sum_{k=1}^{8} a_k^1}+\frac{c_2 a_i^2}{\sum_{k=1}^{8} a_k^2}+\frac{c_3 a_i^3}{\sum_{k=1}^{8} a_k^3}+\frac{c_4 a_i^4}{\sum_{k=1}^{8} a_k^4}\right) \\ & +\frac{g_2}{g_1+g_2}\left(\frac{1}{r_5+r_6}\right)\left(\frac{r_5 a_i^5}{\sum_{k=1}^{8} a_k^5}+\frac{r_6 a_i^6}{\sum_{k=1}^{8} a_k^6}\right). \end{aligned} \tag{3.4}$$

The solution vector U^G contains the overall preferences for all eight network configurations, that is, if $u_i^G > u_j^G$, then the ith alternative is preferred over the jth alternative. The highest value in the solution vector corresponds to the most preferred network configuration.

Using (3.4), the solution vector can be parameterized to analyze the effect of changing the relative rankings. This allows the sensitivity of the solution to the relative rankings in the decision model to be explored.

3.3 Sensitivity analysis

This section describes analytical calculations for sensitivity analysis of the solution to principal criteria and subcriteria rankings. Specifically, an expression for the intersection or crossover point at which the most preferred alternative is equal to the another alternative is presented.

Sensitivity analysis is provided by commercial software implementing AHP methodology, including Expert Choice (2009), using similar calculations. The visual representations of sensitivity analysis in Expert Choice were used as inspiration in this research. However, the following expressions were derived in this research and were used to analyze the sensitivity of the solutions in the three case studies using Excel.

Suppose the most preferred configuration in the solution vector is the ith alternative. A crossover point is desired, in which the ith alternative becomes equal to the jth alternative, indicating that the two alternatives have equal preference. The crossover point is determined by setting $u_i^G = u_j^G$ using (3.4):

$$\begin{aligned}
&\left(\frac{g_1}{g_1+g_2}\right)\left(\frac{1}{\sum_{k=1}^{4} c_k}\right)\left(\frac{c_1 a_i^1}{\sum_{k=1}^{8} a_k^1} + \frac{c_2 a_i^2}{\sum_{k=1}^{8} a_k^2} + \frac{c_3 a_i^3}{\sum_{k=1}^{8} a_k^3} \frac{c_4 a_i^4}{\sum_{k=1}^{8} a_k^4}\right) \\
&+ \left(\frac{g_2}{g_1+g_2}\right)\left(\frac{1}{r_5+r_6}\right)\left(\frac{r_5 a_i^5}{\sum_{k=1}^{8} a_k^5} + \frac{r_6 a_i^6}{\sum_{k=1}^{8} a_k^6}\right) \\
= \;&\left(\frac{g_1}{g_1+g_2}\right)\left(\frac{1}{\sum_{k=1}^{4} c_k}\right)\left(\frac{c_1 a_j^1}{\sum_{k=1}^{8} a_k^1} + \frac{c_2 a_j^2}{\sum_{k=1}^{8} a_k^2} + \frac{c_3 a_j^3}{\sum_{k=1}^{8} a_k^3} + \frac{c_4 a_j^4}{\sum_{k=1}^{8} a_k^4}\right) \\
&+ \left(\frac{g_2}{g_1+g_2}\right)\left(\frac{1}{r_5+r_6}\right)\left(\frac{r_5 a_j^5}{\sum_{k=1}^{8} a_k^5} + \frac{r_6 a_j^6}{\sum_{k=1}^{8} a_k^6}\right). \qquad (3.5)
\end{aligned}$$

Simplifying (3.5):

$$\begin{aligned}
&\left(\frac{g_1}{g_1+g_2}\right)\left[\left(\frac{c_1}{\sum_{k=1}^{4} c_k}\right)\left(\frac{a_i^1-a_j^1}{\sum_{k=1}^{8} a_k^1}\right)+\left(\frac{c_2}{\sum_{k=1}^{4} c_k}\right)\left(\frac{a_i^2-a_j^2}{\sum_{k=1}^{8} a_k^2}\right)\right.\\
&\left.+\left(\frac{c_3}{\sum_{k=1}^{4} c_k}\right)\left(\frac{a_i^3-a_j^3}{\sum_{k=1}^{8} a_k^3}\right)+\left(\frac{c_4}{\sum_{k=1}^{4} c_k}\right)\left(\frac{a_i^4-a_j^4}{\sum_{k=1}^{8} a_k^4}\right)\right]\\
&+\left(\frac{g_2}{g_1+g_2}\right)\left[\left(\frac{r_5}{r_5+r_6}\right)\left(\frac{a_i^5-a_j^5}{\sum_{k=1}^{8} a_k^5}\right)+\left(\frac{r_6}{r_5+r_6}\right)\left(\frac{a_i^6-a_j^6}{\sum_{k=1}^{8} a_k^6}\right)\right]\\
=\;&0. \qquad (3.6)
\end{aligned}$$

Equation (3.6) can then be used to consider the sensitivity of the ordering of alternatives to the relative rankings of criteria and subcriteria decision factors.

3.3.1 Principal criteria: cost savings and business relations

First consider the sensitivity of the solution vector U^G to g_1 and g_2, the rankings corresponding to the cost savings and business relations principal criteria. Let parameter α be defined as follows:

$$\alpha = \frac{g_1}{g_1+g_2}, \quad 1-\alpha = \frac{g_2}{g_1+g_2}.$$

Substituting α into (3.6), collecting terms and manipulating yields the following expression for crossover point $\hat{\alpha}_{i,j}$ between alternatives i and j:

$$\hat{\alpha}_{i,j} = \frac{-\left(\frac{r_5}{r_5+r_6}\right)\left(\frac{a_i^5-a_j^5}{\sum_{k=1}^{8} a_k^5}\right)-\left(\frac{r_6}{r_5+r_6}\right)\left(\frac{a_i^6-a_j^6}{\sum_{k=1}^{8} a_k^6}\right)}{-\left(\frac{r_5}{r_5+r_6}\right)\left(\frac{a_i^5-a_j^5}{\sum_{k=1}^{8} a_k^5}\right)-\left(\frac{r_6}{r_5+r_6}\right)\left(\frac{a_i^6-a_j^6}{\sum_{k=1}^{8} a_k^6}\right)+K} \qquad (3.7)$$

with

$$\begin{aligned}
K =\;&\left(\frac{c_1}{\sum_{k=1}^{4} c_k}\right)\left(\frac{a_i^1-a_j^1}{\sum_{k=1}^{8} a_k^1}\right)+\left(\frac{c_2}{\sum_{k=1}^{4} c_k}\right)\left(\frac{a_i^2-a_j^2}{\sum_{k=1}^{8} a_k^2}\right)\\
&+\left(\frac{c_3}{\sum_{k=1}^{4} c_k}\right)\left(\frac{a_i^3-a_j^3}{\sum_{k=1}^{8} a_k^3}\right)+\left(\frac{c_4}{\sum_{k=1}^{4} c_k}\right)\left(\frac{a_i^4-a_j^4}{\sum_{k=1}^{8} a_k^4}\right). \qquad (3.8)
\end{aligned}$$

The value of $\hat{\alpha}_{i,j}$ is the percentage $g_1/(g_1+g_2)$ at which the jth alternative becomes equal in preference to the ith alternative. The solution is not considered sensitive to α when $\hat{\alpha}_{i,j}$ is outside the interval (0,1] because $g_1, g_2 > 0$ by definition, so only crossover points $0 < \hat{\alpha}_{i,j} \leq 1$ make sense.

It is possible for the denominator in (3.7) to be zero, in which case there is no crossover point between alternatives i and j, i.e., the alternatives are parallel with respect to α.

3.3.2 Subcriteria: business relations

Next consider sensitivity to r_5 and r_6, the rankings corresponding to the two business relations subcriteria: proprietary knowledge and customer interactions. Let parameter β be defined as follows:

$$\beta = \frac{r_5}{r_5+r_6}, \quad 1-\beta = \frac{r_6}{r_5+r_6}.$$

Substituting β into (3.6), gives another crossover point

$$\hat{\beta}_{i,j} = \frac{-\left(\dfrac{a_i^6-a_j^6}{\sum_{k=1}^{8} a_k^6}\right) - \left(\dfrac{g_1}{g_2}\right) K}{\left(\dfrac{a_i^5-a_j^5}{\sum_{k=1}^{8} a_k^5}\right) - \left(\dfrac{a_i^6-a_j^6}{\sum_{k=1}^{8} a_k^6}\right)} \tag{3.9}$$

with K as in (3.8).

The crossover point $\hat{\beta}_{i,j}$ is subject to the same conditions as for $\hat{\alpha}_{i,j}$; if $\hat{\beta}_{i,j}$ is in the interval $(0,1]$, the solution is sensitive to β, otherwise, it is not sensitive.

3.3.3 Subcriteria: cost savings

Finally, consider sensitivity to changes in c_1, c_2, c_3, and c_4, the relative rankings corresponding to the cost savings subcriteria: recycled product, testing, scrap shipped, and original facility. However, because there are four rankings, there is not a simple ratio of two rankings as was the case for g_1, g_2 and for r_5, r_6.

Let four parameters γ_p be defined as follows:

$$\gamma_p = \frac{c_p}{\sum_{k=1}^{4} c_k}, p = 1, \ldots, 4, \tag{3.10}$$

with

$$\gamma_1 + \gamma_2 + \gamma_3 + \gamma_4 = 1.$$

To graph sensitivity for a particular γ_p, the remaining $(1 - \gamma_p)$ is distributed among the other three γ parameters in proportion to their original proportions.

Consider u_i^G for each network configuration as a function of a particular γ_p as it varies between 0 and 1. Suppose γ_1 is fixed at a specific value between 0 and 1; to re-assign $(1-\gamma_1)$ among the other three γ parameters while maintaining their original proportions, let

$$\hat{\gamma_q}^1 = \left(\frac{c_q}{\sum_{k=2}^{4} c_k}\right)(1 - \gamma_1), q = 2, 3, 4 \tag{3.11}$$

where $\hat{\gamma_q}^1$ is the coefficient that has been assigned its proportion of $(1 - \gamma_1)$.

Using γ_1, $\hat{\gamma_2}^1$, $\hat{\gamma_3}^1$, and $\hat{\gamma_4}^1$ from (3.10) and (3.11) in (3.4) and solving for u_i^G,

$$\begin{aligned} u_i^G = & \frac{g_1}{g_1 + g_2}\left[\gamma_1\left(\frac{a_i^1}{\sum_{k=1}^{8} a_k^1}\right) + \hat{\gamma_2}^1\left(\frac{a_i^2}{\sum_{k=1}^{8} a_k^2}\right)\right. \\ & \left. + \hat{\gamma_3}^1\left(\frac{a_i^3}{\sum_{k=1}^{8} a_k^3}\right) + \hat{\gamma_4}^1\left(\frac{a_i^4}{\sum_{k=1}^{8} a_k^4}\right)\right] \\ & + \frac{g_2}{g_1 + g_2}\left(\frac{1}{r_5 + r_6}\right)\left(\frac{r_5 a_i^5}{\sum_{k=1}^{8} a_k^5} + \frac{r_6 a_i^6}{\sum_{k=1}^{8} a_k^6}\right). \end{aligned} \tag{3.12}$$

Thus, as γ_1 varies between 0 and 1, u_i^G is a function of γ_1 from (3.12), where $\hat{\gamma_2}^1$, $\hat{\gamma_3}^1$, and $\hat{\gamma_4}^1$ are given in (3.11). A similar procedure is applied to obtain sensitivity to γ_2, γ_3 and γ_4. Sensitivity to the γ parameters in the three case studies are illustrated in graphs in the following section.

3.4 Three new case studies

This section describes three case studies from real-world applications that were used to validate the conceptual framework and to demonstrate the multicriteria AHP model. The case studies are taken from actual reverse logistics systems, and they are: (1) medical device remanufacturing, (2) residential carpet fiber recycling, and (3) commercial carpet fiber recycling. Because they are drawn from different products, business situations, or both, the three case studies illustrate different producer preferences and different network configurations. Experts were interviewed in company or organization to construct the case study. After information on the reverse logistics system had been gathered, the conceptual framework was applied to identify the network configuration represented by the case study. The multicriteria AHP model was then applied on each case study based on information provided by the experts, and sensitivity analysis was performed to determine the sensitivity of the decisions to each criteria and subcriteria.

Each case study is first described briefly followed by the associated network configuration using the conceptual framework. Then the implementation of the AHP model for each case study is explained, and the results for sensitivity analysis are presented and discussed.

3.4.1 Description and network configuration

Case study 1: Medical device remanufacturing.

Phillips Healthcare, a major medical device manufacturer on the West Coast, has an ultrasound device remanufacturing program, which operates on a trade-in basis with customers under a service contract. An outdated machine may be either shipped back to the manufacturer's facility for remanufacturing or shipped directly to a national electronics recycler in Chicago, Sims/URI (see Figure 3.4).

At the customer site, the outdated product is evaluated for recycling or possible remanufacturing. Products to be recycled are shipped to the electronics recycler directly, reducing transportation costs that would be incurred if the product was shipped first to the manufacturer's warehouse on the West Coast and then to the recycling facility. Products that may be remanufactured are shipped to a warehouse near the manufacturing plant. They are

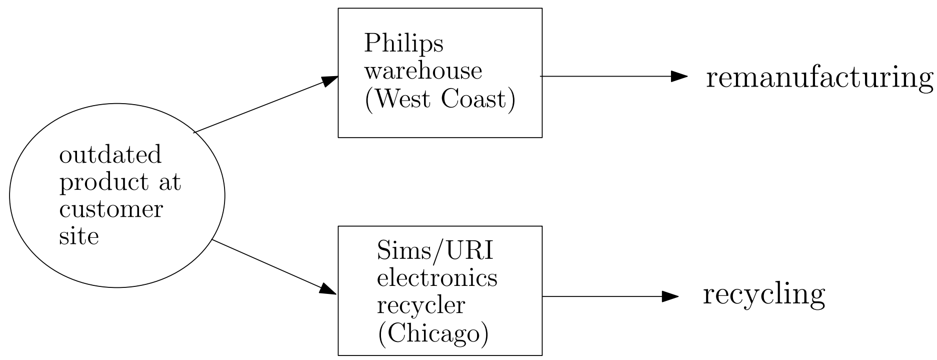


Figure 3.4: Medical device remanufacturing.

held until a customer order is received, and then they are remanufactured to fill the order, avoiding the investment of unnecessary cost to remanufacture a product that does not get sold. Periodically, the manufacturer's warehouse inventory is culled for excess inventory, and unneeded machines are sent to the electronics recycler.

The electronics recycler has the capability to recover spare parts for the manufacturer's service part inventory. This provides valuable spare parts to repair older machines still in use by customers, which are under a service contract for seven to ten years.

This system has the following advantages:

- On-site evaluation for sort-test. Transportation costs are minimized by avoiding shipping scrap to the manufacturer's warehouse before shipping to the recycler.

- Remanufacture on customer order. Because machines are remanufactured to order, unnecessary costs are avoided that would be incurred if a machine was remanufactured and remained unsold.

- Flexible spare part recovery. Spare parts can be recovered either by the recycler or at the manufacturing plant, allowing flexibility in maintaining outdated machine spare parts.

This system's major challenge is uncertainty in supply and demand. The volume and condition of return products is highly variable, complicating sales forecasting and inventory control of used machines. The producer's holding warehouse provides some mitigation as an inventory buffer.

Framework: network configuration (P,D,O). The medical device remanufacturing case study has proprietary collection, distributed sort-test, and original facility processing. Because the medical device manufacturer's system involves a single manufacturer's product in which proprietary knowledge is critical, proprietary collection and original facility processing are preferable. This case has the advantage of distributed sort-test, shipping scrap directly from the customer site to the recycler, saving transportation costs. Performing sorting and testing at the collection site is preferable over centralized sorting and testing whenever possible. Dealing with pre-sorted returned product reduces costs at the processing center and reduces transportation costs for product that cannot be processed. For example, in the business lease-return computer case study (Fleischmann, 2000; Fleischmann et al., 2004), all return computers came into a central facility before they were recycled or remanufactured, unlike the system in this new case study.

Case study 2: Residential carpet fiber recycling.

Shaw Industries, a Dalton, Georgia flooring manufacturer, collects used residential carpet from a number of individual third-party recycling centers located nation-wide. Used carpet is not limited to Shaw Industries' products alone, but it accepted from all carpet manufacturers' products. The carpet is sorted at the recycling centers for a specific type of fiber (nylon 6), then bundled and shipped to Shaw's secondary nylon 6 recycling plant in Georgia (see Figure 3.5).

Used carpet is tested at the third-party recycling center with a hand-held device that identifies the fiber content. Nylon 6 carpet is separated from other carpet types and bundled by the recycler, then shipped to a warehouse near the Shaw recycling plant. The carpet is unbundled and tested again; if a bundle is 96% or greater nylon 6 fiber, a bonus payment is given to the recycler. It is then stored in the warehouse both to adjust the humidity level of the carpet, and to buffer seasonal variations in inventory levels.

Used carpet is processed at the depolymerizing plant, producing raw caprolactum fiber, the basis for nylon 6 fiber. The quality of the caprolactum fiber is actually higher than

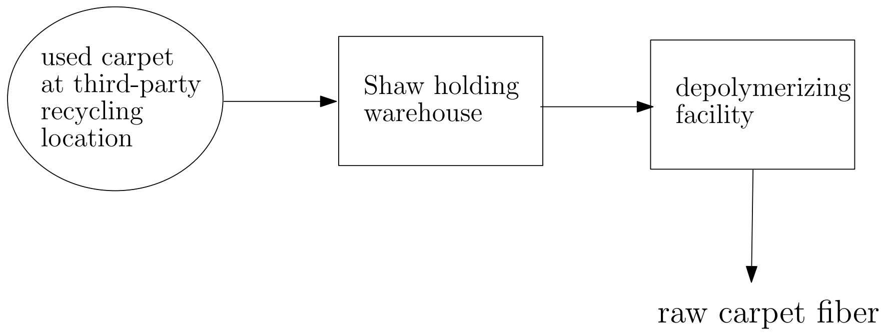


Figure 3.5: Residential carpet fiber recycling.

fiber obtained elsewhere by Shaw for carpet production, and it can be sold by Shaw to other carpet manufacturers. Shaw's customers indicate that, given a comparable price point between products made from recycled fiber and those made from virgin fiber, they will consistently buy the recycled product.

This system has the following advantages:

- Collection site testing incentive program. Over the years, Shaw has found that the content of baled carpet bundles is consistently above 98% nylon 6, due to their incentive program.

- Customer preference for recycled product. Having a recycling process for carpet production translates to increased customer sales.

- Economies of scale. Having an industry-wide, nation-wide collection program helps promote efficiencies in transportation and processing of used carpet.

This system's major challenge is capital investment and costs of production. Under current conditions, production costs of recycled fiber slightly exceed the cost to purchase raw material. However, changing conditions, such as an increase in the cost of oil, may make recycled fiber more cost-effective.

Framework: network configuration (I,D,S). The residential carpet recycling case study has industry-wide collection, distributed sort-test, and secondary facility processing.

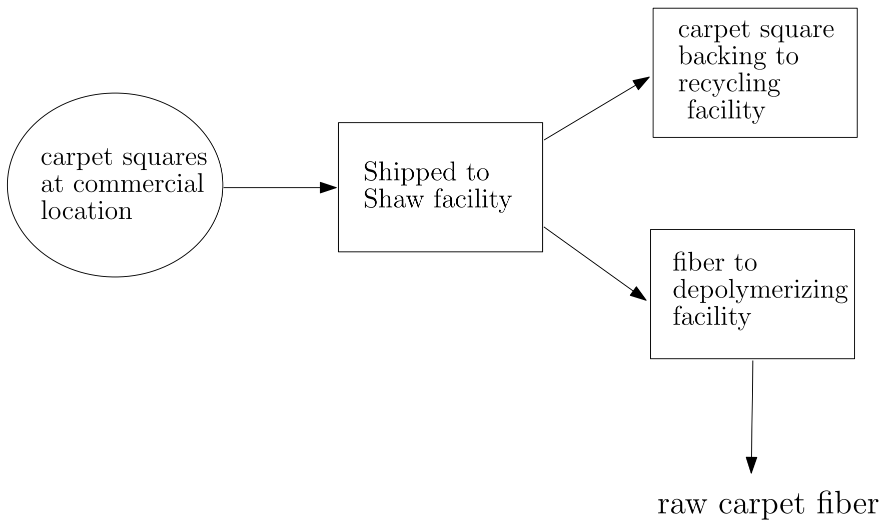


Figure 3.6: Commercial carpet fiber recycling.

Although the recycled fiber is used in its original manufacturing facility, the recycling processing is performed at a secondary facility, which is typical for an industry-wide collection system. The distributed sort-test feature is an improvement over the prior carpet case study listed in Realff et al. (2000). The advantage of testing at the collection site is that the returned product is pre-sorted, avoiding excess transportation costs for non-nylon 6 carpet.

Case study 3: Commercial carpet fiber recycling.

Shaw Industries has developed a commercial carpet product that consists of nylon 6 carpet squares with a fully recyclable backing. The product comes with a lifetime guarantee that Shaw will pick up the used carpet from the customer location and recycle it. Each carpet square has a toll-free telephone number stamped on the back, and with a minimum square footage, the commercial customer can call to have the carpet collected by a Shaw-dispatched freight carrier. The carpet is sent to Shaw's secondary nylon 6 recycling plant (see Figure 3.6).

Sorting takes place at the customer location. Because the product is modular, in removable squares rather than a large carpet expanse, only the worn carpet is collected, reducing waste. Since the product is under a lifetime guarantee, the content is already known at the time of collection, eliminating the need for additional testing for fiber content. Nylon 6 fiber processing is the same as for residential carpet.

This system has the following advantages:

- Direct customer relationships. Providing a lifetime guarantee fosters strong direct customer relationships, potentially increasing sales.

- Reduces testing costs. Collecting from the customer under the lifetime guarantee ensures purity of carpet fiber collected, avoiding post-consumer testing needed in the residential carpet recycling system.

- Waste reducing in post-consumer product. Providing the product as carpet squares eliminates unnecessary disposal of usable carpet.

One challenge of this system is collecting sufficient volume of used product to satisfy the volume needed for the Shaw secondary processing facility. The reason the residential carpet recycling system collects from across the country is to meet capacity to make the caprolactum facility fully operational. However, if combined with the residential program, volumes have been sufficient in the past few years.

Framework: network configuration (P,D,S). The commercial carpet recycling case study has proprietary collection, distributed sort-test, and secondary facility processing. Even though carpet is considered a commodity-type product and has no significant proprietary product knowledge, the manufacturer wants to retain control over the system and has implemented a proprietary collection system. The higher investment in cost for a proprietary system is offset by retaining direct customer relationships, which generates additional sales potential. It also eliminates the need for testing. Proprietary collection may be more widely implemented in the future if manufacturers move from a waste-collection paradigm to a service-providing model, in which companies deliver the service of a product to customers rather than the product itself.

Next, the AHP decision model is demonstrated on the three case studies.

Table 3.9: Relative rankings for three case studies.

Criteria-Subcriteria	Ranking	Medical Device	Residential Carpet	Commercial Carpet
Cost Savings	g_1	1	5	1
Business Rel's	g_2	5	1	5
Recycled	c_1	1	6	6
Testing	c_2	2	2	2
Scrap	c_3	5	5	5
Facility	c_4	6	1	1
Propr. Knowl.	r_5	2	1	1
Customer Int's	r_6	1	1	5

3.4.2 AHP demonstration and sensitivity analysis

Based on information obtained in expert interviews, the relative rankings for the two principal criteria (g_1, g_2) and for the six subcriteria (c_1, c_2, c_3, c_4, r_5, and r_6) were assigned for each case study. The rankings are listed in Table 3.9.

Relative rankings for the alternative-subcriteria relationships a_i^m, $i = 1, \ldots, 8$, $m = 1, \ldots, 6$ were provided earlier in Table 3.8, and were determined from information in all case studies. These rankings are the same for all three case studies, because the rankings of the alternatives relative to each criteria do not depend on the business situation or company values. Only the rankings for criteria and subcriteria change for each case study.

The AHP methodology with the alternative-subcriteria rankings in Table 3.8 and the criteria and subcriteria rankings in Table 3.9 results in the solution vectors in Table 3.10. The most preferred network configuration for each case study appears in boldface type in the solution vector.

The results of the AHP model for each case study are described next.

Case study 1: Medical device remanufacturing.

In the medical device remanufacturing operation, the manufacturer developed a trade-in program to take back outdated versions of the medical device. The return product will either be remanufactured or disposed, depending on market demand.

Table 3.10: Solutions vectors for three case studies (preferred configuration in **bold**).

Configuration	Medical Device	Residential Carpet	Commercial Carpet
(P,C,O)	0.21	0.10	0.19
(P,C,S)	0.16	0.10	0.18
(P,D,O)	**0.22**	0.13	**0.20**
(P,D,S)	0.16	0.13	0.19
(I,C,O)	0.07	0.11	0.06
(I,C,S)	0.05	0.13	0.05
(I,D,O)	0.08	0.15	0.06
(I,D,S)	0.05	**0.16**	0.06

The producer in this case study considers business relations to be more important than cost savings alone, because the producer has invested significantly in direct cusomer relationships, through long-term customer service contracts. The producer has also invested heavily in proprietary product design, and needs to protect proprietary knowledge in its product. Thus, the business relations criterion is ranked 5 ($g_2 = 5$), while the cost savings criterion is the benchmark ($g_1 = 1$).

Among the four cost savings subcriteria, the producer considers the recycled product subcriterion to be the least valuable. Because the product will be remanufactured, it will not be recycled into raw material, so there is no opportunity to reduce costs through the recycled product subcriterion. Therefore, recycled product is the benchmark subcriterion ($c_4 = 1$). The testing subcriterion is also considered to be of low value by the producer. Testing costs are very low, and no specialized equipment or labor is needed, as the testing assessment is based on the model type and year. Thus, cost savings may not be possible through the testing subcriterion. The testing subcriterion is valued only slightly higher than the benchmark subcriteria, so it is ranked 2 ($c_2 = 2$).

On the other hand, the producer has more than sufficient in-plant capacity in its original manufacturing facility for remanufacturing, together with availability of specialized labor and equipment. This provides a rich opportunity for cost savings by not having to lease or purchase a secondary facility for remanufacturing. Consequently, the original facility subcriterion is the highest ranked subcriterion ($c_4 = 6$). The shipping scrap subcriterion is also highly valued. The producer can realize significant cost savings by identifying scrap machines early and shipping them directly to a recycler for disposal, avoiding unnecessary freight costs. The shipping scrap subcriterion is valued only slightly lower than the original facility subcriterion, ranked 5 ($c_3 = 5$).

As for the business relations subcriteria, the producer considers it vital to protect its proprietary knowledge from competitors. This interest is considered more valuable than customer interactions, although both are important to the producer. The proprietary knowledge subcriterion is therefore ranked 2 ($r_5 = 2$), while the benchmark subcriterion is customer interactions ($r_6 = 1$).

The solution vector for this case study (see Table 3.10) shows that network configurations with proprietary collection, (P,_,_), are preferred significantly over network configurations with industry-wide collection, (I,_,_), with fourteen percentage points separating the most favored configuration, (P,D,O), from the most favored among industry-wide collection configurations, (I,D,O). This indicates proprietary collection is clearly a preferred option for this producer's network configuration.

The results indicate that this producer should strongly consider either the (P,D,O) or (P,C,O) network configurations. The (P,D,O) and (P,C,O) alternatives are separated by five or six percentage points from the next alternatives. Although distributed testing site configurations are slightly preferred over centralized testing site locations, the distinction is one percentage point or less; the choice between a distributed or centralized testing site option would depend on the degree to which the producer wants to avoid shipping scrap.

Case Study 2: Residential carpet recycling.

In the second case study, residential carpet fiber recycling, carpet from residential customers is typically returned through retailers, installers and other disposal centers, then sorted to identify the needed carpet fiber type from other types and debris, and converted into raw materials Realff et al. (2004). Handheld fiber testing devices are used to test the used carpet for a specific fiber type, and all other fiber types cannot be recycled in a recycling facility and must be disposed of.

In this case study, cost savings is very important to the producer, far outweighing business relationships. The producer has no direct relations with retail carpet customers in the carpet recycling stream, and no need to protect proprietary knowledge. Thus, the cost savings criterion is ranked 5 ($g_1 = 5$, and the business relations criterion is the benchmark ($g_2 = 1$). This is typical for a recycled material operation, where the return product is part of a waste stream, and no direct relationships exist with the final user. This is the opposite of the medical device case study, where customer relationships and proprietary knowledge were paramount.

Among the four costs savings subcriteria, the producer considers the original facility subcriterion to be the least valuable. Because there is no capacity in the original plant for processing, there is little potential to reduce costs through the original facility subcriterion. Original facility is therefore the benchmark subcriterion ($c_4 = 1$). This is the reverse of the medical device case study, where the producer was set up to perform product remanufacturing in its original facility. The testing subcriterion is also considered to be of low value. Testing costs are relatively low and can be easily performed at the collection site with a handheld tester, so not much cost savings can be realized through the testing subcriterion ($c_2 = 2$).

Because the return product will be recycled into raw material, there is great opportunity to reduce costs through the recycled product subcriterion, which is ranked 6 ($c_4 = 6$). Again, this is the reverse of the medical device case study, where the product was not part of a recycling waste stream. Like the medical device case study, the producer highly values the scrap subcriterion ($c_3 = 5$), because it has high potential for cost reductions.

Regarding the business relations subcriteria, proprietary knowledge and customer interactions are not significant factors in residential carpet recycling. Thus, the proprietary knowledge subcriterion ($r_5 = 1$) is valued equally to the customer interactions subcriterion ($r_6 = 1$).

The solution vector in Table 3.10 indicates that the network configurations are much more closely clustered than in the medical device case study. The highest preferred alternative is (I,D,S), with a close second choice of (I,D,O). The (I,D,S) and (I,D,O) configurations share common decision options for collection (industry-wide) and testing (distributed testing). Industry-wide collection systems and early testing reduce costs by exploiting efficiencies of volume, and by allowing scrap to be shipped directly from collection to disposal.

The (I,_,_) configurations denote a collection system that collects products from multiple manufacturers, rather products from the producer alone, as was the case in the medical device case study. It is interesting to note that network configurations with industry-wide collection and secondary facility processing, (I,D,S) and (I,C,S), are by far the most common configurations for a recycled product; Barker and Zabinsky (2008) found that in 15 recycled product case studies, all had either (I,D,S) or (I,C,S) network configurations. By contrast, in the medical device case study, proprietary collection systems were preferred over industry-wide collection because of the value of proprietary product knowledge and strong customer relations. A proprietary collection system could be considered for a recycling system under certain conditions, as the third case study shows.

Case study 3: Commercial carpet recycling.

In the third case study, the commercial carpet product has a lifetime guarantee that the manufacturer will pick up and recycle used carpet directly from the commercial customer. Unlike the residential carpet case study, the manufacturer maintains a direct relationship with the commercial customer due to volume and type of product; it does not have a direct relationship with residential customers, who purchase through a retailer or installer.

As in the medical device case study, the producer has fostered strong customer relationships. Consequently, the business relations criterion is ranked 5 ($g_2 = 5$), while the cost savings criterion is the benchmark ($g_1 = 1$).

Among the four costs subcriteria, the rankings are the same as for the residential carpet case study. The benchmark subcriterion is original facility ($c_4 = 1$), and testing is ranked 2 ($c_2 = 2$), shipping scrap is ranked 5 ($c_3 = 5$), and recycled product is ranked 6 ($c_4 = 6$). This is nearly opposite to the medical device case study, in which recycled product was ranked 1, and original facility had the highest ranking of 6.

For the business relations subcriteria, the producer is highly interested in sustaining customer relationships, but has no interest in protecting proprietary knowledge. The customer interactions subcriterion is ranked 5 ($r_6 = 5$), and the proprietary knowledge subcriterion is the benchmark ($r_5 = 1$). This is in contrast to the medical device case study, in which the producer wanted to have both strong customer relations and proprietary protection and control. It is also in contrast to the residential carpet case study, in which neither customer relations nor proprietary knowledge were important to the producer.

In the solution vector in Table 3.10, network configurations with proprietary collection are widely preferred over those with industry-wide collection. All proprietary collection configurations are closely clustered, and they are separated from industry-wide collection configurations by at least thirteen percentage points. This is more similar to the medical device case study than the residential carpet case study. Even though the cost savings subcriteria rankings c_1, c_2, c_3, and c_4 are the same for residential carpet and commercial carpet case studies, the rankings for the principal criteria g_1 and g_2 are the same for the first and third case studies (medical devices and commercial carpet).

The proprietary network configurations are closely grouped, where (P,D,O) is the most preferred, with (P,C,O) and (P,D,S) tied for second, and (P,C,S) a close third. This indicates the producer should focus on a proprietary collection configuration. The testing decision and the processing decision would not be critical, and could be made based on updated information or other considerations.

The sensitivity of the network configuration to criteria and subcriteria rankings is discussed next.

3.4.3 Sensitivity for the three case studies

Sensitivity analysis was performed using equations in Section 3.3. Table 3.11 summarizes the results for the three case studies to parameters α, β and $\gamma_1, \ldots, \gamma_4$. Sensitivity analysis to each of the criteria and subcriteria for the three case studies is also illustrated graphically in this section using charts produced in Excel.

As shown in Table 3.11, all three case studies are sensitive to the principal criteria α. The medical device and residential carpet case studies are insensitive to the business relations subcriteria β, and the commercial carpet case study is slightly sensitive. While residential carpet is sensitive to all four cost savings subcriteria, medical devices and commercial carpet

Table 3.11: Sensitivity results for three case studies.

Parameter		Medical Devices	Residential Carpet	Commercial Carpet
α	Principal criteria	slightly sensitive	sensitive	sensitive
β	Business Relations subcriteria	insensitive	insensitive	slightly sensitive
γ_1	Recycled Costs subcriteria	insensitive	sensitive	insensitive
γ_2	Testing Costs subcriteria	sensitive	sensitive	sensitive
γ_3	Scrap Costs subcriteria	sensitive	sensitive	sensitive
γ_4	Facility Costs subcriteria	insensitive	sensitive	insensitive

are sensitive to the cost savings testing and scrap shipped subcriteria only. The results are discussed in detail below.

Sensitivity to α parameter.

The three graphs in Figure 3.7 illustrate the relationships among the decision alternatives with regard to the principal criteria parameter α. As the value of α increases (from left to right along the horizontal axis), the preference u_i^G of each decision alternative i follows a linear path. These paths can be considered sensitivity lines. The solid vertical line on the graph indicates the current value of α for each case study. At that point, the network configuration with the highest preference on the vertical axis is the most preferred alternative in the solution. The dotted crossover point is the point at which the most preferred alternative has an equal preference with another alternative.

All three case study solutions are sensitive to α. The (P,_,_) and (I,_,_) solutions are widely separated at α near 0, then (P,_,_) solutions decrease and (I,_,_) solutions increase in preference as α increases toward 1. For all three solutions, (P,D,O) is the preferred alternative when α is closer to zero, which is when the business relations criterion dominates the cost savings criterion. As α increases toward 1 and the cost savings criterion becomes dominant over the business relations criterion, an (I,_,_) solution eventually becomes preferred.

Specifically, in the medical device case study, the (I,D,O) network configuration becomes preferred over (P,D,O) if α surpasses 95%, while in the residential carpet case study, (I,D,S) becomes preferred over (P,D,O) if α is greater than at 72%. In the commercial case

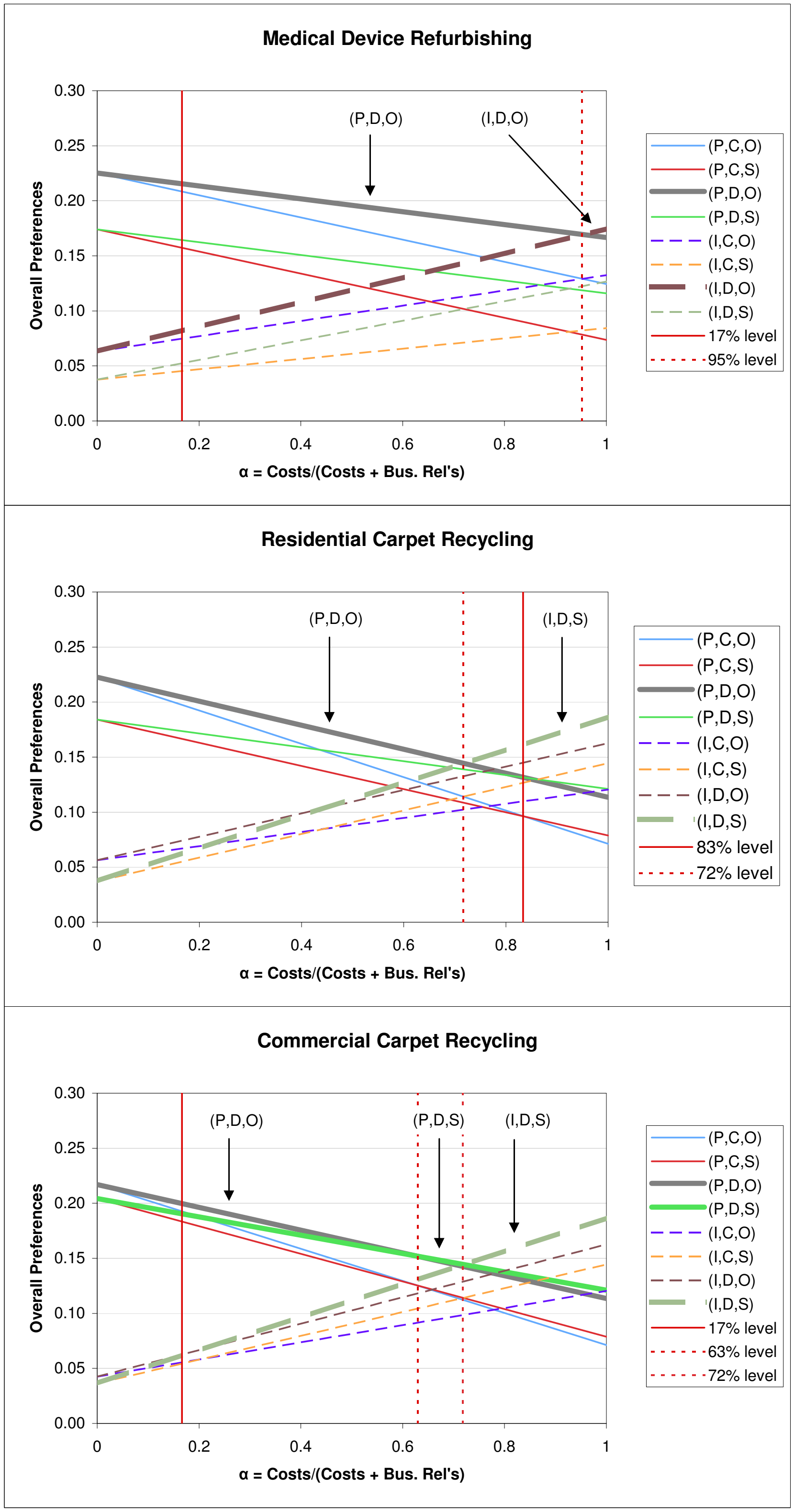


Figure 3.7: Sensitivity to α for case studies.

study, there are two crossover points: (P,D,S) is preferred over (P,D,O) in the short interval between 63% and 72%, and (I,D,S) is preferred at above 72%.

Overall, the parameter α largely impacts the collection decision (proprietary or industry-wide), with secondary effects on the sort-test and processing network decisions.

Sensitivity to β parameter.

Figure 3.8 contains the graphs for the business relations subcriteria parameter β. The first two case studies, medical devices and residential carpet, have no crossover point for β, while the third case study, commercial carpet, has one crossover point at $\beta = 2\%$. Thus, the first two are insensitive to the β parameter, and only the third is slightly sensitive to β.

It can be seen in the three graphs that the eight network configuration preferences have sensitivity lines that are parallel to one another in pairs; that is, the lines for (P,D,O) and (P,C,O) are parallel to one another and have the same slope. The same is true for (P,D,S) and (P,C,S), for (I,D,O) and (I,C,O), and for (I,D,S) and (I,C,S). The only difference among the two network configurations in these pairs is the middle decision choice: whether sort-test is distributed (_,D,_) or centralized (_,C,_). Therefore there is no impact from β on the sort-test decision choice.

The sensitivity lines for original facility network configurations (_,_,O) have increasing values as β increases, while the sensitivity lines for secondary facility network configurations (_,_,S) have decreasing values as β increases. In the first two case studies, there is no impact from β on processing choice. In the third case study, however, there is one crossover point at 2%; below that point (P,D,S) is preferred, and above it, (P,D,O) is preferred. Thus β has a slight impact on the processing decision choice in commercial carpet only.

Sensitivity to γ parameters.

Figures 3.9, 3.10, and 3.11 contain the graphs for the four cost savings subcriteria parameters γ_1, γ_2, γ_3, γ_4 in Case Studies 1, 2 and 3 respectively. Case Studies 1 and 3 have no crossover points for γ_1 and γ_4, hence are insensitive to γ_1 and γ_4. They have one crossover point each for γ_2 and γ_3, while the Case Study 2 has crossover points for all four γ parameters. Case Studies 1 and 3 are sensitive to γ_2 and γ_3, and Case Study 2 is sensitive to all γ parameters.

First consider sensitivity to γ_2 and γ_3, which affect all three case studies. In Case Studies

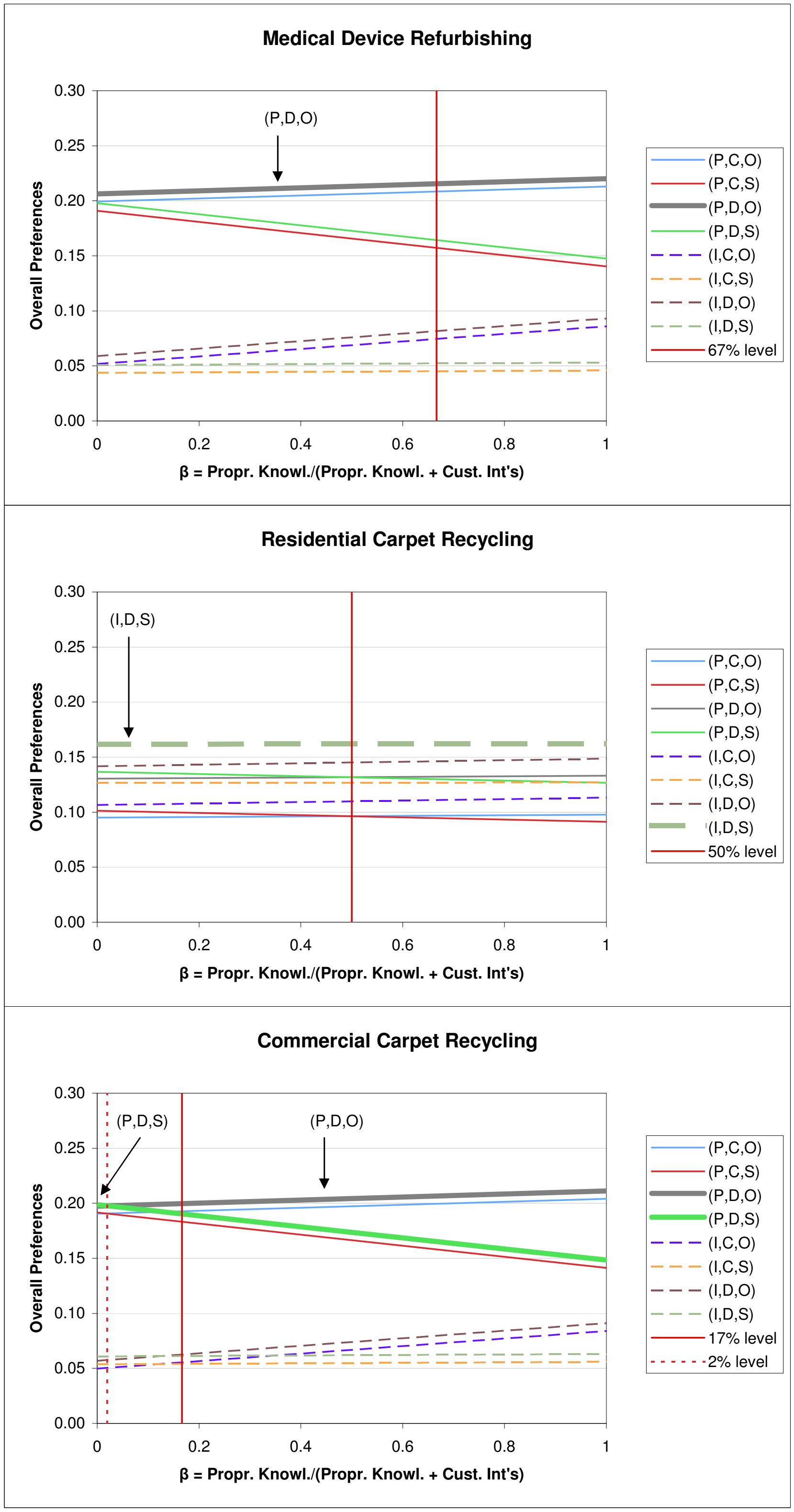


Figure 3.8: Sensitivity to β for case studies.

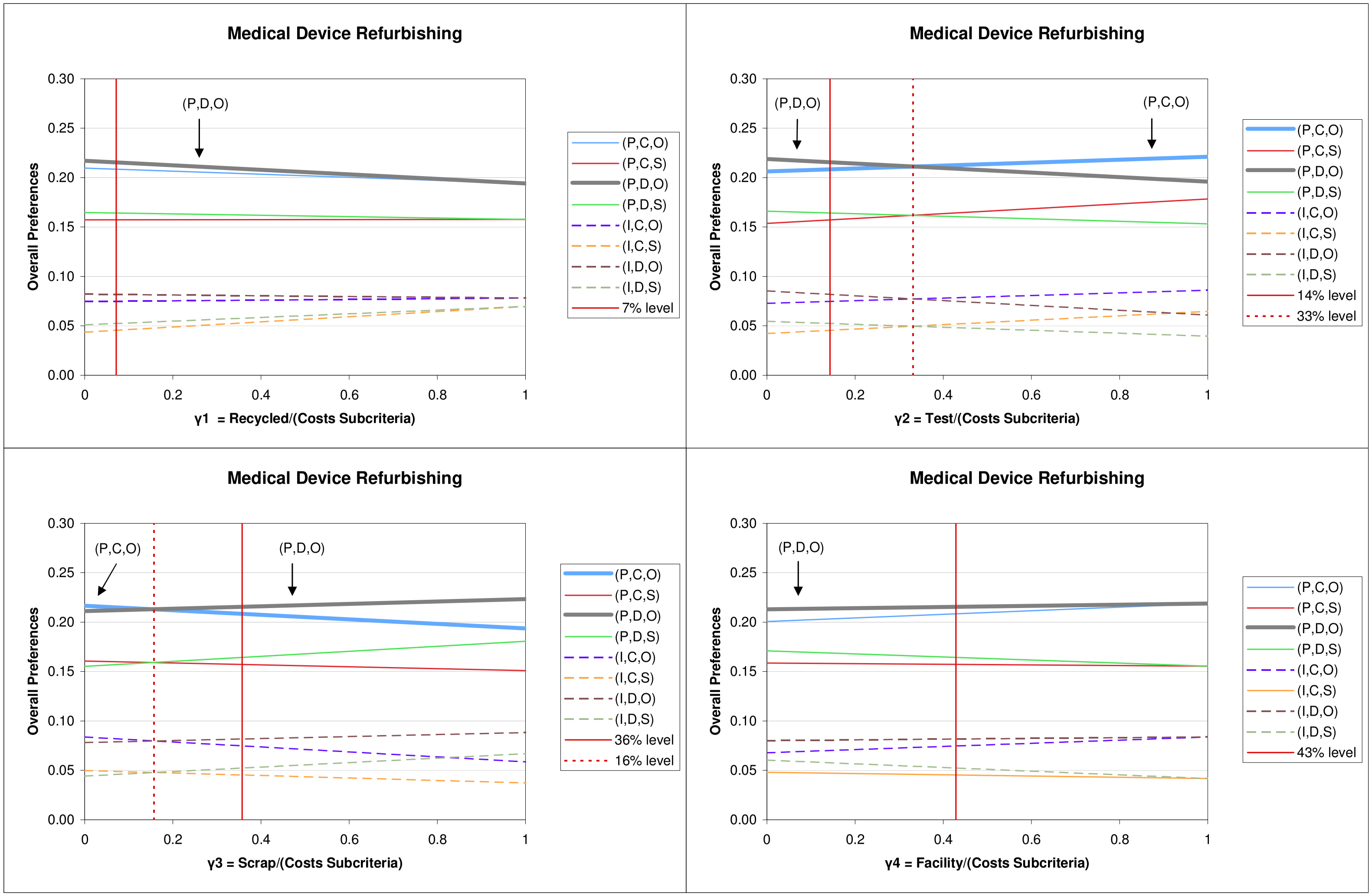


Figure 3.9: Sensitivity to γ for medical device remanufacturing.

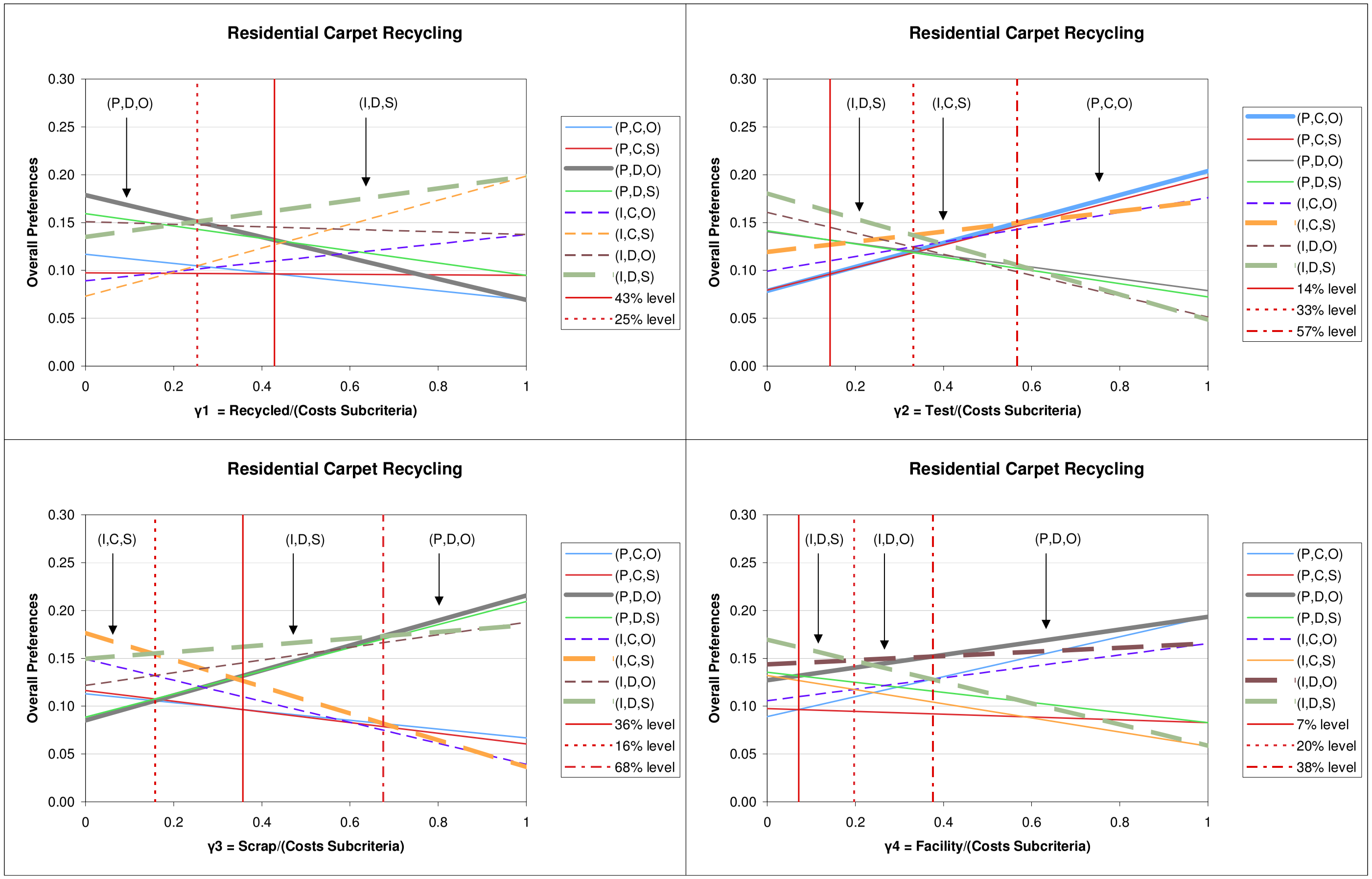


Figure 3.10: Sensitivity to γ for residential carpet recycling.

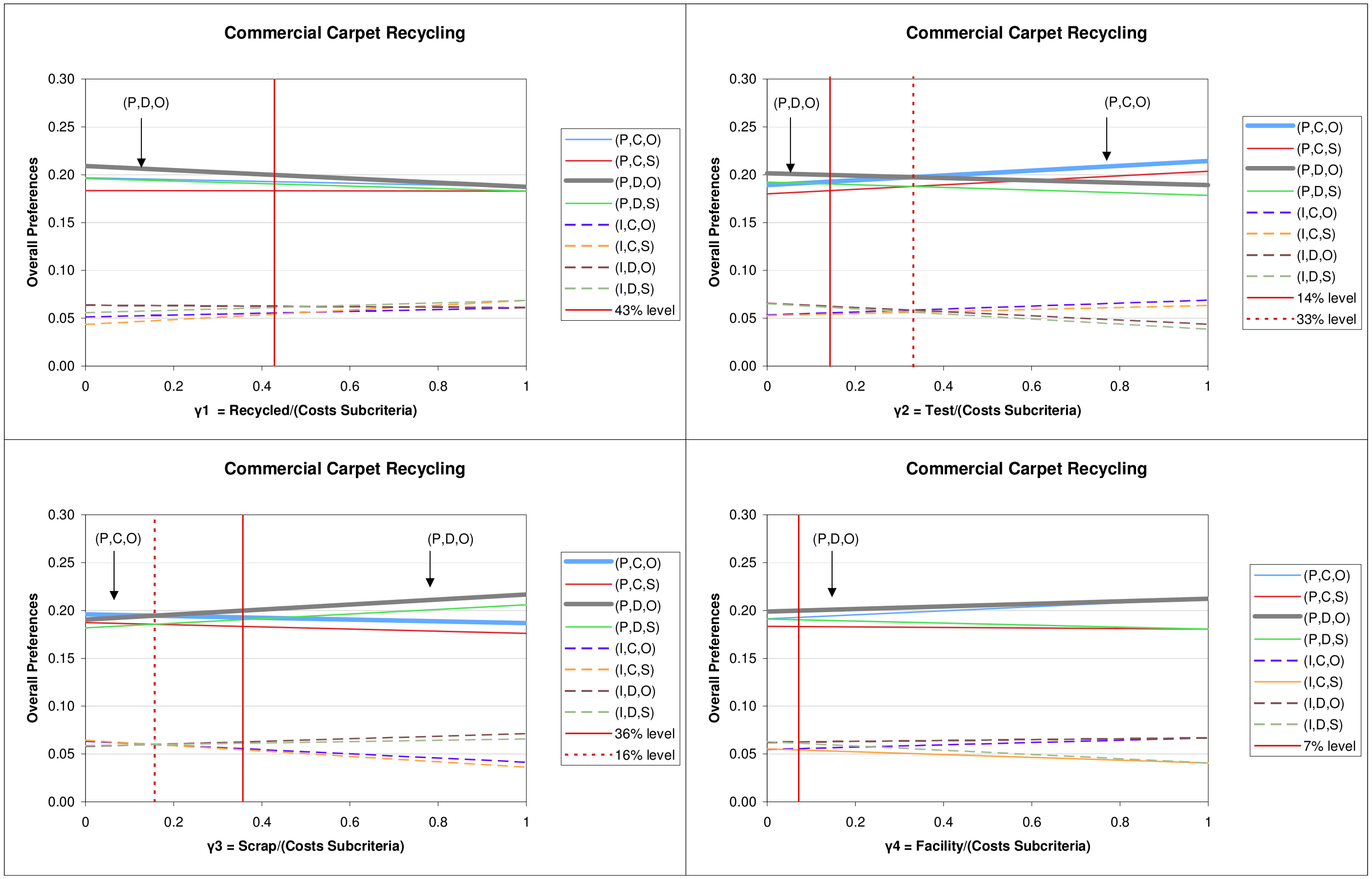


Figure 3.11: Sensitivity to γ for commercial carpet recycling.

1 and 3, when γ_2 is less than 33% (P,D,O) is the preferred configuration, and above that point, (P,C,O) is preferred. In Case Study 2, if γ_2 is less than 33%, (I,D,S) is preferred, between 33% and 57% (I,C,S) is preferred, and above 57% (P,C,O) is preferred. When γ_2 is near zero and the testing costs subcriterion is dominated by the other three subcriteria, a (_,D,_) alternative is preferred, and as γ_2 increases and the testing costs subcriterion becomes more dominant, a (_,C,_) alternative is eventually preferred.

Looking next at γ_3, when γ_3 is less than 16% in Case Studies 1 and 3, (P,C,O) is the preferred configuration, and above that point, (P,D,O) is preferred. For Case Study 2, if γ_3 is less than 16%, (I,C,S) is preferred, between 16% and 68% (I,D,S) is preferred, and above 68% (P,D,O) is preferred. Thus, when γ_3 is near zero and the scrap shipped subcriterion is dominated by the other three subcriteria, a (_,C,_) alternative is preferred, but as γ_3 increases and the scrap shipped subcriterion becomes more dominant, a (_,D,_) alternative is eventually preferred.

Sensitivity to γ_2 and γ_3 have an impact on the sort-test decision in opposite ways. When γ_2 is high, there is more potential to reduce testing costs, which favors centralized testing configurations (_,C,_). When γ_3 is high, there is more potential to reduce costs for shipping scrap, which favors distributed testing configurations (_,D,_). The same pattern occurs in all three case studies for the impact of γ_2 and γ_3 on the sort-test decision.

Next consider sensitivity to γ_1 and γ_4, which occurs only in Case Study 2. If γ_1 is less than 25%, (P,D,O) is preferred, and above that point, (I,D,S) is preferred. The sensitivity lines for γ_1 in configurations with industry-wide collection and secondary facility processing (I,_,S) have increasing values as γ_1 increases, while the sensitivity lines for configurations with proprietary collection and original facility processing (P,_,O) have decreasing values as γ_1 decreases. This indicates that values of γ_1 near zero, when the recycled product subcriterion is dominated by the other three subcriteria, will lead to (P,_,O) configurations. As the recycled product subcriterion becomes more dominant, increasing values of γ_1 will lead to (I,_,S) configurations. Although Case Studies 1 and 3 do not have a crossover point for γ_1, the findings show that if their principal criteria changed to give more ranking to cost savings than to business relations, the same effect occurs as in Case Study 2. Thus, the collection and the processing decision choices would be impacted in a similar way as in Case Study 2, and γ_1 would impact the collection and processing decisions.

Looking at sensitivity to γ_4, in Case Study 2 if γ_4 is less than 20%, (I,D,S) is preferred, between 20% and 38% (I,D,O) is preferred, and above 38% (P,D,O) is preferred. The sensitivity lines for γ_4 in all three case studies indicate that configurations with secondary facility processing (_,_,S) have decreasing values as γ_4 increases, while the sensitivity lines for configurations with original facility processing (_,_,O) have increasing values as γ_4 increases. Thus it may be expected, as seen in Case Study 2, that values of γ_4 near zero, when the original facility subcriterion is dominated by the other three subcriteria, will lead to (_,_,S) configurations. In Case Studies 1 and 3, the crossover point is less than zero, so a (_,_,S) configuration is never realized. This is due to the large difference in principal criteria, as discussed next. However, it is clear that γ_4 has an impact on the processing decision choice.

One distinction between Case Study 2 and Case Studies 1 and 3 is the principal criteria rankings; Case Study 2 has a high ranking for the cost savings primary criterion, whereas Case Studies 1 and 3 have a low ranking for the cost savings criterion ($g_1 = 5$ vs. $g_1 = 1$ as shown in Table 3.10). Because the cost savings criterion dominates the business relations criterion in Case Study 2, it is reasonable to expect Case Study 2 to be sensitive to all four costs savings subcriteria. By contrast, Case Studies 1 and 3 have a high ranking for the business relations criterion, which impacts the collection and processing decisions, e.g., (P,_,_) and (,_,O), as indicated in the last two columns of Table 3.10. Since the sort-test decision is impacted by the testing subcriterion and the shipping scrap subcriterion (see Table 3.10), Case Studies 1 and 3 are sensitive to γ_2 and γ_3.

Looking at the distinction between sensitivity in Case Studies 1 and 3 vs. Case Study 2, sensitivity to all four cost savings criteria results when the cost savings criterion dominates the business relations criterion. Therefore the four cost savings subcriteria need to be most carefully ranked when the cost savings principal criteria are ranked highest relative to business relations.

Even though Case Study 2 is very sensitive to the γ parameters, at the current γ evaluation levels (as indicated by the solid red line in Figure 5), the preferred solution is (I,D,S), and for γ_1, γ_2 and γ_3, that solution remains preferred for a reasonable interval around the current levels. The γ_4 parameter has a smaller interval for which (I,D,S) remains preferred, but based on the sensitivity results, (I,D,S) is a robust solution for Case Study 2.

Overall sensitivity to parameters. Generally speaking, α impacts collection, (P,_,_) and (I,_,_). The β parameter has a slight influence on processing, (_,_,O) and (_,_,S). The γ_1 parameter impacts the collection-processing combinations of (P,_,O) and (I,_,S). The γ_2 and γ_3 parameters impact sort-test (_,C,_) and (_,D,_), and γ_4 impacts processing (_,_,O) and (_,_,S).

3.5 Summary and discussion

A better understanding of the tradeoffs inherent in network design decisions is essential for producers and industries to develop efficient reverse logistics networks. This chapter presented a conceptual framework consisting of eight network configurations. The framework was developed by identifying key tradeoff considerations through by case study analysis of 37 published case studies. This work was extended into a multicriteria decision model using AHP methodology. The AHP model establishes overall preferences among the eight alternative network configurations, and the AHP methodology lends itself well to sensitivity analysis. The framework was validated and the AHP model with sensitivity analysis was demonstrated using three case studies taken from real-world applications.

The results in the AHP model provide the following insights into the network configuration decision process. The decision for how to collect return products is determined by the producer's ranking for business relations relative to cost savings, and it is sensitive to α, the ratio of rankings between these two factors. A high ranking for business relations over cost savings favors a proprietary system (P,_,_), while a high preference for cost savings over business relations favors an industry-wide collection system (I,_,_).

The sorting and testing decision is determined by the potential cost savings from testing and the cost savings from the proportion of scrap that needs to be identified early and sent directly to disposal, and it is sensitive to γ_2 and γ_3. If cost savings from testing has a high ranking, then a centralized system (_,C,_) is favored, while if cost savings from shipping scrap has a high ranking, then a distributed system (_,D,_) is favored. The sorting and testing decision is not at all sensitive to β, the business relations parameter.

The decision for whether to do reprocessing at the original factory or by a third-party reprocessor is slightly influenced by the business relations parameter β. If the ranking of customer relationships dominates proprietary knowledge within business relations, the processing decision favors reprocessing at a secondary facility (_,_,S). However, if proprietary knowledge is very important to the producer, it favors reprocessing at the original facility (_,_,O). The processing decision is also impacted by the cost savings parameter γ_4; a high potential for cost savings from use of original facility favors original facility configurations (_,_,O), and secondary facility configurations (_,_,S) are favored otherwise. Finally, collection and processing is influenced by γ_1; industry-wide collection and secondary processing alternatives (I,_,S) are favored where there is a high potential for cost savings from recycled product, and proprietary collection and original processing (P,_,O) alternatives are favored where there is no such potential savings.

The three case studies were developed through interviews with three industry collaborators who provided information on reverse logistics designs in their company or organization. Information shared by the collaborators about the designs helped inform the decision framework and AHP decision model in this research. Followup interviews were done with the industry collaborators to obtain their feedback on the conceptual framework and the AHP decision model. The responses consistently indicated that the decision model in this research would be useful to explore reverse logistics options. The collaborators mentioned that the model would add value in particular for an organization with analysis as part of its business practice (Aanenson, 2010; Conyers, 2010; Spille, 2010). One collaborator also stated that there is a significant need to raise awareness of the need for reverse logistics planning and to indicate what the critical decisions are, and that the model in this research would increase the awareness of those decisions and the tradeoffs involved (Aanenson, 2010).

The conceptual framework and AHP decision model provide insights into high-level decisions. Detailed decisions are integrated through a suite of MILP models, which is the topic of the next chapter.

Chapter 4

OPTIMIZATION MODEL UNDER UNCERTAINTY

This chapter presents an optimization model integrating the conceptual model described in Chapter 3 with an MILP model that incorporates uncertainty. The model addresses uncertainty with a set of variations using CCP, SP, and robust optimization. This suite of MILPs evaluates the impact of uncertainty on the problem, and the CCP variation determines a cost vs. reliability tradeoff. Finally, the fixed configuration model is contrasted with a "blended" model, exploring the sensitivity of high-level vs. blended configuration decision. The suite of MILPs is then demonstrated on a European office documents company example introduced in Salema et al. (2007).

4.1 Model

This research proposes a suite of mixed-integer linear programming models that integrate a facility location model. The foundation of the optimization model is a generalized MILP developed by Fleischmann et al. (2001) and extended by Salema et al. (2007), and this study combines the MILP with a multicriteria AHP model using eight associated network configurations developed in the previous chapter.

The model incorporates sets of locations for forward flow and reverse flow stages, as illustrated in Figure 4.1. The forward flow locations are grouped into processing plants (set I), warehouses or distribution centers (set J), and customers (set K). The reverse flow locations are grouped into sets for the three stages (collection, sort-test and processing) with two options for each stage. These options reflect the eight possible configurations in Table 3.2. For each of the eight configurations, only one of the sets is used at each stage. Collection can preserve proprietary relationships with individual customers and collect from set K, or collection may be industry-wide with a set of potential locations in set $\tilde{K}$. The sort-test stage can take place at centralized locations, which may be co-located with warehouses in set J, or in dedicated and distributed locations in set $\tilde{J}$. The processing stage may occur at the original plants, set I, or at secondary processing plants, set $\tilde{I}$. In the (P,C,O) configuration, collection would be performed only at proprietary sites K, sort-test at central sites J, and processing at original sites I, while for the (I,D,O) configuration, collection would be performed only at industry-wide sites $\tilde{K}$, sort-test at distributed sites $\tilde{J}$, and processing at original sites I, and so on.

Site locations in Figure 4.1 are also labeled with the potential facility site locations used in the numerical study in Section 4.2. These potential site locations are illustrated in Figure 4.2. There are five original potential plant locations in set I, labeled P1-P5, and two secondary processing sites in set $\tilde{I}$, P6 and P7. For sort-test, there are five central locations in set J, T1-T5, and eight distributed locations in set $\tilde{J}$, T6-T13. For collection, there are fifteen proprietary locations in set K, C1-C15, and three industry-wide locations in set $\tilde{K}$, C16-C18. Centralized sort-test sites are assumed to be co-located with warehouse sites in set J in the numerical study, although the model could be adapted to include distinct sites by using appropriate data. A location for landfill disposal is included in the diagram, which represents the proportion of returns that are sent to disposal rather than to a processing plant.

The following MILP models all include binary variables z^p, z^t, and z^c to indicate the network configuration and select the set of sites to be used in the reverse flow: z^p to indicate processing site set I or $\tilde{I}$, z^t to indicate sort-test site set J or $\tilde{J}$, and z^c to indicate collection site set K or $\tilde{K}$.

First the deterministic model is described along with a blended configuration version, followed by the CCP, SP and robust optimization models.

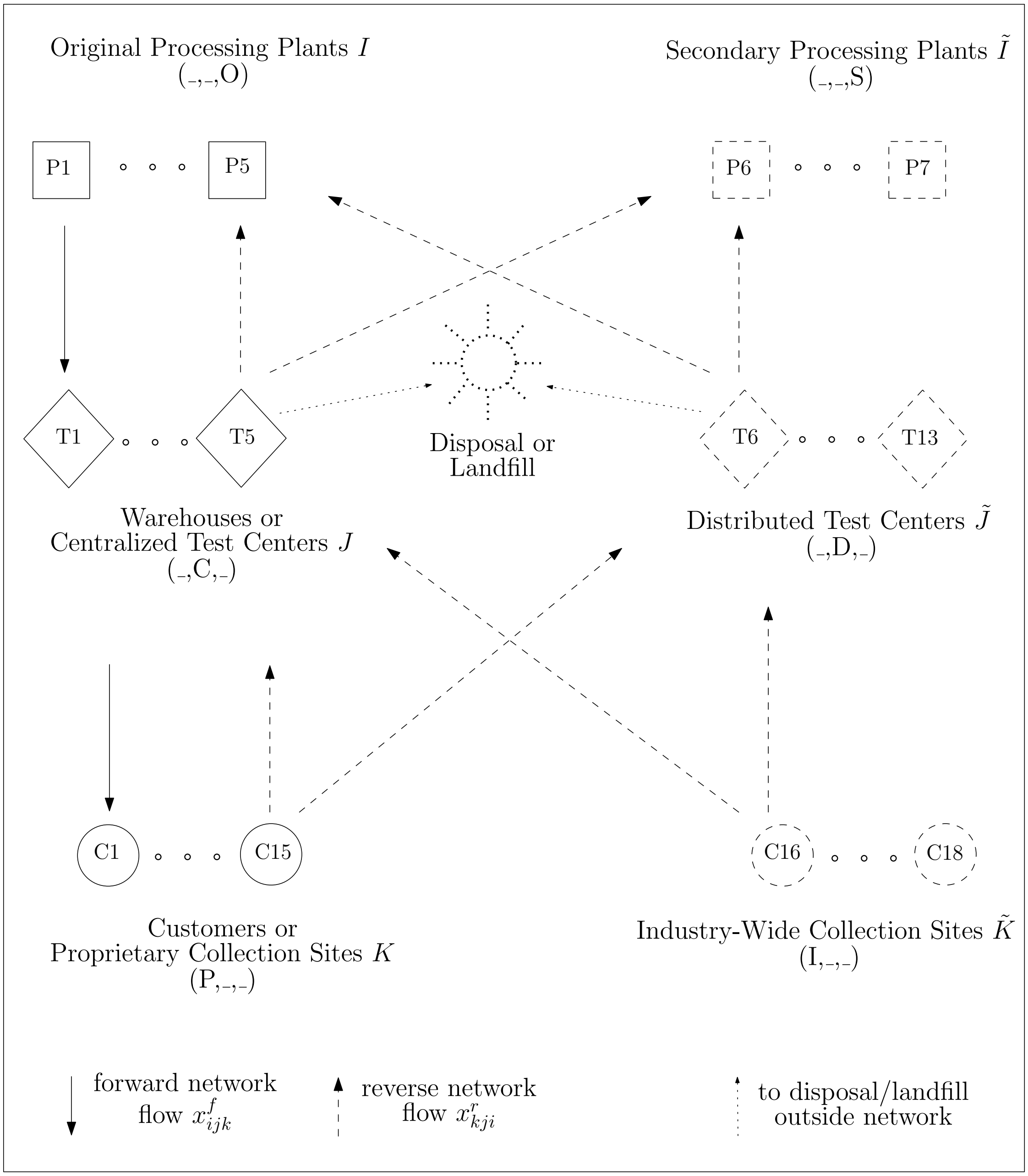


Figure 4.1: Forward and reverse logistics diagram, adapted from Fleischmann et al. (2004).

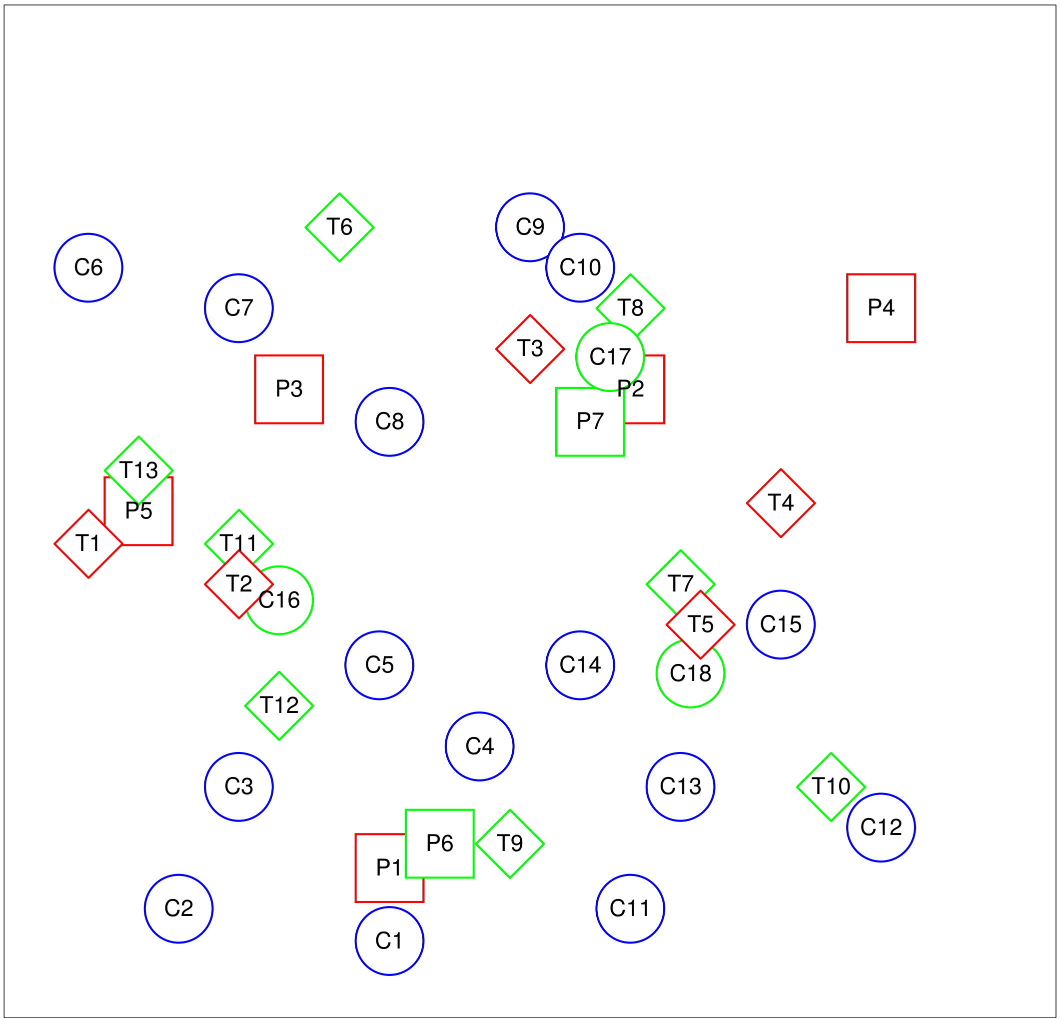


Figure 4.2: Facility sites for example (actual scaled distances), adapted from Salema et al. (2007).

4.1.1 Deterministic model

The deterministic MILP model that underlies our probabilistic models is first presented. As mentioned previously, the optimal solution is one of eight network configurations. Also described is a blended model that removes the network configuration constraints that allows any site to be selected.

Index sets

I = candidate original plant locations

$\tilde{I}$ = candidate secondary processing plant locations

J = candidate distribution centers and central test locations

$\tilde{J}$ = candidate distributed test locations

K = fixed customer collection locations

$\tilde{K}$ = candidate industry-wide collection locations

Variables

Flow variables

x^f_{ijk} = demand served by plant $i \in I$ to distribution center $j \in J$ to customer $k \in K$, forward flow

x^r_{kji} = returns from collection site $k \in K \cup \tilde{K}$ to test center $j \in J \cup \tilde{J}$ to processing plant $i \in I \cup \tilde{I}$, reverse flow

Site indicator variables–forward flow

$$y^{fp}_i = \begin{cases} 1 \text{ if plant site } i \text{ is open, } i \in I \\ 0 \text{ otherwise} \end{cases}$$

$$y^{ft}_j = \begin{cases} 1 \text{ if warehouse site } j \text{ is open, } j \in J \\ 0 \text{ otherwise} \end{cases}$$

Site indicator variables–reverse flow

$$y^{rp}_i = \begin{cases} 1 \text{ if processing plant site } i \text{ is open, } i \in I \cup \tilde{I} \\ 0 \text{ otherwise} \end{cases}$$

$$y^{rt}_j = \begin{cases} 1 \text{ if test site } j \text{ is open, } j \in J \cup \tilde{J} \\ 0 \text{ otherwise} \end{cases}$$

$$y^{rc}_k = \begin{cases} 1 \text{ if collection site } k \text{ is open, } k \in K \cup \tilde{K} \\ 0 \text{ otherwise} \end{cases}$$

Network configuration indicator variables

$$z^p = \begin{cases} 1 \text{ if only original processing sites } I \text{ are used} \\ 0 \text{ if only secondary processing sites } \tilde{I} \text{ are used} \end{cases}$$

$$z^t = \begin{cases} 1 \text{ if only centralized test sites } J \text{ are used} \\ 0 \text{ if only distributed test sites } \tilde{J} \text{ are used} \end{cases}$$

$$z^c = \begin{cases} 1 \text{ if only customer collection sites } K \text{ are used} \\ 0 \text{ if only industry-wide collection sites } \tilde{K} \text{ are used} \end{cases}$$

Parameters

Opening costs–forward flow

f_i^{fp} = opening costs for plant facility site $i \in I$

f_j^{ft} = opening costs for distribution center $j \in J$

Opening costs–reverse flow

f_i^{rp} = opening costs for processing plant facility site $i \in I \cup \tilde{I}$

f_j^{rt} = opening costs for test center $j \in J \cup \tilde{J}$

f_k^{rc} = opening costs for collection site $k \in K \cup \tilde{K}$

Transportation and processing costs

c_{ijk}^{f} = costs per unit of forward flow
from plant $i \in I$ through distribution center $j \in J$ to customer $k \in K$

c_{kji}^{r} = costs per unit of reverse flow
from collection site $k \in K \cup \tilde{K}$ through test center $j \in J \cup \tilde{J}$
to processing plant $i \in I \cup \tilde{I}$

Capacities–forward flow

g_i^{fp} = maximum capacity of forward plant $i \in I$

g_j^{ft} = maximum capacity of forward distribution center $j \in J$

Capacities–reverse flow

g_i^{rp} = maximum capacity of reverse processing center $i \in I \cup \tilde{I}$

g_j^{rt} = maximum capacity of reverse sort-test center $j \in J \cup \tilde{J}$

g_k^{rc} = maximum capacity of reverse collection site $k \in K \cup \tilde{K}$

Demand and return parameters

d_k = demand of customer $k \in K$

r_k = returns from customer $k \in K$

$\tilde{r}_k$ = returns from customer $k \in \tilde{K}$

Objective

$$
\begin{aligned}
\min \quad & \sum_{i\in I} f_i^{fp} y_i^{fp} + \sum_{j\in J} f_j^{ft} y_j^{ft} \\
& + \sum_{i\in I\cup\tilde{I}} f_i^{rp} y_i^{rp} + \sum_{j\in J\cup\tilde{J}} f_j^{rt} y_j^{rt} + \sum_{k\in K\cup\tilde{K}} f_k^{rc} y_k^{rc} \\
& + \sum_{i\in I}\sum_{j\in J}\sum_{k\in K} c_{ijk}^{f} x_{ijk}^{f} + \sum_{k\in K\cup\tilde{K}}\ \sum_{j\in J\cup\tilde{J}}\ \sum_{i\in I\cup\tilde{I}} c_{kji}^{r} x_{kji}^{r} \qquad (4.1)
\end{aligned}
$$

Constraints

$$
\begin{aligned}
\sum_{i\in I}\sum_{j\in J} x_{ijk}^{f} &\geq d_k \quad \forall\, k \in K & (4.2)\\
\sum_{j\in J,\tilde{J}}\ \sum_{i\in I,\tilde{I}} x_{kji}^{r} &\geq r_k z^c \quad \forall\, k \in K & (4.3)\\
\sum_{j\in J,\tilde{J}}\ \sum_{i\in I,\tilde{I}} x_{kji}^{r} &\geq \tilde{r}_k (1 - z^c) \quad \forall\, k \in \tilde{K} & (4.4)
\end{aligned}
$$

$$
\begin{aligned}
\sum_{k\in K}\sum_{j\in J} x_{ijk}^{f} &\leq g_i^{fp} y_i^{fp} \quad \forall\, i \in I & (4.5)\\
\sum_{i\in I}\sum_{k\in K} x_{ijk}^{f} &\leq g_j^{ft} y_j^{ft} \quad \forall\, j \in J & (4.6)\\
\sum_{k\in K,\tilde{K}}\ \sum_{j\in J,\tilde{J}} x_{kji}^{r} &\leq g_i^{rp} y_i^{rp} \quad \forall\, i \in I, \tilde{I} & (4.7)\\
\sum_{k\in K,\tilde{K}}\ \sum_{i\in I,\tilde{I}} x_{kji}^{r} &\leq g_j^{rt} y_j^{rt} \quad \forall\, j \in J, \tilde{J} & (4.8)\\
\sum_{j\in J,\tilde{J}}\ \sum_{i\in I,\tilde{I}} x_{kji}^{r} &\leq g_k^{rc} y_k^{rc} \quad \forall\, k \in K, \tilde{K} & (4.9)
\end{aligned}
$$

$$
\begin{aligned}
y_i^{rp} &\leq z^p \quad \forall\, i \in I && (4.10)\\
y_i^{rp} &\leq 1 - z^p \quad \forall\, i \in \tilde{I} && (4.11)\\
y_j^{rt} &\leq z^t \quad \forall\, j \in J && (4.12)\\
y_j^{rt} &\leq 1 - z^t \quad \forall\, i \in \tilde{J} && (4.13)\\
y_k^{rc} &\leq z^c \quad \forall\, k \in K && (4.14)\\
y_k^{rc} &\leq 1 - z^c \quad \forall\, k \in \tilde{K} && (4.15)
\end{aligned}
$$

$$
\begin{aligned}
x_{ijk}^f &\geq 0 \quad \forall\, i \in I, j \in J, k \in K && (4.16)\\
x_{kji}^r &\geq 0 \quad \forall\, i \in I, \tilde{I}, j \in J, \tilde{J}, k \in K, \tilde{K} && (4.17)\\
y_i^{fp}, y_j^{ft} &\in \{0,1\} \quad \forall\, i \in I, j \in J && (4.18)\\
y_i^{rp}, y_j^{rt}, y_k^{rc} &\in \{0,1\} \quad \forall\, i \in I, \tilde{I}, j \in J, \tilde{J}, k \in K, \tilde{K} && (4.19)\\
z^p, z^t, z^c &\in \{0,1\} && (4.20)
\end{aligned}
$$

The objective (4.1) of the model is to minimize costs. The first two terms represent the cost of opening plants and warehouses in forward flow, and the next three terms represent the cost of opening facilities for collection, sort-test and processing in reverse flow. The final two terms represent the cost of processing and transporting product, with one term for forward flow and another term for reverse flow.

Constraints (4.2)-(4.4) govern customer demand and returns. The demand constraint (4.2) ensures that forward flow is at least equal to demand from each customer. The return constraint (4.3) determines reverse flow from proprietary (customer) collection sites, while (4.4) determines reverse flow from industry-wide collection sites. Reverse flow is at least equal to returns from each collection site. Customer demand and collection returns are given as parameters d_k, r_k, and $\tilde{r}_k$.

Because collection may be performed either from customers (in set K) or from industry-wide sites (in set $\tilde{K}$) but not both, (4.3) and (4.4) are either-or constraints, with z^c as the indicator variable for the active constraint. This avoids “double-collection” for returns from both proprietary (customer) sites and industry-wide sites. Note that although (4.3) and (4.4) are inequalities, they become binding constraints because the formulation is minimizing costs in the objective function. This drives the flow variables x to their lowest value, making the constraints in effect equalities. However, the inequality relationship becomes important when a probabilistic constraint is added in the CCP approach in the next section.

Constraints (4.5)-(4.9) are the capacity constraints, which include the indicator variables for open facilities. The first two equations are capacity constraints for forward flow through plants I and warehouses J respectively, while the latter three constraints are capacity constraints for reverse flow through processing facilities I and $\tilde{I}$, sort-test facilities J and $\tilde{J}$, and collection facilities K and $\tilde{K}$. The model assumes separate capacity availability and separate fixed opening costs for forward and reverse flow.

Constraints (4.10)-(4.15) are mutual exclusivity constraints for reverse flow. In each network configuration, only one set of processing sites can be active (I or $\tilde{I}$), and z^p is the indicator variable for the active constraint. As well, only one set of sort-test sites can be active (J or $\tilde{J}$) with z^t the indicator variable, and only one set of collection sites can be active (K or $\tilde{K}$) with z^c the indicator variable. These equations ensure that only one site set at each stage will have open facilities.

Constraints (4.16)-(4.20) are the non-negativity and binary variable constraints.

As in the original model developed by Fleischmann et al. (2001), this deterministic model can be used for either open- or closed-loop networks by setting parameters d_k, r_k and $\tilde{r}_k$ appropriately. A closed-loop supply chain (both demand and returns are handled in the network) is modeled when the demand and return parameters are both non-zero, while an open-loop supply chain (a returns-only network) is modeled when the demand parameter is zero and the returns parameters are non-zero. Parameters are set for each individual customer and collection site so that the model can be customized to a particular application. Note that industry-wide collection sites and proprietary (customer) collection sites are not required to have comparable return quantities. Because collection is done at either industry-wide or proprietary sites but not both, the r_k and $\tilde{r}_k$ parameters should be set so that the sum of all r_k is equal to the sum of all $\tilde{r}_k$, ensuring that the total amount of returns are the same regardless of which collection choice is made.

Blended configuration modification. The blended configuration formulation removes the binary variables z^p and z^t and the configuration constraints on sort-test and processing sites, (4.10)-(4.13). This allows sort-test and processing sites to be chosen freely from all possible sites. This allows the evaluation of the sensitivity of the model to the configuration constraints.

Note that the configuration constraints on K and $\tilde{K}$ are retained in the blended configuration, so that collection is still done either directly from customers or from industry-wide collection sites, but not both. Although collection sites could be chosen freely as well, removing the configuration constraint on K and $\tilde{K}$ causes the model to "double-count" return volumes, collecting from both K and $\tilde{K}$. The problem could be avoided by associating particular customers to specific industry-wide collection locations and allowing collection only from the customer or from the industry-wide site, but in this work it was decided not to, primarily because it is difficult to determine which customer sites should be associated with which industry-wide location, and it was felt that assigning customer sites to industry-wide sites would be an artificial construct.

4.1.2 Chance-constrained programming (CCP) model

In the CCP model, the demand and return volumes are represented by a random variable, rather than a deteministic value (Charnes and Cooper, 1959). The objective function (4.1) is the same as in the deterministic model. Constraints (4.2), (4.3) and (4.4) are replaced in the CCP model with:

$$
\begin{aligned}
\Pr\left(\sum_{i\in I}\sum_{j\in J} x^f_{ijk} \geq D_k\right) &\geq \varepsilon_d \quad \forall\, k \in K \\
\Pr\left(\sum_{j\in J,\tilde{J}}\sum_{i\in I,\tilde{I}} x^r_{kji} \geq R_k\right) &\geq \varepsilon_r z^c \quad \forall\, k \in K \\
\Pr\left(\sum_{j\in J,\tilde{J}}\sum_{i\in I,\tilde{I}} x^r_{kji} \geq \tilde{R}_k\right) &\geq \varepsilon_{\tilde{r}}(1 - z^c) \quad \forall\, k \in \tilde{K},
\end{aligned}
$$

where

D_k = random variable for demand of forward flow for customer $k \in K$,

R_k = random variable for returns of used products from customers $k \in K$,

$\tilde{R}_k$ = random variable for returns of used products from collection sites $k \in \tilde{K}$,

and

ε_d = satisfaction level of probabilistic demand constraint for $k \in K$,

ε_r = satisfaction level of probabilistic returns constraint for $k \in K$,

$\varepsilon_{\tilde{r}}$ = satisfaction level of probabilistic returns constraint for $k \in \tilde{K}$,

with $0 \leq \varepsilon_d, \varepsilon_r, \varepsilon_{\tilde{r}} \leq 1$.

Reformulating the probabilistic constraints (Prékopa, 1995),

$$\begin{aligned}
\sum_{i \in I} \sum_{j \in J} x_{ijk}^f &\geq F_{D_k}^{-1}(\varepsilon_d) \quad \forall\, k \in K \\
\sum_{j \in J \cup \tilde{J}} \sum_{i \in I \cup \tilde{I}} x_{kji}^r &\geq F_{R_k}^{-1}(\varepsilon_r z^c) \quad \forall\, k \in K \\
\sum_{j \in J \cup \tilde{J}} \sum_{i \in I \cup \tilde{I}} x_{kji}^r &\geq F_{\tilde{R}_k}^{-1}(\varepsilon_{\tilde{r}}(1 - z^c)) \quad \forall\, k \in \tilde{K},
\end{aligned}$$

where $F_{D_k}^{-1}$, $F_{R_k}^{-1}$, and $F_{\tilde{R}_k}^{-1}$ are the inverse cumulative probability distribution functions for random demand and returns, and note that $F^{-1}(\varepsilon z^c) = F^{-1}(\varepsilon) z^c$ because z^c is binary.

Chance-constrained programming gives us a model in which the right-hand side of the demand and returns constraints, $F^{-1}(\varepsilon)$, evaluates to a value which is dependent on ε. Setting the parameter ε to a particular probability level, such as 0.50, 0.75, or 0.99, gives a right-hand side value that reflects a certain level of satisfaction.

Expressions for $F^{-1}(\varepsilon)$ are provided for uniform and triangular distributions (Johnson and Kotz, 1970; Evans et al., 2000), which were used in the numerical study (see Appendix A for details on the $F^{-1}(\varepsilon)$ expressions). A uniform distribution on $[a, b]$ has an expected value of $\frac{1}{2}(a + b)$, and given a satisfaction level of $0 \leq \varepsilon \leq 1$,

$$F^{-1}(\varepsilon)_{uniform} = (b - a) \cdot \varepsilon + a.$$

A triangular distribution on $[a, b]$ with mode h has an expected value of $\frac{1}{3}(a+b+h)$, and given a satisfaction level of $0 \leq \varepsilon \leq 1$,

$$F^{-1}(\varepsilon)_{triangular} = \begin{cases} a + \sqrt{\varepsilon(b-a)(h-a)} & \text{if } 0 \leq \varepsilon \leq \dfrac{h-a}{b-a} \\ b - \sqrt{(1-\varepsilon)(b-a)(b-h)} & \text{if } \dfrac{h-a}{b-a} \leq \varepsilon \leq 1. \end{cases}$$

In the numerical study, the demand and returns volumes in the deterministic model are related to the expected value of demand and returns in the CCP model, i.e., $E[D_k] = d_k$, $E[R_k] = r_k$, and $E[\tilde{R}_k] = \tilde{r}_k$.

Blended configuration modification for CCP. As in the deterministic model, sort-test and processing sites are allowed to be chosen freely from all possible sites for the blended model. For the blended configuration the binary variables z^p and z^t and the configuration constraints (4.10)-(4.13) were removed.

4.1.3 Stochastic programming (SP) model

The SP model is a scenario-based two-stage stochastic program with recourse (Birge and Louveaux, 1997). The site indicator variables (y_i^{fp}, y_j^{ft}, y_i^{rp}, y_j^{rt}, y_k^{rc}) and the network configuration indicator variables (z^p, z^t, z^c) remain as first stage variables in the SP model. Let Ω be the set of all possible scenarios and $\omega \in \Omega$ a particular scenario. The flow variables are augmented for each scenario and treated as second stage recourse variables. The demand and return parameters are similarly extended to represent scenarios.

The stochastic programming model is extended from the deterministic model as follows. The flow variables are modified to be second stage recourse variables that depend on scenarios:

$$\begin{aligned} x_{ijk\omega}^{f} &= \text{demand served by plant } i \in I \text{ to distribution center } j \in J \\ &\quad\ \text{to customer } k \in K\text{, for scenario } \omega \in \Omega \\ x_{kji\omega}^{r} &= \text{returns from collection site } k \in K \cup \tilde{K} \text{ to test center } j \in J \cup \tilde{J} \\ &\quad\ \text{to processing plant } i \in I \cup \tilde{I}\text{, for scenario } \omega \in \Omega. \end{aligned}$$

The demand and return parameters are modified to be scenario-dependent:

$$\begin{aligned}
\pi_\omega &= \text{probability of scenario } \omega \in \Omega \\
d_{k\omega} &= \text{demand of customer } k \in K, \text{ for scenario } \omega \in \Omega \\
r_{k\omega} &= \text{returns from customer } k \in K, \text{ for scenario } \omega \in \Omega \\
\tilde{r}_{k\omega} &= \text{returns from customer } k \in \tilde{K}, \text{ for scenario } \omega \in \Omega.
\end{aligned}$$

Objective function (4.1) is replaced by

$$\begin{aligned}
\min \quad & \sum_{i \in I} f_i^{fp} y_i^{fp} + \sum_{j \in J \cup \tilde{J}} f_j^{ft} y_j^{ft} \\
& + \sum_{i \in I \cup \tilde{I}} f_i^{rp} y_i^{rp} + \sum_{j \in J \cup \tilde{J}} f_j^{rt} y_j^{rt} + \sum_{k \in K \cup \tilde{K}} f_k^{rc} y_k^{rc} \\
& + \sum_{\omega \in \Omega} \pi_\omega \left[\sum_{i \in I} \sum_{j \in J} \sum_{k \in K} c_{ijk}^f x_{ijk\omega}^f + \sum_{k \in K \cup \tilde{K}} \sum_{j \in J \cup \tilde{J}} \sum_{i \in I \cup \tilde{I}} c_{kji}^r x_{kji\omega}^r \right].
\end{aligned}$$

Constraints (4.2), (4.3) and (4.4) representing demand and returns are augmented by scenario, and are replaced in the SP model with

$$\begin{aligned}
\sum_{i \in I} \sum_{j \in J} x_{ijk\omega}^f &\geq d_{k\omega} \quad \forall\, k \in K, \omega \in \Omega \\
\sum_{j \in J \cup \tilde{J}} \sum_{i \in I \cup \tilde{I}} x_{kji\omega}^r &\geq r_{k\omega} z^c \quad \forall\, k \in K, \omega \in \Omega \\
\sum_{j \in J \cup \tilde{J}} \sum_{i \in I \cup \tilde{I}} x_{kji\omega}^r &\geq \tilde{r}_{k\omega}(1 - z^c) \quad \forall\, k \in \tilde{K}, \omega \in \Omega.
\end{aligned}$$

The capacity constraints (4.5)-(4.9) are similarly augmented by scenario as follows:

$$\begin{aligned}
\sum_{k \in K} \sum_{j \in J} x^f_{ijk\omega} &\leq g^{fp}_i y^{fp}_i \quad \forall\, i \in I, \omega \in \Omega \\
\sum_{i \in I} \sum_{k \in K} x^f_{ijk\omega} &\leq g^{ft}_j y^{ft}_j \quad \forall\, j \in J, \omega \in \Omega \\
\sum_{k \in K \cup \tilde{K}} \sum_{j \in J \cup \tilde{J}} x^r_{kji\omega} &\leq g^{rp}_i y^{rp}_i \quad \forall\, i \in I, \tilde{I}, \omega \in \Omega \\
\sum_{k \in K \cup \tilde{K}} \sum_{i \in I \cup \tilde{I}} x^r_{kji\omega} &\leq g^{rt}_j y^{rt}_j \quad \forall\, j \in J, \tilde{J}, \omega \in \Omega \\
\sum_{j \in J \cup \tilde{J}} \sum_{i \in I \cup \tilde{I}} x^r_{kji\omega} &\leq g^{rc}_k y^{rc}_k \quad \forall\, k \in K, \tilde{K}, \omega \in \Omega.
\end{aligned}$$

The non-negativity constraints for the second stage variables are:

$$\begin{aligned}
x^f_{ijk\omega} &\geq 0 \quad \forall\, i \in I, j \in J, k \in K, \omega \in \Omega \\
x^r_{kji\omega} &\geq 0 \quad \forall\, i \in I, \tilde{I}, j \in J, \tilde{J}, k \in K, \tilde{K}, \omega \in \Omega.
\end{aligned}$$

Blended configuration modification for SP. The blended configuration model again removes the binary variables z^p and z^t and the configuration constraints (4.10)-(4.13).

4.1.4 Robust optimization model

The robust optimization model is a scenario-based probabilistic approach, similar to the stochastic programming model. Although this model is scenario-based, there is no probability associated with a specific scenario, and no expected value of the objective function. Instead, the model minimizes the maximum cost of the objective function for each scenario (Kouvelis and Yu, 1997). Letting Ω be the set of all possible scenarios and $\omega \in \Omega$ a particular scenario, the robust optimization model replaces objective function (4.1) with

$$minimize \qquad \phi,$$

under the following additional scenario constraint:

$$\begin{aligned}
\phi \quad \geq \quad & \sum_{i \in I} f_i^{fp} y_i^{fp} + \sum_{j \in J} f_j^{ft} y_j^{ft} \\
& + \sum_{i \in I \cup \tilde{I}} f_i^{rp} y_i^{rp} + \sum_{j \in J \cup \tilde{J}} f_j^{rt} y_j^{rt} + \sum_{k \in K \cup \tilde{K}} f_k^{rc} y_k^{rc} \\
& + \sum_{i \in I} \sum_{j \in J} \sum_{k \in K} c_{ijk}^{f} x_{ijk\omega}^{f} + \sum_{k \in K \cup \tilde{K}} \sum_{j \in J \cup \tilde{J}} \sum_{i \in I \cup \tilde{I}} c_{kji}^{r} x_{kji\omega}^{r} \quad \forall\, \omega \in \Omega.
\end{aligned}$$

All other constraints remain the same as in the stochastic programming model.

Blended configuration modification for robust optimization. Again the binary variables z^p and z^t are removed, along with the configuration constraints (4.10)-(4.13).

4.2 Numerical study

4.2.1 Description of example

The model and the impact of uncertainty are demonstrated using an example from a case study provided in Salema et al. (2007). The case study involves an office document company based in Spain and Portugal. Products are manufactured and shipped from factories to distribution warehouses and then to customers. At the end of the product life, products are collected from customers, sent to disassembly centers for initial processing, and then shipped back to company plants for remanufacturing.

In terms of high-level decisions, the Salema et al. (2007) case study would be characterized as a remanufacturing operation for a company that wishes to protect its proprietary knowledge to prevent competitors from duplicating its products. It is typical to have direct customer relationships in this type of operation due to service or maintenance contracts, and remanufacturing is commonly done at the original facility, rather than at a secondary plant, because of the specialized technical knowledge required.

A similar case study was presented for a medical device remanufacturing operation in the previous chapter, and the AHP ranking of network configurations for this example is assumed to be the same as for the medical device remanufacturing case study. Therefore, the highest-ranked network configuration would be (P,D,O): proprietary collection, distributed sort-test and original processing. The (P,D,O) configuration indicates that collection would be done directly from the customer, that sort-test is performed at the customer site, perhaps by assessing the age and model of the product, and that the processing would be done at the original plant. The suite of MILP models will be used to explore the network configuration model.

The sites for numerical study are shown in Figure 4.2. A set of secondary processing sites was added to the data provided in Salema et al. (2007). industry-wide collection sites were also added, and the existing warehouse and disassembly sites were used for distributed and centralized test sites. New sites were identified by consulting a map of the Iberian peninsula for reference to major transportation routes, cities and urban centers, and geographic proximity to already-provided sites. Note that the facility locations shown in Figure 4.2 have distances to scale, and that sites from the original case study were used wherever possible to preserve authenticity of data in the case study.

There are five original plant sites in set I. Two secondary plant sites were designated for set $\tilde{I}$ and placed near two major cities with existing plants, under the assumption that factory space is more likely to be available in those locations. There are five centralized sort-test locations in set J that correspond to the five disassembly locations in the original case study, and there are eight distributed sort-test locations in set $\tilde{J}$ that are geographically distributed. The proprietary collection sites in set K are located at fifteen customer sites of the case study. Three industry-wide collection sites constituted set $\tilde{K}$. These sites were positioned to be along a highway route, geographically dispersed, and proximate to a major city.

The parameters for the model include fixed costs for opening each type of facility, per unit costs for transporting and processing products between locations, and demand quantities for new products and return quantities of used products (Table 4.1), and maximum capacities per facility (Table 4.2). As in the Salema et al. (2007) case study returns are two-thirds of demand, implying that one-third of forward flow is lost in the return process to landfill or other disposal. Return volumes for industry-wide collection sites in $\tilde{K}$ were determined by calculating the total return volume and dividing it by the number of sites. Collection sets are always exclusive, to prevent double-collecting. Fixed costs by type of facility were based on data provided, while per unit costs are dependent on distances.

Demand and return quantities were adapted from the case study. Table 4.3 lists the demand and return parameters for the deterministic model and the CCP model with uniform and triangular distributions. The parameter values a, b, and h in the two CCP distributions were calculated to allow the expected value of the distribution to be equal to the deterministic parameter. For the uniform distribution, the following parameters were used:

$$D_k : [a = 7,000, b = 13,000], R_k : [a = 5,000, b = 8,340], \tilde{R}_k : [a = 25,000, b = 41,700],$$

and for the triangular distribution:

$$D_k : [a = 7,000, b = 14,200], R_k : [a = 5,000, b = 9,000], \tilde{R}_k : [a = 25,000, b = 45,000],$$

with modes

$$D_k : h = 8,800, R_k : h = 6,000, \tilde{R}_k : h = 30,000.$$

Note that in the triangular distribution for CCP, mode h was set to be the value at 1/4 the distance between the minimum a and the maximum b, $h = \frac{1}{4}(b - a) + a$.

The data in Table 4.3 also lists a set of three scenarios from Salema et al. (2007) for the SP and robust optimization models. The probability π_ω for each scenario for SP is also included, and the probabilities were chosen to allow the average values of the data to be equal to the deterministic values. Robust optimization does not use probabilities, but the same set of three scenarios was used.

4.2.2 Integrating high-level and detailed network design decisions

To integrate high-level decisions into the model, the AHP model was used. The AHP model results in a vector of AHP rankings for the eight possible network configurations, with

Table 4.1: Costs data adapted from Salema et al. (2007).

Description	Parameter	Cost (monentary units/unit)
Opening costs – forward flow		
Plant	f^{fp}	$36,000$
Whse	f^{ft}	$18,000$
Opening costs – reverse flow		
Processing – original	f^{rp}	$24,000$
Processing – secondary	f^{rp}	$60,000$
Test – centralized	f^{rt}	$120,000$
Test – distributed	f^{rt}	$50,000$
Collection – proprietary	f^{rc}	$7,800$
Collection – industry-wide	f^{rc}	$39,000$
Transportation & processing costs		
Forward flow	c^{f}_{ijk}	$2 \cdot dist_{ij} + 7 \cdot dist_{jk}$
Reverse flow	c^{r}_{kji}	$5 \cdot dist_{kj} + 4 \cdot dist_{ji}$
where $dist_{mn}$ is the distance between site m and site n		

Table 4.2: Site capacity data adapted from Salema et al. (2007).

Description	Parameter	Capacity	No. of sites
Capacities – forward flow			
Plant	g^{fp}	$60,000$	5
Warehouse	g^{ft}	$60,000$	5
Customer	$--$	$--$	15
Capacities – reverse flow			
Processing – original	g^{rp}	$40,000$	5
Processing – secondary	g^{rp}	$100,000$	2
Test – centralized	g^{rt}	$40,000$	5
Test– distributed	g^{rt}	$25,000$	8
Collection – proprietary	g^{rc}	$13,000$	15
Collection – industry-wide	g^{rc}	$5,000$	3

Table 4.3: Demand and returns data adapted from Salema et al. (2007).

Description	Demand	Returns (proprietary)	Returns (industry-wide)
Deterministic (expected value)			
	d_k	r_k	$\tilde{r}_k$
	$10,000$	$6,667$	$33,335$
CCP with Uniform			
	$F^{-1}_{D_k}(\varepsilon_d)$	$F^{-1}_{R_k}(\varepsilon_r)$	$F^{-1}_{\tilde{R}_k}(\varepsilon_{\tilde{r}})$
$\varepsilon = 0.50$	$10,000$	$6,670$	$33,335$
$\varepsilon = 0.60$	$10,600$	$7,004$	$35,020$
$\varepsilon = 0.70$	$11,200$	$7,338$	$36,690$
$\varepsilon = 0.80$	$11,800$	$7,672$	$38,360$
$\varepsilon = 0.90$	$12,400$	$8,006$	$40,030$
$\varepsilon = 0.99$	$12,940$	$8,307$	$41,533$
CCP with Triangular			
	$F^{-1}_{D_k}(\varepsilon_d)$	$F^{-1}_{R_k}(\varepsilon_r)$	$F^{-1}_{\tilde{R}_k}(\varepsilon_{\tilde{r}})$
$\varepsilon = 0.50$	$9,791$	$6,551$	$32,753$
$\varepsilon = 0.60$	10.256	$6,809$	$34,046$
$\varepsilon = 0.70$	10.785	$7,103$	$35,513$
$\varepsilon = 0.80$	$11,411$	$7,451$	$37,254$
$\varepsilon = 0.90$	$12,228$	$7,905$	$39,525$
$\varepsilon = 0.99$	$13,576$	$8,654$	$43,270$
SP and Robust optimization with 3 scenarios			
	$d_{k\omega}$	$r_{k\omega}$	$\tilde{r}_{k\omega}$
Scenario 1 (moderate demand)			
$\pi_\omega = 0.10$	$10,000$	$6,667$	$33,350$
Scenario 2 (most likely)			
$\pi_\omega = 0.75$	$9,000$	$6,000$	$30,000$
Scenario 3 (highest demand)			
$\pi_\omega = 0.15$	$15,000$	$10,000$	$50,000$
Average	$10,000$	$6,667$	$33,350$

Table 4.4: Solutions by configuration, highest AHP ranking and lowest cost configuration in **bold**.

Config	AHP Ranking	Deterministic	Uniform CCP $\varepsilon = 0.90$	Triangular CCP $\varepsilon = 0.90$
(P,C,O)	0.208	1,117,822	1,411,060	1,262,977
(P,C,S)	0.157	1,170,251	1,442,588	1,315,323
(P,D,O)	**0.216**	971,397	1,145,436	1,113,216
(P,D,S)	0.164	1,021,899	1,171,555	1,163,359
(I,C,O)	0.075	1,039,836	1,319,495	1,168,538
(I,C,S)	0.045	1,033,676	1,347,794	1,220,872
(I,D,O)	0.082	**911,531**	**1,133,105**	**1,102,195**
(I,D,S)	0.052	914,103	1,162,744	1,154,497
Blended	–	**911,531**	**1,126,353**	**1,102,195**

the most preferred configuration has the highest numerical ranking and the least preferred configuration has the lowest numerical ranking.

For remanufacturing, the highest-ranked network configuration for the example is (P,D,O): proprietary collection, distributed sort-test and original processing. In the (P,D,O) configuration, collection would be done directly from the customer, sort-test is performed at the customer site, perhaps by assessing the age and model of the product, and the processing done at the original plant. The AHP ranking vector is shown in Table 4.4. The highest-ranked network configuration was (P,D,O) with 0.216, followed closely by (P,C,O) with 0.208. This indicates that the critical choices are to collect directly from customers to maintain propretary product knowledge, and to process at the original facilities. The sort-test decision of distributed or centralized would have minimal impact on the network design.

Having determined the high-level network rankings, the deterministic and CCP models were run to obtain the lowest-cost network configuration. The CCP models were implemented with a uniform distribution and a triangular distribution with $\varepsilon = 0.90$. In addition, these models were run to determine the cost of each network configuration by fixing the binary variables z^p, z^t and z^c at the corresponding values for all eight network configurations. For comparison, the blended configuration models were run for deterministic and CCP models by removing binary variables z^p, z^t and the set exclusivity constraints. The results are listed in Table 4.4. The (I,D,O) network configuration was consistently the best with respect to the lowest cost.

Figure 4.3 illustrates the relationship between cost and AHP ranking for the deterministic and CCP models. Note that for all three models, the lowest cost solution of (I,D,O) is highlighted, as is the most preferred AHP configuration, (P,D,O). The least cost configuration (I,D,O) dominates the other (I,_,_) configurations, while the most preferred AHP configuration (P,D,O) dominates the (P,_,_) configurations and a few others.

Comparing the cost of a configuration that has a higher AHP ranking to the lowest-cost solution gives the cost to implement the network configuration with the best AHP rankings. From Table 4.4, implementing the preferred configuration (P,D,O) would cost about 6.6% more than lowest-cost configuration (I,D,O) for the deterministic case, and about 1% more for the CCP case (either uniform or triangular).

Incorporating both the high-level and detailed decisions through the integrated model provides a quantitative measure of the tradeoffs between lowest cost and highest AHP preference. Further, over all three models – deterministic, CCP uniform and CCP triangular – the results are consistent: (I,D,O) is the least costly configuration, yet implementing the most preferred AHP configuration (P,D,O) has a relatively minor impact on cost.

4.2.3 Impact of uncertainty

To determine the degree to which uncertainty affects network configurations, the SP and robust optimization models were run with the set of three scenarios provided in the example. Note that the first-stage variables y^{fp}, y^{ft}, y^{rp}, y^{rt} and y^{rc} govern the configuration decisions made before demand and returns are known, and the second-stage or recourse variables x^f and x^r govern the flow. In SP, the recourse variables are determined by minimizing the expected value of overall costs in the set of scenarios, while in robust optimization, they are determined by minimizing the maximum cost over all scenarios.

Table 4.5 shows the detailed solutions for all five models. Costs are presented, with

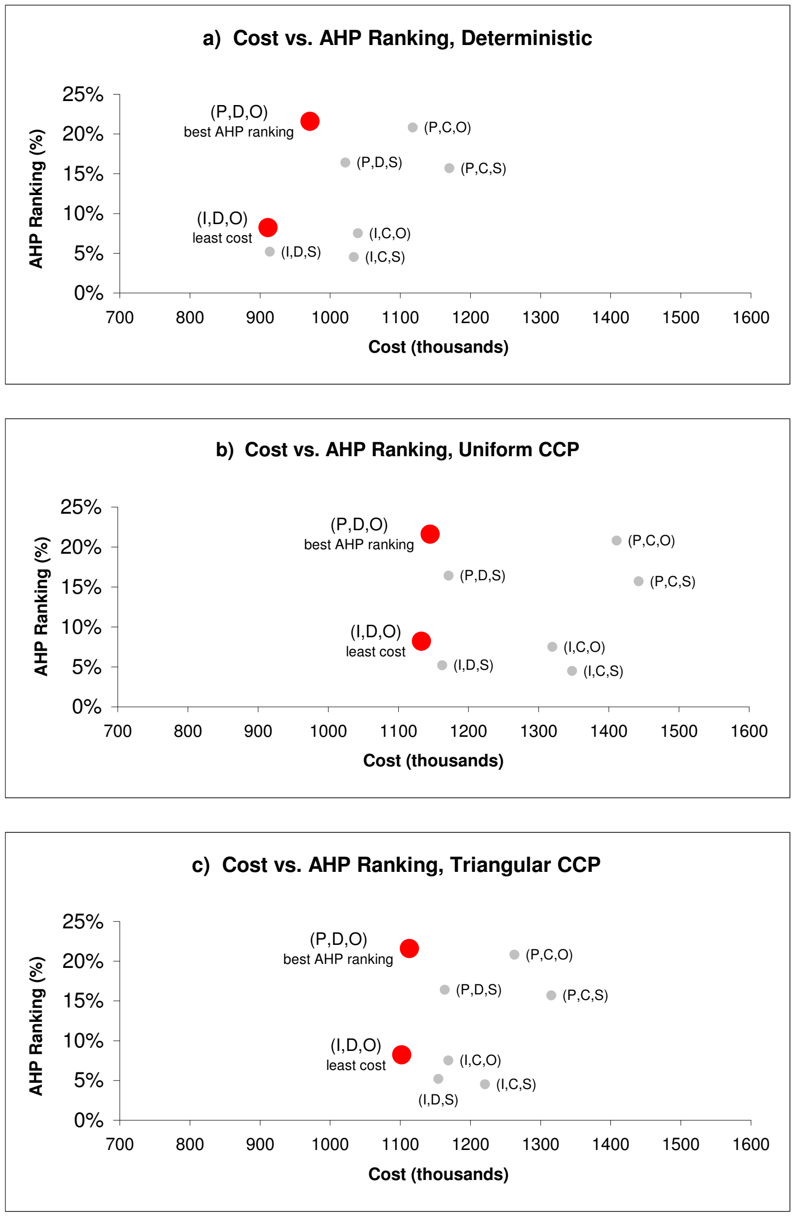


Figure 4.3: AHP ranking vs. cost for a) deterministic model, b) uniform CCP model, and c) triangular CCP model.

opening facilities costs in the second column, transportation/processing costs in the third column, and total cost in the fourth column. Detailed site locations for each solution are shown in the remaining columns, and sites that are common to all solutions are in bold type.

All five MILP models with fixed configuration have the same optimal configuration choice: (I,D,O). The blended configuration solution for each model is indicated below the fixed configuration solution. Note that in all models except for uniform CCP, the blended configuration solution is identical to the the fixed configuration solution. The findings indicate that configuration is relatively insensitive to uncertainty of return volumes. In fact, the optimal configuration may be much more sensitive to the specific site layout, that is, to the relative distances among sites, than to uncertainty in flow volumes.

The blended configuration for uniform CCP shows sensitivity to site selection. The forward flow sites were identical, but reverse flow sites were slightly different. The blended configuration solution drew from both original and secondary processing facilities: P1 in I and P7 in $\tilde{I}$ rather than P1, P2, P4 and P5 in I for the fixed configuration. The sort-test sites were all selected within the distributed sort-test set $\tilde{J}$: T7, T8, and T11 appeared in both solutions, with T10 and T13 in the blended configuration replacing sites T9 and T12 in the fixed configuration. Collection sites were the same: C16, C17, and C18. Thus a fixed configuration solution is relatively stable under uncertainty, because even when sites could be chosen freely, in four of the five models the blended configuration solution was identical to the fixed configuration solution.

While the configuration decision is stable, the site selection decision does vary across the five fixed configuration models. In forward flow, plants P4 and P5 were open in all models, but the deterministic model also had P1 open, while CCP, SP and robust had P2 and P3 open instead of P1. Similarly, warehouses T2 and T3 were open in all models, but T5 was also open in the deterministic, uniform CCP and SP models, and it was replaced with T4 in triangular CCP. In reverse flow, plants P1, P2, and P5 were open in all fixed configuration models, but uniform CCP also had P4 open, and SP and robust replaced it with P3. Sort-test sites T7, T8, T11 and T12 were open in all models, but T9 was open in

Table 4.5: Detailed solution information for all five models (sites common to all solutions in **bold**).

	COSTS			SITES				
	Opening	Transportation/	Total	Forward		Reverse		
Model	Facilities Cost	Processing Cost	Cost	Plants	Whses	Plants	Test	Collect.
Deterministic	551,000	360,531	911,531	P1	**T2**	**P1**	**T7**	**C16**
(I,D,O)				**P4**	**T3**	P2	**T8**	**C17**
Blended – identical solution				**P5**	T5	P5	**T11**	**C18**
							T12	
CCP (uniform)	679,000	454,105	1,133,105	P2	T1	**P1**	**T7**	**C16**
(I,D,O)				P3	**T2**	P2	**T8**	**C17**
				P4	**T3**	P4	T9	**C18**
				P5	T5	P5	**T11**	
							T12	
Blended	667,000	459,353	1,126,353	P2	T1	**P1**	**T7**	**C16**
				P3	**T2**	P7	**T8**	**C17**
				P4	**T3**		T10	**C18**
				P5	T5		**T11**	
							T13	
CCP (triangular)	655,000	447,195	1,102,195	P2	T1	**P1**	**T7**	**C16**
(I,D,O)				P3	**T2**	P2	**T8**	**C17**
Blended – identical solution				**P4**	**T3**	P4	T9	**C18**
				P5	T4	P5	**T11**	
							T12	
SP	729,000	346,041	1,075,041	P2	T1	**P1**	T6	**C16**
(I,D,O)				P3	**T2**	P2	**T7**	**C17**
Blended – identical solution				**P4**	**T3**	P3	**T8**	**C18**
				P5	T5	P5	T9	
							T11	
							T12	
Robust	729,000	574,939	1,303,939	— Same as SP —				
(I,D,O)								
Blended – identical solution								

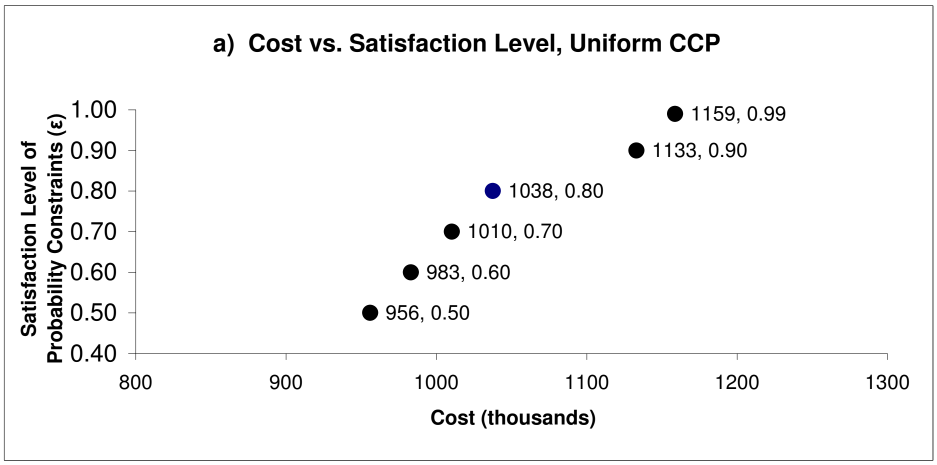
uniform and triangular CCP, while SP and robust had both T6 and T9 open. Collection sites were the same: C16, C17, and C18.

The sensitivity of the CCP model to different satisfaction levels of the probabilistic constraints was explored by setting ε in the CCP models to the six values listed in Table 4.3. Figure 4.4 illustrates the relationship between cost and satisfaction ε for uniform CCP and for triangular CCP. Each point in Figure 4.4 is labeled with the cost and the value of ε for that point.

All levels of ε tested have the same optimal configuration choice, (I,D,O), supporting the conclusion that the high-level decision is relatively insensitive to fluctuations in demand and return volumes. However, costs increase as ε increases. This suggests a cost-reliability tradeoff in which a producer could balance costs with an acceptable satisfaction level of the probabilistic constraints. For instance, in uniform CCP decreasing ε from 0.90 to 0.80 results in an 8.4% cost savings, while increasing ε from 0.90 to 0.99 increases the cost by 2.3%. Similarly, in triangular CCP decreasing ε from 0.90 to 0.80 results in a 7.5% cost savings, and increasing ε from 0.90 to 0.99 increases the cost by 11.3%. Li and Zabinsky (2009) also presented this cost-reliability tradeoff in a vendor selection problem using CCP.

What insights do these results provide about sensitivity to uncertainty? First, the configuration decision remains stable in the presence of uncertainty. However, there is some sensitivity to uncertainty in the site location decisions, as evidenced by site substitutions and added sites for different models and for different ε values. For example, in Figure 4.4, increasing ε from 0.90 to 0.99 in the triangular CCP model gives a larger percentage cost increase than in the uniform CCP model. This is explained by an additional site opening in the triangular CCP model to accommodate the increased return volumes, whereas the uniform CCP model can handle the return volumes with fewer facilities.

Second, it turns out that the deterministic and CCP models are essentially the same MILP with different right-hand sides for demand and return volumes, listed in Table 4.3. The study results show that the configuration decision is relatively insensitive to changes in the right-hand side, although the site selection decisions are affected by variability in return constraints. The deterministic and CCP models are relatively inexpensive to run, because they require less computation than scenario-based models. On the other hand,



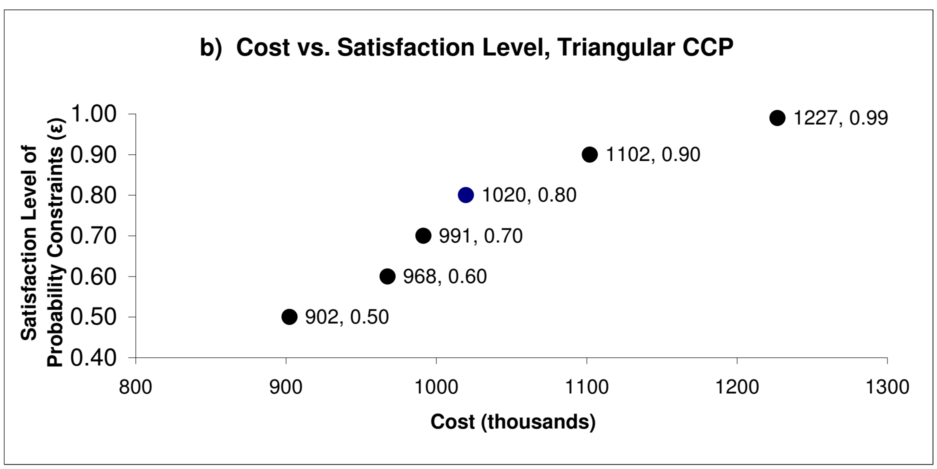


Figure 4.4: Satisfaction of probabilistic constraints vs. cost for a) uniform CCP model, and b) triangular CCP model.

through recourse variables, SP and robust optimization can adjust flow volumes to account for uncertainty. The scenario-based models invest more heavily in infrastructure: SP and robust optimization have slightly higher opening facilities costs than deterministic and CCP solutions (see Table 4.5), i.e, 729,000 monentary units vs. 551,000-679,000 monentary units. Although SP and robust optimization models may be more expensive to run, they may provide better detailed site selection decisions.

4.3 Summary and discussion

Producers need to design their supply chains to include reverse logistics in response to shrinking environmental resources and increasing consumer and government pressures. However, the lowest-cost network design is not necessarily the most effective design for a particular manufacturer's needs. Uncertainty has been established as a significant factor in reverse logistics, but its impact depends on the specific problem. Integrating high-level and detailed design decisions under uncertainty can help to determine the best network configuration and to assess the impact of uncertainty.

This work presents a suite of MILPs with an integrated network design model to determine an optimal configuration or allow a blended model. The optimization models also identify the optimal facility locations for collection, sort-testing and processing, and quantify the investment needed to achieve the highest AHP-ranked configuration. This enables a producer to determine the network configuration that is cost-effective and that supports its business needs. It also determines the associated site locations in the detailed network design.

The suite provides three approaches to uncertainty. The study compared three probabilistic methods – CCP, SP and robust optimization – to evaluate the sensitivity of the configuration decision to uncertainty. The same configuration choice was the lowest-cost solution for both deterministic and probabilistic models. In addition, varying the satisfaction levels of the probabilistic constraints ε in CCP resulted in the same configuration for the lowest-cost solution, indicating that the high-level decisions are relatively insensitive to uncertainty.

When considering the sensitivity of the CCP model to different levels of ε, the study found that costs increase as ε increases. This cost-reliability tradeoff provides an opportunity for producers to offset increased costs against an appropriate satisfaction level of the probabilistic constraints. Varying ε showed that overall cost is impacted more greatly by fixed costs for opening facilities than by transportation costs for flow.

What insights can be gained in comparing the fixed configuration vs. the blended model? In going to a blended model, the AHP ranking that indicates which configuration is most preferable for a particular producer's business needs is lost. However, for all but one of the five models the blended solution matched the fixed configuration solution, indicating that the fixed configuration solution is relatively stable.

In summary, the high-level network layout seems to be relatively insensitive to variability in flow volumes, and the deterministic and CCP models are a relatively inexpensive way to determine an optimal network configuration. Sensitivity to specific site locations seems to be well-addressed through recourse variables in SP and robust optimization. Future research will explore the application of this model to a variety of different producer applications to generalize the conclusions.

Chapter 5

INDUSTRY STUDY: CONSUMER ELECTRONICS RECYCLING

This chapter describes an industry study in electronic waste recycling. In this study, the methodology is applied to demonstrate the model and to provide additional insights. The background for the study is first described, followed by the application of the AHP model and the suite of optimization models. Results and insights are presented in a discussion, along with industry feedback on the model.

5.1 Background

Effective January 2009, government legislation in Washington State mandates that certain consumer electronics products must be collected and recycled at a cost to the manufacturer rather than to the consumer. Manufacturers of TVs, computer monitors and computers sold in Washington State are now required to provide for the recycling of those products instead of those products being sent to landfill for disposal. This research investigates the potential situation in which a consumer electronics manufacturer is considering how to comply with the legislation to set up a consumer electronics recycling program.

This research was motivated by discussions with the solid waste manager of City of Bellevue, Washington (Spille, 2010), which has had a curbside electronics recycling program since 2004, and with industry experts in electronics products recycling (Friedrick, 2010; Linnell, 2010). In this section, the decision model in this research is applied to a reverse logistics situation for an individual consumer electronics manufacturer. Because data in the electronics manufacturing industry is considered highly proprietary, representative data for the industry was obtained from interviews with collectors and recyclers of electronics products and with national industry leaders in solid waste management and electronics recycling.

5.2 Description

Assume a manufacturer of consumer electronics products is implementing reverse logistics in the state of Washington. The manufacturer wishes to explore the options of setting up a proprietary system to collect and process its own products vs. participating in a multi-manufacturer industry-wide system. The manufacturer is considering opening additional retail stores to build brand loyalty, and in doing so it could encompass a recycling system within the retail and warehousing supply chain. On the other hand, the manufacturer could participate in a state-wide manufacturer-funded recycling system such as the program managed by Washington Materials Management and Financing Authority (Washington Materials Management and Financing Authority (WMMFA), 2009), which would likely provide economies of scale and reduced costs over a proprietary system.

For this study, it is assumed that the producer sells products in Washington and has at least one existing retail location, located in Seattle. For the purposes of this study, the model will be limited to reverse flow only, and the products will not be reused or remanufactured, only recycled, according to the terms of the government legislation.

The sites for the study are listed in Table 5.1. Processing consists of complete product recycling, and can be performed at either one original processing facility located in an industrial section of Seattle, or at three secondary facilities in Seattle, Vancouver and Tacoma. Centralized sort-test will be done at the processing facilities, while distributed sort-test will be done at the collection sites. Testing procedures are minimal and do not involve significant costs, since testing will likely consist of superficial inspection by personnel to determine if the returned product fits the program criteria (e.g., produced by the manufacturer and one of the covered types of products). Collection sites consist of manufacturer's retail locations in Seattle, Vancouver or Spokane to which the customer must transport the product to the location, or through a curbside collection process at residential customer sites.

5.3 Numerical data

The data for the model are shown in Tables 5.2, 5.3, 5.4, and 5.5. The system has reverse flow only, so forward flow costs and volumes are zero. Note that volumes are based on

Table 5.1: Ewaste processing, sort-test and collection site locations.

Description	Location
Processing	
Original plants (set I)	
P1	Seattle
Secondary plants (set $\tilde{I}$)	
P2	Seattle
P3	Vancouver
P4	Tacoma
Sort-test	
Centralized (set J)	
T1	— performed at processing sites —
Distributed (set $\tilde{J}$)	
T2	— performed at collection sites —
Collection	
Proprietary (set K)	
C1	Seattle
C2	Vancouver
C3	Spokane
Industry-wide (set $\tilde{K}$)	
C4	— curbside collection by contractor —

Table 5.2: Costs data (in dollars).

Description	Parameter	Cost (in dollars)	Source
Forward flow			
Transportation-processing	c^{f}_{ijk}	0	
Reverse flow			
Transportation (per ton per mile)	c^{r0}_{kji}	0.73	Vander Pol (2010), Kramer (2010)
Processing (per ton)	c^{r1}_{kji}		
Original facility		430.00	Kramer (2010)
Secondary facility		480.00	Linnell (2010)
Sort-test			
Centralized		— included in processing —	
Distributed		— included in collection —	
Collection (per ton)			
Proprietary		138.00	Hong et al. (2006), Clifford (2010)
Industry-wide		4.50	O'Brien (2010), Friedrick (2010)
Total cost (per ton)	$c^{r}_{kji} = c^{r0}_{kji} \cdot d_{kji} + c^{r1}_{kji}$,		
where d_{kji} = distance between collection site k and processing site i (in miles)			

Table 5.3: Site capacity data (in tons).

Description	Parameter	Capacity	No. of sites
Processing – original	g^{rp}	200	1
Processing – secondary	g^{rp}	70	3
Test – centralized	g^{rt}	200	1
Test– distributed	g^{rt}	200	1
Collection – proprietary	g^{rc}	70	3
Collection – industry-wide	g^{rc}	200	1

Table 5.4: Returns data (in tons).

Description	Demand	Returns (proprietary)	Returns (industry-wide)
Deterministic (expected value)			
	d_k	r_k	$\tilde{r}_k$
	0	50.667	152.0
CCP with Uniform			
	$F^{-1}_{D_k}(\varepsilon_d)$	$F^{-1}_{R_k}(\varepsilon_r)$	$F^{-1}_{\tilde{R}_k}(\varepsilon_{\tilde{r}})$
$\varepsilon = 0.50$	0	50.667	152.0
$\varepsilon = 0.60$	0	52.333	157.6
$\varepsilon = 0.70$	0	54.400	163.2
$\varepsilon = 0.80$	0	56.267	168.8
$\varepsilon = 0.90$	0	58.133	174.4
$\varepsilon = 0.99$	0	59.813	179.4
CCP with Triangular			
	$F^{-1}_{D_k}(\varepsilon_d)$	$F^{-1}_{R_k}(\varepsilon_r)$	$F^{-1}_{\tilde{R}_k}(\varepsilon_{\tilde{r}})$
$\varepsilon = 0.50$	0	50.016	150.5
$\varepsilon = 0.60$	0	51.464	154.4
$\varepsilon = 0.70$	0	53.108	159.3
$\varepsilon = 0.80$	0	55.058	165.2
$\varepsilon = 0.90$	0	57.599	172.8
$\varepsilon = 0.99$	0	59.396	185.4
SP and Robust optimization with 3 scenarios			
	$d_{k\omega}$	$r_{k\omega}$	$\tilde{r}_{k\omega}$
Scenario 1 (most likely)			
$\pi_\omega = 0.33$	0	50.667	152.0
Scenario 2 (20% higher returns)			
$\pi_\omega = 0.33$	0	60.800	182.4
Scenario 3 (20% lower returns)			
$\pi_\omega = 0.33$	0	41.333	124.0
Average	0	50.667	152.0

Table 5.5: Distances between sites (in miles)

		I Plant 1 Seattle (Original)	Plant 2 Seattle (Secondary)	$\tilde{I}$ Plant 3 Vancouver (Secondary)	Plant 4 Tacoma (Secondary)
K	Collect. 1 Seattle (Proprietary)	8	7	170	39
	Collect. 2 Vancouver (Proprietary)	163	164	5	136
	Collect. 3 Spokane (Proprietary)	281	280	357	294
$\tilde{K}$	Collect. 4 Curbside (Industry-wide)	1	1	164	38
	(*per mile costs included in collection costs within Seattle*)				

the assumption that the manufacturer is comparable to a leading manufacturer in volume, and volumes and costs are calculated for one year of implementation. Below is a detailed description of the data.

Transportation costs. The estimated cost to ship a pound of electronics was calculated using the cost to ship a pallet of electronics from Spokane to Seattle, a distance of 280 miles at a cost of \$50 to \$75. The weight of a pallet is estimated to be 500 to 800 pounds, and the calculations to determine cost per pound per mile yielded an average of \$0.0003656 per pound or \$0.73 per ton per mile. The Spokane-Seattle trip costs are representative of a typical cost for LTL (less-than-truckload) service, according to information obtained from an LTL freight expert, and the pallet weight estimate was obtained from an electronics recycler representative (Table 5.2).

Processing costs. The cost to recycle electronics in a proprietary facility runs from \$0.16 to \$0.27 per pound or \$320 to \$540 per ton depending on volume, according to a large electronics recycler, which is the estimate used for original processing facility costs. Secondary processing estimates were \$0.24 per pound or \$480 per ton, which is the average cost to manufacturers using the WMMFA program using secondary recycling facilities, as reported by a national electronics recycling organization representative (Table 5.2).

Collection costs. Proprietary collection is to be done at three retail locations. Volume per day per site is anticipated to be relatively modest at roughly 300 pounds per day, the equivalent of 4-5 TV units or 10-12 computer units. Products will be received by store personnel, and then processed by one additional employee one day a week at each site. Labor costs are calculated by estimating wages at \$12 per hour, 8 hours per day, 52 days per year, then increased by 40% to account for overhead and benefits. Overhead and benefits calculation were taken from a 2010 article appearing in *CNN Money.com* (Clifford, 2010). The results are about \$21,000 per year for all three sites, divided by 152 tons per year collected, or \$138 per ton. Industry-wide collection is to be done through curbside collection by separate contractor, which runs about \$0.00238 per pound or \$4.405 per ton, calculated from information from Solid Waste Association of North America (SWANA) and census information for the State of Washington (Table 5.2).

Facility opening costs. While the model has the capability to include facility opening costs, this study includes only transportation and processing costs per unit. Facility costs might have been incurred for a) the original processing facility and b) proprietary collection facilities. However, facility costs were found to be highly variable and dependent on a number of factors, and could not be readily provided by industry contacts. It was assumed that opening costs for a processing facility would be assessed carefully if original facility was chosen in the preferred network configuration. On the other hand, opening costs for proprietary collection facilities could be considered incremental to development costs for new retail locations that the manufacturer is planning to open, if proprietary collection were chosen. Costs for testing facilities were assumed to be covered by processing and collection facilities.

Capacities. Facility capacities were calculated by allowing sufficient capacity to process return volume parameters (Table 5.3).

Return volume. The projected return volume was calculated from the total volume of returned electronics products in 2009 (39,348,674 pounds), and Sony USA products account for 0.8%, which was considered to be representative, resulting in 304,000 pounds or 152 tons (Washington Materials Management and Financing Authority (WMMFA), 2009). The return volume was assigned equally among the number of sites in each collection site set. Volume statistics were provided by the annual report produced by WMMFA. Three scenarios were developed for stochastic programming and robust optimization. Scenario 1 reflects 2009 volumes, while scenario 2 is 20% higher volumes and scenario 3 is 20% lower volumes. In the stochastic programming model, the three scenarios were treated as equally likely (Table 5.4).

Distances. Distances were obtained from road distances via internet mapping software (Table 5.5).

5.4 AHP model

Evaluating the conceptual or high-level decisions through the AHP model requires assigning rankings to AHP criteria, subcriteria, and alternatives as described in Chapter 3. The rankings for the alternatives do not depend on the particular manufacturing situation and are the same as in Table 3.8; the table is duplicated in Table 5.6 for completeness.

The rankings for criteria and subcriteria, however, do depend on the manufacturing situation. The rankings for this study are listed in Table 5.7 and are described below. How were the rankings assigned for this study? Like those in Chapter 3, rankings were assigned based on information garnered in interviews with industry experts. The numeric values were designed to be consistent with rankings of previous case studies and the alternatives rankings. The ranking scale may be described as: 1 = benchmark (of least importance), 2 = mildly important, 3-4 = moderately important, and 5-6 = extremely important. Each

Table 5.6: Relative AHP rankings for network configurations.

i	Config.	Recycled a_i^1	Testing a_i^2	Scrap a_i^3	Facility a_i^4	Propr. Knowl. a_i^5	Customer Int.'s a_i^6
1	(P,C,O)	1	4	1	3	6	6
2	(P,C,S)	2	4	1	1	4	6
3	(P,D,O)	1	1	6	3	6	6
4	(P,D,S)	2	1	6	1	4	6
5	(I,C,O)	4	4	1	3	2	1
6	(I,C,S)	6	4	1	1	1	1
7	(I,D,O)	4	1	6	3	2	1
8	(I,D,S)	6	1	6	1	1	1

Table 5.7: Criteria and subcriteria rankings for electronic waste study.

Criteria or Subcriteria	Ranking	
Cost savings	g_1	3
Business relations	g_2	1
Recycled product	c_1	6
Testing	c_2	1
Scrap shipped	c_3	5
Original facility	c_4	1
Proprietary knowledge	r_5	1
Customer interactions	r_6	3

ranking is assigned relative to the benchmark criterion within the set of criteria or subcriteria.

Principal criteria: Cost savings vs. Business relations. Because the study involves electronic waste which will be completely recycled, cost savings is important. However, the assumption in this study is that the producer may be interested in increasing its customer relationships by opening new retail locations. The business relations criterion is the benchmark (g_2=1) and cost savings is moderately more important ($g_2 = 3$).

Cost savings subcriteria: Recycled product, Testing, Scrap shipped, and Original facility. Like carpet recycling in Chapter 3, the recycled product and scrap shipped criteria will be most valuable, because the operation involves recycling, and because there may be scrap in terms of other manufacturers' products that should be identified early to avoid unnecessary shipping. The least valuable subcriteria are testing, which is extremely low-cost, and original facility, because the producer is unlikely to already have processing facilities readily available for recycling. Therefore, original facility is the benchmark ($c_4 = 1$), testing is also ranked 1 ($c_2 = 1$), scrap shipped is ranked 5 ($c_3 = 5$) and recycled product is ranked 6 ($c_1 = 6$).

Business relations subcriteria: Proprietary knowledge and Customer interactions. In terms of electronic waste, neither proprietary knowledge nor customer interactions is particularly important. Nevertheless, assuming that the manufacturer may be interested in promoting stronger customer relationships, the customer interactions subcriterion may be ranked higher than a proprietary knowledge subcriterion ($r_5 = 1$, $r_6 = 3$).

The AHP solution for this study is illustrated in Figure 5.1. The most preferred configuration is (I,D,S), yet there are 3 additional configurations that are very close in preference: (P,D,S), (I,D,O) and (P,D,O). The close ranking between these four configurations reflects the near equal priority that the manufacturer places on stronger customer relationships relative to the desire for cost savings.

Sensitivity analysis for the α and β parameters is shown in Figure 5.2. The α parameter governs the relationship between cost savings and business relations, and consistent with case studies in Chaper 3, the configuration decision is sensitive to α. When the ranking of cost savings over business relations falls below 70%, (P,D,O) becomes preferred instead of (I,D,S). Although the collection and processing decisions are sensitive to α, the test decision is not sensitive. In fact, the sensitivity lines for all the (P,_,_) configurations are closely related to the (P,D,O) sensitivity line as α becomes closer to zero and business relations dominates cost savings. Thus, it would be highly strategic for the producer to consider proprietary collection in its network design, especially when thinking about future business conditions.

Sensitivity to the business relations subcriteria β is similar in this study to the previous case studies. The sensitivity lines are relatively parallel to each other with no crossover points for (I,D,S), and thus β, the ratio between proprietary knowledge and customer interactions, has no impact on the configuration choices.

As shown in Figure 5.3, the configuration decision is highly sensitive to cost savings parameters γ, which was also the case in the earlier case studies. When the ranking for cost savings is higher than the ranking for business relations, the configuration decision is very sensitive to the four cost savings subcriteria.

The γ_2 and γ_3 parameters primarily affect the test decision, in which the preferred configuration changes from a (_,D,_) configuration to a (_,C,_) configuration, with secondary effects on collection and processing decisions. As γ_2 increases from 8% to 29% the preferred configuration changes from (I,D,S) to (P,D,O), and if γ_2 increases to 33% the preferred configuration changes to (P,C,O). As γ_3 decreases from 38% to 10%, the preference goes from (I,D,S) to (I,C,S); if γ_3 increases from 38% to 53%, (P,D,O) is preferred. Thus collection goes from an (I,_,_) to a (P,_,_) configuration and processing goes from an (_,_,S) configuration to an (_,_,O) configuration as the test cost subcriterion or the shipping scrap subcriterion dominates the other subcriteria.

The γ_1 parameter affects the choice between (I,_,S) and (P,_,O) configurations. As γ_1 decreases from 46% to 37%, the preferred configuration goes from (I,D,S) to (P,D,O), reflecting the dominance of the recycled product subcriterion. Finally, the γ_4 parameter determines the processing choice with a secondary effect on the collection decision. As γ_4 goes from 8% to 16% the configuration preference goes from (I,D,S) to (P,D,O). The testing decision is not affected by γ_1 or γ_4.

In summary, the configuration decision is sensitive to all parameters except β. Although the most preferred solution is (I,D,S), there is ample opportunity for the producer to explore the relationship between the decision choices and the producer's goals and values. Is the focus primarily on cost savings? Or will it be better to foster stronger customer relationships? Does proprietary control play an important role in the producer's business model, such as for Apple's iPhone products, or are the products considered "throwaway"? Is there a potential for recovering value, such as by harvesting spare parts or remanufacturing certain products? Because the high-level decisions in this case study are so sensitive to the AHP model parameters, the goals and values of the producer will be critical in determining the configuration decision. The decision makers will better understand the tradeoffs of those goals and values and the impact on the high-level decisions through the AHP model.

5.5 MILP model

Implementing the suite of MILP models with the numerical data in this study gives the results in Table 5.8. All five models resulted in the same lowest-cost configurations, (I,D,O) and (I,C,O). Note that because testing costs were assumed to be included in processing or collection costs for this study, the testing decision does not affect costs.

The configuration choice seems to be insensitive to uncertainty, since the amount of flow ranged from 152 tons in the deterministic model to 182 tons in the robust optimization model, yet the configuration choice was the same. The selection among sites may be more sensitive to uncertainty, although in this study, the sites selected were identical among all models, including the blended model. Because the study involved a small number of sites, the sensitivity may be more apparent for a larger number of candidate sites.

Even though the results for the blended solution are the same as for the fixed configuration solution, the AHP configuration model gives a measurement of the difference in cost between the lowest-cost solution and a solution that is more preferred.

The relationship between cost and AHP ranking for the deterministic model is shown

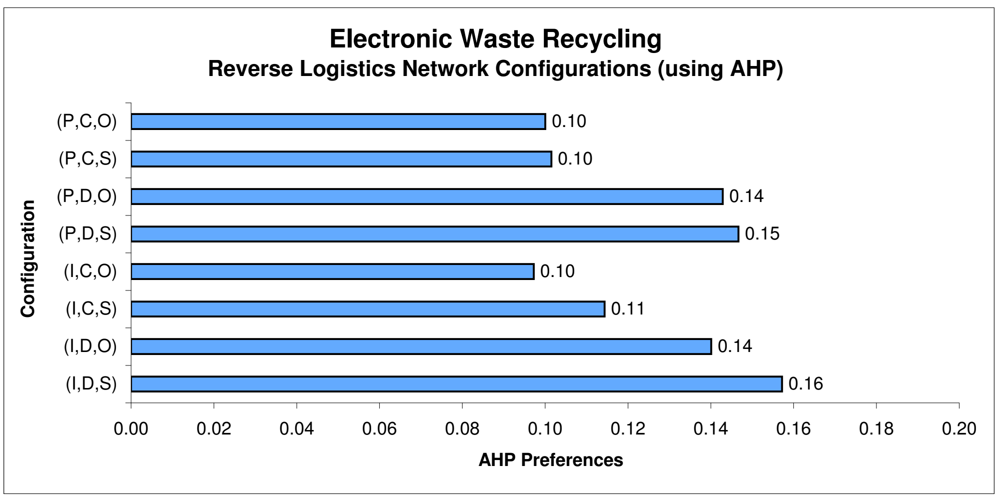


Figure 5.1: AHP solution for electronic waste study.

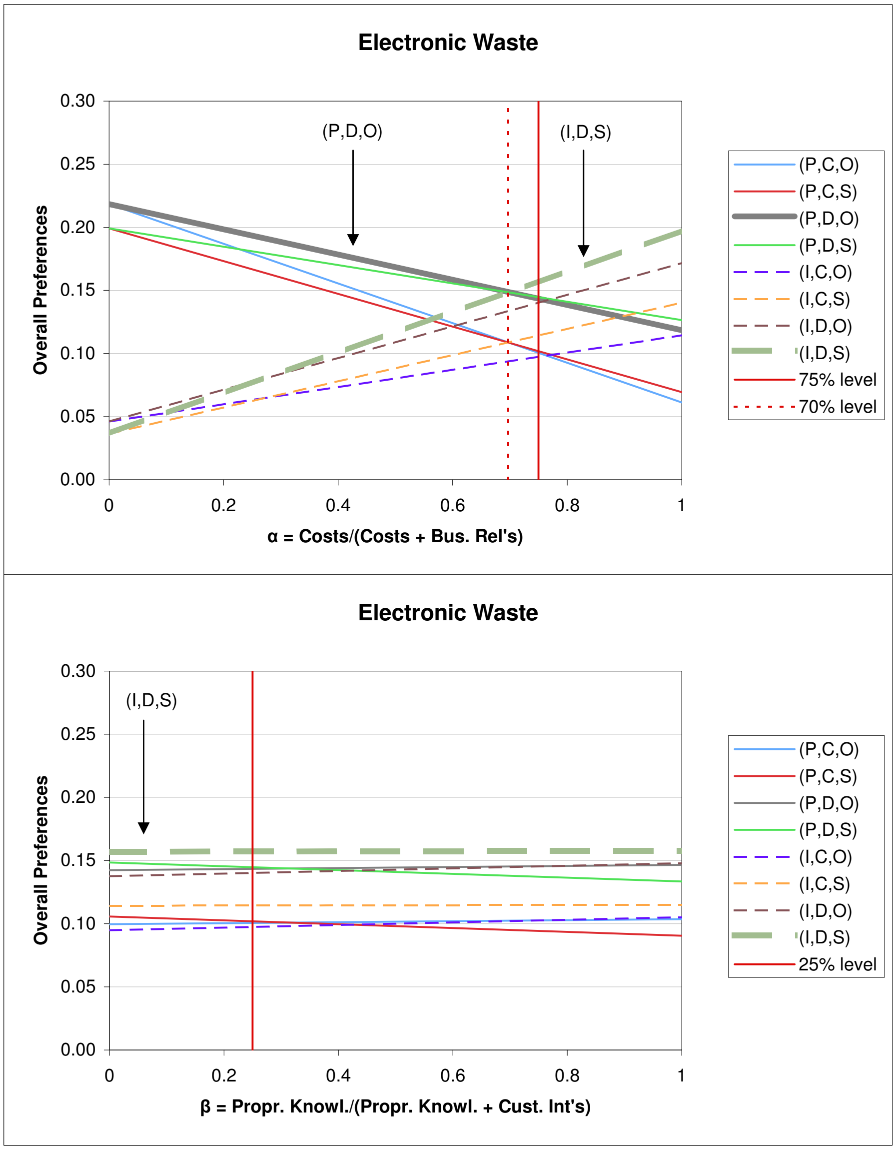


Figure 5.2: Sensitivity analysis for α and β parameters in electronic waste study.

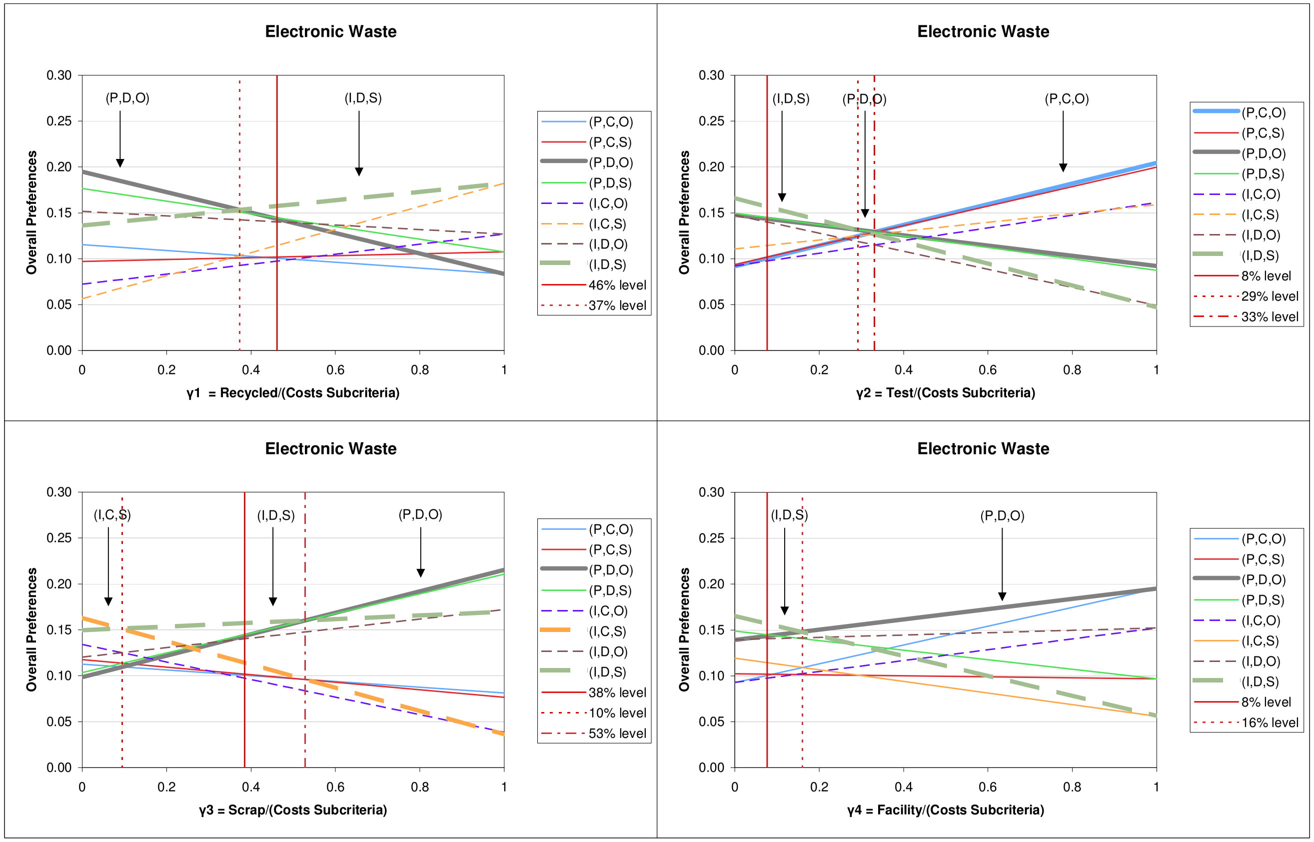


Figure 5.3: Sensitivity analysis for α parameter and β parameter in electronic waste study.

Table 5.8: MILP models solutions for electronic waste study, highest AHP ranking and lowest cost configuration in **bold**.

Config	AHP Preference	Deterministic	Uniform CCP $\varepsilon = 0.90$	Triangular CCP $\varepsilon = 0.90$	Stochastic Programming	Robust Optimization
(P,C,O)	0.10	103,055				
(P,C,S)	0.10	105,118				
(P,D,O)	0.14	103,055				
(P,D,S)	0.15	105,118				
(I,C,O)	0.10	**66,044**	**75,777**	**75,081**	**65,728**	**79,253**
(I,C,S)	0.11	78,293				
(I,D,O)	0.14	**66,044**	**75,777**	**75,081**	**65,728**	**79,253**
(I,D,S)	**0.16**	78,293				
Blended	–	**66,044**	**75,777**	**75,081**	**65,728**	**79,253**

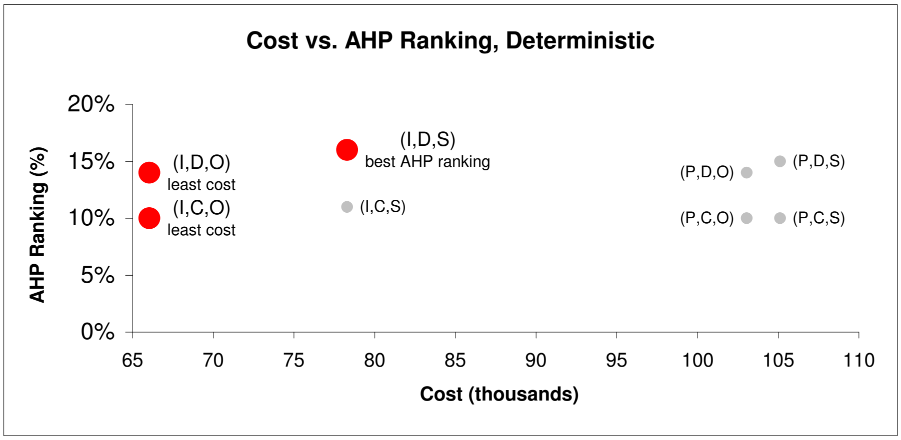
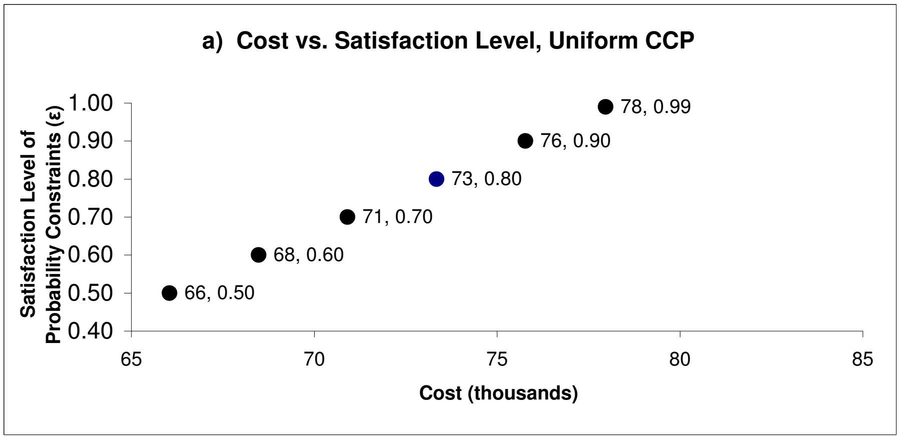


Figure 5.4: Cost vs. AHP ranking for electronic waste study.



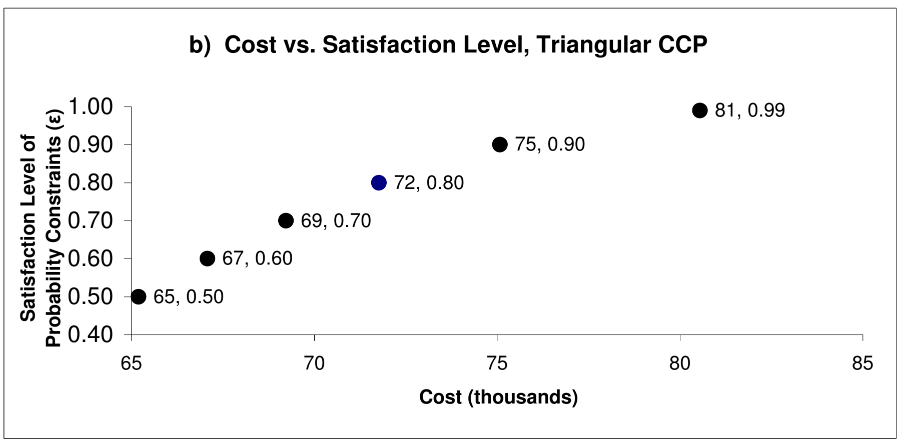


Figure 5.5: Cost vs. satisfaction level ε for electronic waste study: a) uniform CCP and b) triangular CCP.

in Figure 5.4. Each point is labeled with the the cost and the value of ε. The cost to implement the preferred configuration (I,D,S) over the lowest-cost configuration (I,D,O) or (I,C,O) would be about 18.5% higher. Implementing (P,D,S), which was also highly preferred, would be a substantially greater investment at about 60% greater cost over the lowest-cost solution.

The relationship between cost and satisfaction ε for uniform CCP and triangular CCP is shown in Figure 5.5. Increasing or decreasing the level of satisfaction ε has a relatively minor impact on costs. For uniform CCP, decreasing ε from 0.80 to 0.90 gives only a 3% decrease in costs, and increasing ε from 0.90 to 0.99 is a 3% increase. The results are similar for triangular CCP: decreasing ε from 0.90 to 0.80 is a 4.5% decrease and increasing ε from 0.90 to 0.99 is a 3% increase.

From the results of this study, it is evident that the producer should weigh the benefits of cost savings relative to a desire to strengthen customer relations. The most significant decision will be collection, and the configuration choice is relatively sensitive to the cost savings and business relations factors, as indicated in the AHP sensitivity analysis. In addition, testing costs are minimal, and processing costs are equivalent between original and secondary facility. In fact, in this case the original facility processing option would not merit serious consideration, because it is a recycling operation and processing can be readily performed by a third party, as third-party electronic recycling capability is widely available.

In general, proprietary collection is more costly than industry-wide collection. However, industry-wide collection is most efficient for high volumes, and under more moderate or low volumes, a proprietary collection system could make sense. Because freight costs are relatively low in proportion to other costs such as labor for collection, non-freight costs could be analyzed to make a proprietary system more cost-effective.

In future research for this study, facility opening costs and industry-wide collection costs should be explored more thoroughly. As well, it would be interesting to increase the number of secondary processing sites to evaluate the impact of uncertainty on site selection further.

5.6 Summary and discussion

In this chapter the decision model was applied to an industry study of electronic waste recycling. The high-level design decisions were determined using AHP, and the detailed decisions were performed using a suite of five MILP models that include probabilistic models. The cost-preference relationships and the cost-satisfaction level relationships were used to evaluate the inherent tradeoffs between decision choices.

The AHP model identified the most preferred configuration to be (I,D,S), although (P,D,S), (I,D,O) and (P,D,O) were also highly preferred. Sensitivity analysis showed that the collection decision is highly sensitive to the preference ratio between business relations and cost savings α, and that the collection, sort-test and processing decisions were sensitive to the ratio among the four cost savings parameters γ corresponding to testing costs, proportion of scrap in the return stream, recycled product content and original facility processing availability. The decisions were not sensitive, however, to the business relations subcriteria ratio β.

Because of significant sensitivity of the configuration decision to α and γ, the producer has an opportunity to balance the tradeoffs inherent in network design. Whether to focus on strengthening customer relationships or cost savings, if there may be valuable proprietary or intellectual knowledge to protect, can economic value be realized from the return product – these considerations can be weighed effectively by the AHP model in which competing priorities are resolved to determine the most preferred configuration and to understand what the tradeoffs may be.

Like the numerical study, the configuration choice is stable for all models, even under uncertainty and in the blended model when the sites can be chosen freely. The AHP model tells the producer which configurations are most preferred for its business model, and the relationship between cost and AHP ranking indicates the difference in cost between the lowest-cost and the most preferred configuration. Sensitivity analysis in the AHP model indicates that the choice of configuration is sensitive to the ranking of cost savings vs. business relations, and if the producer increases the ranking of business relations to cost savings, the preferred configuration will change. Increasing or decreasing the satisfaction level ε has an impact on overall cost, as indicated by the relationship between cost and satisfaction level for both uniform CCP and triangular CCP, and that relationship provides an opportunity for the producer to determine an acceptable balance between cost and satisfaction level or reliability of the probabilistic constraints.

Chapter 6

SUMMARY AND FUTURE RESEARCH

Producers need to design their reverse logistics network tailored to both their business needs and cost savings. The research is in three major parts.

In the first part of this work, a conceptual framework was developed to evaluate high-level decision choices. The conceptual framework provides a better understanding of the tradeoffs in network design decisions, giving manufacturers a structured approach to designing their reverse logistics network.

The second part of the work is a multicriteria AHP decision model that quantifies the high-level decisions based on the conceptual framework. The model gives a ranking among eight possible network configurations according to a set of criteria derived from the conceptual framework. Sensitivity analysis provides insights for decision makers into the potential tradeoffs in high-level decisions and the network configuration decision process. The conceptual framework and AHP decision model, derived from case study analysis of forty case studies, were demonstrated on three case studies: a medical device remanufacturing system, a residential carpet recycling process and a commercial carpet recycling process.

Sensitivity analysis in the AHP model determined that the collection decision is governed by the producer's ranking for cost savings relative to business relations and is sensitive to the ratio between the rankings α: a higher ranking for business relations favors a proprietary system (P,_,_), while a higher ranking for cost savings points to an industry-wide system (I,_,_). The sort-test decision is determined by potential cost savings from reducing testing costs and identifying scrap early to avoid unnecessary transportation costs and is sensitive to the rankings ratios γ_2 and γ_3: higher test costs lead to centralized testing (_,C,_) while higher proportion of scrap in the return stream favors distributed testing (_,D,_). Collection and processing are affected by potential cost savings from recycled product content and is sensitive to the rankings ratio γ_1: if the product is to be recycled, then (I,_,S) configurations are more preferred, otherwise (P,_,O) configurations are preferred. Finally, processing is impacted by the potential for cost savings from original facility processing capability and is sensitive to the rankings ratio γ_4: if original facility space is present, then (_,_,O) configurations are preferred, else (_,_,S) configurations are preferred. The processing decision is also slightly sensitive to the business relationship rankings ratio β, in that a high desire for proprietary knowledge favors (_,_,O) configurations.

The third part of the work combines the high-level decisions with detailed design decisions for a flexible, integrated decision model. A suite of MILP models was developed that determines the lowest-cost network configuration and yields the cost of implementing a more preferred configuration from the producer's viewpoint. Further, the model evaluates the cost-reliability relationship, in which a producer can balance the tradeoff of meeting a satisfaction higher level of demand for return products against the associated increased costs.

Because variability is higher in return volumes than in forward flow, uncertainty may be critical in the choice of configuration. The suite of MILP models includes three methods for addressing uncertainty: chance-constrained programming, stochastic programming, and robust optimization. Results of a numerical study using these methods show that the choice of network configuration is relatively insensitive to variability in flow volumes. However, there is sensitivity to site location decisions, which can be well-addressed by recourse variables in SP and robust optimization models.

An industrial case study was presented for electronic waste recycling to demonstrate the methodology with integrating the AHP model and the suite of MILP models. The study involved a situation in which an electronics manufacturer is implementing a reverse logistics system for its products in Washington State. The methodology was applied to the industrial study to determine the most preferred network configuration and to evaluate sensitivity to the high-level decisions, as well as measuring the difference in cost between the lowest-cost solution and the most-preferred solution. The configuration preference decision was sensitive to the balance between the cost savings and business relations criteria as well as the balance among cost savings criteria, but not among the business relations subcriteria. For the industry study on consumer electronics recycling, the limited number of individual site selections were insensitive to uncertainty and the configuration decision was insensitive to uncertainty.

In addition to network design, researchers are working on other reverse logistics topics. These topics include: 1) pricing structures for new and return products to determine the best prices for recycled, reused and remanufactured products, 2) analysis of customer characteristics in primary and secondary markets to better address product positioning for recovered products, 3) assessing the risk of "cannibalization" of markets, that is, to what degree resale of return product erodes sale of new product, 4) evaluation of incentive effectiveness to motivate customer returns, and 5) improved forecasting and standardizing of quantity and frequency of return product.

Design for sustainability is another actively developing research area. What characteristics are most critical for designing a reusable or remanufacturable product? Promising areas include design for disassembly (such as use of removable fasteners instead of permanent ones), design for efficient recycling (such as materials being clearly marked as to content for easier recycling upon disassembly), design for repair (such as modular product design so that spare parts can be readily replaced rather than whole-product disposal), and other product characteristics. The growing awareness of the need for more environmentally-conscious manufacturing is indicated by a relevant political cartoon reprinted in Appendix B.

This research developed a multiobjective decision model for reverse logistics that determines the high-level decisions through an AHP model and then links those decisions with the detailed decisions through a suite of MILP models that address uncertainty. The model provides sensitivity analysis for the high-level decisions and evaluates the impact of uncertainty on the high-level and detailed decisions. The value of the model is supported by industry collaborators, and applying the model to a variety of case studies demonstrates the efficacy of the model in a number of industrial contexts.

BIBLIOGRAPHY

John Aanenson. Personal communication, August, 2010. Senior Manufacturing Manager, Philips Healthcare Ultrasound, Bothell, WA.

Necati Aras and Deniz Aksen. Locating collection centers for distance- and incentive-dependent returns. *International Journal of Production Economics*, 111:316–333, 2008.

Theresa J. Barker and Zelda B. Zabinsky. Reverse logistics network design: a conceptual framework for decision making. *International Journal of Sustainable Engineering*, 1(4): 250–260, 2008.

Theresa J. Barker and Zelda B. Zabinsky. A multi-criteria decision making model for reverse logistics using Analytic Hierarchy Process. *In revision*, 2009.

Theresa J. Barker and Zelda B. Zabinsky. An optimization model for reverse logistics under uncertainty using chance constraints, stochastic programming and robust optimization. *In review*, 2010.

A.I. Barros, R. Dekker, and V. Scholten. A two-level network for recycling sand: A case study. *European Journal of Operational Research*, 110:199–214, 1998.

Thomas Bartel. Recycling program for printer toner cartridges and optical photoconductors. In *Proceedings of the IEEE International Symposium on Electronics and the Environment*, pages 225-228, Orlando, FL, USA, May 1-3, 1995.

U.K. Bhattacharya. A chance constraints goal programming model for the advertising planning problem. *European Journal of Operational Research*, 192(2):382–395, 2009.

John R. Birge and François Louveaux. *Introduction to Stochastic Programming*. Springer, New York, 1997.

J.M. Bloemhof-Ruwaard, L.N. Van Wassenhove, H.L. Gabel, and P.M. Weaver. An environmental life cycle optimization model for the European pulp and paper industry. *Omega*, 24:615–629, 1996.

F.A. Campos, J. Villar, and M. Jimenez. Robust solutions using fuzzy chance constraints. *Engineering Optimization*, 38(6):627–645, 2006.

Craig R. Carter and Lisa Ellram. Reverse logistics: A review of the literature and framework for future investigation. *Journal of Business Logistics*, 19(1):85–102, 1998.

Ni-Bin Chang and Y.L. Wei. Siting recycling drop-off stations in urban area by genetic algorithm-based fuzzy multiobjective nonlinear integer programming modeling. *Fuzzy Sets and Systems*, 114:133–149, 2000.

A. Charnes and W. W. Cooper. Chance-constrained programming. *Management Science*, 6(1):73–79, 1959.

Marc Chouinard, Sophie D'Amours, and Daoud Aït-Kadi. A stochastic programming approach for designing supply loops. *International Journal of Production Economics*, 113: 657–677, 2008.

Catherine Clifford. Why a $14 hour employee costs $20. CNN Money.com, March 2010. http://money.cnn.com/2010/03/26/smallbusiness/employee_costs/index.htm, accessed 08/09/10.

John Conyers, Jr. Personal communication, August, 2010. Director of Manufacturing Staff Operations, Shaw Industries Group Inc., Dalton, GA.

M. de Brito and R. Dekker. Chapter 1: A framework for reverse logistics. In Rommert Dekker, Moritz Fleischmann, Karl Inderfurth, and Luk N. Van Wassenhove, editors, *Reverse Logistics Quantitative Models for Closed-Loop Supply Chains*. Springer-Verlag, Berlin, 2004.

Marisa P. DeBrito and Rommert Dekker. Modelling product returns in inventory control

– exploring the validity of general assumptions. *Production Economics*, 81-82:225–241, 2003.

Marisa P. DeBrito, Rommert Dekker, and Simme D. P. Flapper. Reverse logistics – a review of case studies. In *ERIM Report Series ERS-2003-045-LIS*, the Netherlands, April 2003. ERIM Report Series ERS-2003-045-LIS, Erasmus University Rotterdam.

Enrique Del Castillo and Jeffery K. Cochran. Optimal short horizon distribution operations in reusable container systems. *Journal of the Operational Research Society*, 47:48–60, 1996.

Angel Diaz and Michael C. Fu. Models for multi-echelon repairable item inventory systems with limited repair capacity. *European Journal of Operational Research*, 97:480–492, 1997.

Rochelle Duhaime, Diane Riopel, and Langevin Andre. Value analysis and optimization of reusable containers at Canada Post. *Interfaces*, 31(3):3–15, 2001.

Merran Evans, Nicholas Hastings, and Brian Peacock. *Statistical Distributions*. Wiley, New York, 2000.

Expert Choice. Expert Choice 11.5, Powerful Performance for Organizational Decision-Making. http://www.expertchoice.com/products-services/expert-choice-115, accessed 07/19/10, 2009.

Paul H. Farrow, Richard R. Johnson, and Andrea L. Larson. Entrepreneurship, innovation, and sustainability strategies at Walden Paddlers, Inc. *Interfaces*, 30(3):215–225, 2000.

Isabel Fernández, Javier Puente, Nazario García, and Alberto Gómez. A decision-making support system on a products recovery management framework. a fuzzy approach. *Concurrent Engineering: Research and Applications*, 16(2):129–138, 2008.

Simme Douwe P. Flapper. Logistic aspects of reuse. In *First International Working Seminar on Reuse*, Eindhoven University of Techonology, Faculty of Technology Management, pages 109-118, Eindhoven, The Netherlands, Nov 11-13, 1996.

Moritz Fleischmann. *Quantitative Models for Reverse Logistics.* PhD thesis, Erasmus University Rotterdam, the Netherlands, 2000.

Moritz Fleischmann, Jacqueline M. Bloemhof-Ruwaard, Rommert Dekker, Erwin van der Laan, Jo A.E.E. van Nunen, and Luk N. Van Wassenhove. Quantitative models for reverse logistics: A review. *European Journal of Operational Research*, 103:1–17, 1997.

Moritz Fleischmann, Hans Ronald Krikke, Rommert Dekker, and Simme Douwe P. Flapper. A characterisation of logistics networks for product recovery. *Omega*, 28:653–666, 2000.

Moritz Fleischmann, Patrick Buellens, Jacqueline M. Bloemhof-Ruwaard, and Luk N. Van Wassenhove. The impact of product recovery on logistics network design. *Production and Operations Management*, 10(2):156–173, 2001.

Moritz Fleischmann, Jacqueline M. Bloemhof-Ruwaard, Patrick Buellens, and Rommert Dekker. Chapter 4: Reverse Logistics Network Design. In Rommert Dekker, Moritz Fleischmann, Karl Inderfurth, and Luk N. Van Wassenhove, editors, *Reverse Logistics Quantitative Models for Closed-Loop Supply Chains.* Springer-Verlag, Berlin, 2004.

John Friedrick. Personal communication, August, 2010. Executive Director, Washington Materials Management and Financing Authority (WMMFA), http://www.wmmfa.net/.

Kate Goggin and Jim Browne. Towards a taxonomy of resource recovery from end-of-life products. *Computers in Industry*, 42:177–191, 2000.

N. Growe. Estimated stochastic programs with chance constraints. *European Journal of Operational Research*, 101(2):285, 1997.

V. Daniel R. Guide Jr. and Luk N. Van Wassenhove. Rough-cut capacity planning for remanufacturing firms. *Production Planning and Control*, 8(3):237–244, 1997.

V. Daniel R. Guide Jr. and Luk N. Van Wassenhove. Managing product returns for remanufacturing. *Production and Operations Management*, 10(2):142–155, 2001.

Tarun Gupta and Subrata. Chakraborty. Looping in a multistage production system. *International Journal of Production Research*, 22(2):299–311, 1984.

I-Hsuan Hong, Tiravat Assavapokee, Jane Ammons, Chuck Boelkins, Kennon Gilliam, Devon Oudit, Matthew J. Realff, Juan Martín Vannícola, and Wuthichai Wongthatsanekorn. Planning the e-scrap reverse production system under uncertainty in the state of Georgia: A case study. *IEEE Transactions on Electronics Packaging Manufacturing*, 29:150–162, 2006.

Vaidyanathan Jayaraman, Raymond A. Patterson, and Erik Rolland. The design of reverse distribution networks: Models and solution procedures. *European Journal of Operational Research*, 150:128–149, 2003.

Norman I. Johnson and Samuel Kotz. *Continuous Univariate Distributions*, volume 2. Houghton Mifflin Company, Boston, 1970.

G. Kannan, A.N. Haq, and P. Sasikumar. An application of the analytical hierarchy process and fuzzy analytical hierarchy process in the selection of collecting centre location for the reverse logistics multicriteria decision-making supply chain model. *International Journal of Management and Decision Making*, 9(4):350–365, 2008.

Markus Klausner and Chris T. Hendrickson. Reverse-logistics strategy for product take-back. *Interfaces*, 30(3):156–165, 2000.

U. Kleineidam, A.J.D. Lambert, J. Blainsjaar, J.J. Kok, and R.J.J van Heijningen. Optimising product recycling chains by control theory. *International Journal of Production Economics*, 66:185–195, 2000.

Panos Kouvelis and Gang Yu. *Robust Discrete Optimization and Its Applications*. Kluwer, Boston, 1997.

Susan Kramer. Personal communication, August, 2010. Senior Account Manager, Sims Recycling Solutions, West Chicago, IL.

H.R. Krikke, A. van Harten, and P.C. Schuur. Business case Océ: Reverse logistic network re-design for copiers. *OR Spektrum*, 21:381–409, 1999a.

H.R. Krikke, A. van Harten, and P.C. Schuur. Business case Roteb: recovery strategies for monitors. *Computers and Industrial Engineering*, 36:739–757, 1999b.

Leo Kroon and Gaby Vrijens. Returnable containers: an example of reverse logistics. *International Journal of Physical Distribution & Logistics Management*, 25(2):56–68, 1995.

Dennis W. Krumwiede and Chwen Sheu. A model for reverse logistics entry by third-party providers. *Omega*, 30:325–333, 2002.

Z. Laslo, G. Gurevich, and B. Keren. Economic distribution of budget among producers for fulfilling orders under delivery chance constraints. *International Journal of Production Economics*, 122(2):656–662, 2009.

Lei Li and Zelda B. Zabinsky. Incorporating uncertainty into a supplier selection problem. *International Journal of Production Economics*, doi:10.1016/j.ijpe.2009.11.007, 2009.

Jason Linnell. Personal communication, August, 2010. Executive Director, National Center for Electronics Recycling (NCER) , http://www.electronicsrecycling.org/public/.

Jonathan Linton and David A. Johnston. A decision support system for planning remanufacturing at Nortel Networks. *Interfaces*, 30(6):17–31, 1999.

Ovidiu Listeş and Rommert. Dekker. A stochastic approach to a case study for product recovery network design. *European Journal of Operational Research*, 160:268–287, 2005.

Kip Louwers, Dirk, Bert J., Edo Peter, Frans Souren, and Simme Douwe P. Flapper. A facility location allocation model for reusing carpet materials. *Computers and Industrial Engineering*, 367:855–869, 1999.

Irena Maslennikova and David Foley. Xerox's approach to sustainability. *Interfaces*, 30(3): 226–233, 2000.

János Mayer. *Stochastic linear programming algorithms: a comparison based on model management system*. Gordon and Breach, London, 1997.

William McDonough and Michael Braungart. *Cradle to Cradle: Remaking the Way We Make Things*. North Point Press, New York, 2002.

Dennis McGavis. The energy bucket and a not-so-drop-in-the-bucket portion of the waste stream, consumables. In *Proceedings, IEEE International Symposium on Electronics and the Environment*, pages 2267-2272, San Francisco, CA, USA, May 2-4, 1994.

Kirstie McIntyre. Delivering sustainability through supply chain management. In D. Waters, editor, *Global Logistics: New Directions in Supply Chain Management*. Kogan Page Limited, London, 2007.

Laura Meade, Joseph Sarkis, and Adrien Presley. The theory and practice of reverse logistics. *International Journal of Logistics Systems and Management*, 3(1):56–84, 2007.

Harvey Meyer. Many happy returns. *Journal of Business Strategy*, 20(4):27–31, 1999.

Oksana Mont, Carl Dalhammar, and Nicholas Jacobsson. A new business model for baby prams based on leasing and product remanufacturing. *Journal of Cleaner Production*, 14: 1509–1518, 2006.

Carsten Nagel and Peter Meyer. Caught between ecology and economy: end-of-life aspects of environmentally conscious manufacturing. *Computers and Industrial Engineering*, 36: 781–792, 1999.

Jeremy O'Brien. Personal communication, August, 2010. Director of Applied Research, Solid Waste Association of North America (SWANA), http://www.swana.org/.

G.M. Ostrovsky, N.N. Ziyatdinov, and T.V. Lapteva. One-stage optimization problem with chance constraints. *Chemical Engineering Science*, 65(7):2373–2381, 2010.

András Prékopa. *Stochastic Programming*. Kluwer Academic Publishers, Dordrecht, 1995.

Matthew J. Realff, Jane C. Ammons, and David Newton. Strategic design of reverse production systems. *Computers and Chemical Engineering*, 24:991–996, 2000.

Matthew J. Realff, Jane C. Ammons, and David Newton. Robust reverse production system design for carpet recycling. *IIE Transactions*, 36:767–776, 2004.

Sergio Rubio, Antonio Chamorro, and Francisco J. Miranda. Characteristics of the research on reverse logistics (1995-2005). *International Journal of Production Research*, 46:1099–1120, 2008.

Nils Rudi, David F. Pyke, and Per Olav Sporsheim. Product recovery at the Norwegian National Insurance Administration. *Interfaces*, 30:166–179, 2000.

Thomas L. Saaty. *Decision Making for Leaders: The Analytical Hierarchy Process for Decisions in a Complex World*. Lifetime Learning Publications, Belmont, CA, 1982.

Thomas L. Saaty. The Seven Pillars of the Analytic Hierarchy Process. In Murat Köksalan and Stanley Zionts, editors, *Multiple criteria decision making in the new millennium*. Springer, Berlin, 2001.

Kristin Sahyouni, R. Canan Savaskan, and Mark S. Daskin. A Facility Location Model for Bidirectional Flows. *Transportation Science*, 41(4):484–499, 2007.

Maria Isabel Gomes Salema, Ana Paula Barbosa-Pavoa, and Augusto Q. Novais. An optimization model for the design of a capacitated multi-product reverse logistics network with uncertainty. *European Journal of Operational Research*, 179:1063–1077, 2007.

Margarete A. Seitz and Ken Peattie. Meeting the closed-loop challenge: The case of remanufacturing. *California Management Review*, 46(2):74–89, 2004.

Th. Spengler, H. Püchert, T. Penkuhn, and O. Renz. Environmental integrated production and recycling management. *European Journal of Operational Research*, 97:308–326, 1997.

Tom Spille. Personal communication, August, 2010. Solid Waste Manager, City of Bellevue, WA.

Walter R. Stahel. From products to services: Selling performance instead of goods. The IPTS Report, No. 27, Institute for Prospective Technological Studies, JRC/EU, Seville. ISSN 1025-9384, Sep 1998.

T. Staikos and S. Rahimifard. A decision-making model for waste management in the footwear industry. *International Journal of Production Research*, 45(18-19):4403–4422, 2007.

Albert Tan and Arun Kumar. A decision making model to maximise the value of reverse logistics in the computer industry. *International Journal of Logistics Systems and Management*, 4(3):297–312, 2008.

Martijn Thierry, Marc Salomon, Jo Van Nunen, and Luk Van Wassenhove. Strategic issues in product recovery management. *California Management Review*, 37(2):114–135, 1995.

Merrle Thomas Jr. Emerging technology: Production scheduling matures. *IIE Solutions*, January:25–29, 1997.

L. Beril Toktay, Lawrence M. Wein, and Stefanos A. Zenios. Inventory management of remanufacturable products. *Management Science*, 46(11):1412–1426, 2000.

John Trotti. Personal communication, August, 2010. Editor, MSW Management Magazine: The Journal for Municipal Solid Waste Professionals, http://www.mswmanagement.com/.

Henry Vander Pol. Personal communication, August, 2010. Freight Specialist, Oak Harbor Freight Lines, Inc., Auburn, WA.

Stein W. Wallace. Decision making under uncertainty: is sensitivity analysis of any use? *Operations Research*, 48(1):20–25, 2000.

Chin-Huang Wang, John C. Even Jr., and Adams S. Keith. A mixed-integer linear model for optimal processign and transport of secondary materials. *Resources, Conservation and Recycling*, 15:65–78, 1995.

Washington Materials Management and Financing Authority (WMMFA). Annual Report of the E-Cycle Washington Program. http://www.ecy.wa.gov/programs/swfa/eproductrecycle/, accessed 08/09/10, 2009.

George L. Yender. Battery recycling technology and collection processes. In *Proceedings of the IEEE International Symposium on Electronics and the Environment*, pages 30-35, Oak Brook, Il, USA, May 4-6, 1998.

Appendix A
UNIFORM AND TRIANGULAR DISTRIBUTIONS

For completeness, the definitions of the uniform and triangular distributions for the CCP model in Chapter 4 follow. Listed are the probability density function $f(x)$, the cumulative probability distribution function $F(x)$, expected value $E(X)$ and variance $V(X)$ (Johnson and Kotz, 1970; Evans et al., 2000). The inverse cumulative distribution function $F^{-1}(\varepsilon)$ is also given for reference.

A.1 Uniform distribution

The uniform distribution on $[a, b]$ has the following probability density function :

$$f(x)_{uniform} = \frac{1}{b-a}, \quad a \leq x \leq b,$$

and the following cumulative distribution function:

$$F(x)_{uniform} = \frac{x-a}{b-a}, \quad a \leq x \leq b,$$

with expected value and variance

$$E(X)_{uniform} = \frac{a+b}{2} \text{ and } V(X)_{uniform} = \frac{(b-a+1)^2-1}{12}.$$

The inverse cumulative distribution function $F^{-1}(\varepsilon)$ for probability ε, $0 \leq \varepsilon \leq 1$ is:

$$F^{-1}(\varepsilon)_{uniform} = (b-a) \cdot \varepsilon + a.$$

A.2 Triangular distribution

The triangular distribution on $[a, b]$ with mode h has the following probability density function:

$$f(x)_{triangular} = \begin{cases} \frac{2(x-a)}{(b-a)(h-a)} & a \leq x \leq h \\ \\ \frac{2(b-x)}{(b-a)(b-h)} & h \leq x \leq b, \end{cases}$$

and the following cumulative distribution function:

$$F(x)_{triangular} = \begin{cases} \frac{(x-a)^2}{(b-a)(h-a)} & a \leq x \leq h \\ \\ 1 - \frac{(b-x)^2}{(b-a)(b-h)} & h \leq x \leq b, \end{cases}$$

with expected value and variance

$$E(X)_{triangular} = \frac{a+b+h}{3} \text{ and } V(X)_{triangular} = \frac{a^2+b^2+h^2-ab-ah-bh}{18}.$$

The inverse cumulative distribution function $F^{-1}(\varepsilon)$ for probability ε, $0 \leq \varepsilon \leq 1$ is:

$$F^{-1}(\varepsilon)_{triangular} = \begin{cases} a + \sqrt{\varepsilon(b-a)(h-a)} & \text{if } 0 \leq \varepsilon \leq \dfrac{h-a}{b-a} \\ \\ b - \sqrt{(1-\varepsilon)(b-a)(b-h)} & \text{if } \dfrac{h-a}{b-a} \leq \varepsilon \leq 1. \end{cases}$$

Appendix B

A RELEVANT POLITICAL CARTOON

Political cartoon appearing in the *Seattle Post-Intelligencer*, Tuesday, November 27, 2007.

(Credit: Jim Borgman and Universal Press Syndicate, used by permission.)