ABSTRACT

SAS, IURII. Logistics of Closed-Loop Textile Recycling. (Under the direction of Jeffrey A. Joines and Kristin A. Barletta).

Post-consumer carpet accounts for more than a quarter of all textiles discarded at municipal solid waste centers. Therefore, recycling of post-consumer carpet may reduce pressure on landfills as well as direct secondary materials back into production. To make recycled materials competitive with virgin materials, the cost of recycled materials needs to be as low as possible. Due to the high bulkiness of carpet, the transportation cost of post-consumer carpet is high which makes carpet reverse logistics a significant portion of the total cost of recycled materials.

This research focuses on two aspects of the carpet reverse logistics problem in the US, the location of collection centers as well as the design of the recycling network. To be economically feasible, acquisition of old carpet has to rely on the willingness of consumers and flooring installers to bring old carpet to collection centers. A well-designed collection network is required, with these centers located in close proximity to highly populated areas. Such a network can provide sufficient volumes of carpet to take advantage of economies of scale at large recycling plants while requiring the minimum number of centers. The collection network problem is formulated as a set covering optimization model with partial coverage. In order to solve difficult instances of this NP-hard problem, a novel greedy randomized heuristic is created by combining and extending greedy approaches for similar problems available in the literature. The design of the heuristic allows it to work efficiently with large unicost covering problems that have sparse coverage matrices. Computational results show that the heuristic performs better than other greedy heuristics proposed in the literature for similar types of problems. By applying the heuristic, a set of nationwide collection networks utilizing different target collection rates has been designed. Two different cases are considered: one extends the current collection network and another builds a new collection network. The relationship between the target collection rate and the required number of collection centers is identified. Using the relationship, an appropriate target

collection rate can be established by considering the effort and investment required to build the corresponding collection network.

In the second part of the research, the design of the recycling network for Nylon 6 carpet is determined. Location of reverse processing facilities in the recycling network, as well as identification of which reverse activities should be performed at each layer of the network can significantly reduce the logistics costs. Three alternative network designs for nationwide carpet recycling systems are developed and compared. In two scenarios, the networks include layers of local collection centers, recycling plants, and markets for recycled materials. In the third scenario, a layer of regional collection centers is inserted before the recycling plants to aggregate carpet for more efficient sorting and transportation. To find the optimal number and locations of the recycling plants (and regional collection centers) and the optimal flows among network facilities, a hierarchical facility location model is formulated. To solve large instances of the problem, a heuristic method based on the alternative location-allocation procedure is developed and a computational study is conducted to assess its performance. Three alternative configurations of a Nylon 6 carpet recycling network in the US are designed, and the scenario that includes the intermediate layer of regional collection centers reduces the total cost of the network significantly. In addition, the cost of recycled Nylon 6 is determined to be very sensitive to the utilization of the recycling plants, and in order to minimize cost, the recycling network should receive a sufficient volume of carpet to operate the recycling plants at full capacity.

Logistics of Closed-Loop Textile Recycling

by
Iurii Sas

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APPROVED BY:

Jeffrey A. Joines Committee Chair	Kristin A. Barletta Committee Co-Chair
Russell E. King	Donald P. Warsing

DEDICATION

To my parents.

BIOGRAPHY

Iurii Sas was born in the Ivano-Frankivsk region, Ukraine in 1982. His parents are Ivan and Oksana, and he has a younger brother Andriy. Iurii graduated from the Ukrainian Lyceum of Physics and Mathematics in 1999 and obtained undergraduate and master's degrees in Quantitative Economics and Econometrics at Taras Shevchenko National University of Kyiv, Ukraine. After graduation, Iurii worked for three years in financial and management positions. In 2009, he returned to academia to pursue a degree in Textile Technology Management at North Carolina State University under the supervision of Dr. Jeffrey Joines and Dr. Kristin Barletta.

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CHAPTER 1: Introduction

In 2010, six billion pounds of post-consumer carpet (PCC) were discarded in the US. Being a bulky product usually composed of synthetic materials, carpet occupies a significant volume of landfill space. In addition, valuable materials that can be recovered from carpet are lost when PCC is landfilled. Despite these issues, only 5.6% of carpet discarded in the US in 2010 was recovered. Such a low diversion rate may be attributed to the low economic attractiveness of carpet recycling.

There are two main options for carpet recycling. Carpet or components recovered from carpet can be used in molded products, where the quality of the resin in not very important. However, the demand for such products is very limited and cannot accommodate the high volumes of PCC disposed each year. Alternatively, polymers with virgin-like quality can be recycled from carpet components using depolymerization. Due to the high value of nylon and the availability of depolymerization technology, this process is used to recycle nylon fibers from carpet. The recycling of Nylon 6 from PCC back to virgin-like materials is the most preferable option since it recovers materials in the most valuable form and enables their reuse for a long time in a closed-loop manner. However, to make recycled materials competitive with virgin materials, the cost of recycled materials should be kept as low as possible. At the recycling plant level, processing costs can be minimized by building large plants that take advantage of economies of scale. However, such plants require a collection network that can supply sufficient volumes of post-consumer carpet to process. In addition, strategic location of facilities in the reverse supply chain significantly reduces the cost of transporting carpet to recycling plants and recycled materials to end-users.

This research studies two logistics problems related to carpet recycling. The first part of the research is focused on the design of carpet collection networks that can provide a specific volume of post-consumer carpet with minimum investment in collection infrastructure. For this purpose, a collection network design problem is formulated that determines the locations of carpet collection centers to achieve target collection rates with the minimum number of centers opened. To solve real-scale instances of the problem, a novel randomized greedy heuristic is developed. The heuristic is specifically designed for problems with a large number of points to cover and potential locations for facilities, with sparse coverage matrices. For such problems, the new heuristic performs better than greedy heuristics in the literature. An estimate of the input parameters required to design a carpet collection network in the US is provided, and the heuristic is used to design nationwide carpet collection networks for different levels of population coverage.

The second part of the research considers the design of a network to recycle Nylon 6 from post-consumer carpet. The best layout in terms of types of facilities used and reverse activities performed at each layer of the network, as well as the optimal locations of these facilities and flows between them, are identified for different levels of post-consumer carpet collected. Three alternative network designs for nationwide carpet recycling systems are developed and compared in terms of network costs. In two scenarios, these networks include layers of local collection centers, recycling plants, and markets for recycled materials. In the third scenario, a layer of regional collection centers is added before the recycling plants to aggregate carpet for more efficient sorting and transportation. To find the optimal number and locations of recycling plants (and regional collection centers) and the optimal flows among network facilities, a hierarchical facility location model is formulated that can be used for the different network configurations considered. To solve large-scale instances of the problem, a heuristic method based on the alternative location-allocation procedure is developed, and a computational study is conducted to assess its performance. The heuristic is used to design and compare recycling networks for three scenarios, each with 13 sets of local collection centers that represent collection networks with different target collection rates.

This dissertation is structured as follows. Chapter 2 is the literature review. It includes main concepts of reverse logistics, a review of papers related to facility location problems in the reverse supply chain, and an overview of the current state of carpet recycling in the US. The carpet collection network and the Nylon 6 carpet recycling network are studied in Chapters 3 and 4, respectively. Chapter 5 provides conclusions and directions for future work.

CHAPTER 2: Literature Review

This chapter provides background to the research. In Section 2.1, the main concepts of reverse logistics are discussed. Supply chain network optimization problems and their application to reverse logistics are reviewed in Section 2.2. Finally, the current state of carpet recycling in the US is discussed in Section 2.3.

2.1 Reverse Logistics

Management of products that flow in the opposite direction to the traditional manufacturer-distributor-customer chain is becoming increasingly important in today's economic environment. While collection and reuse of some post-consumer products and materials, like scrap metal, paper and bottles, is not a new concept, these activities have been motivated by the pure economic benefits for the collectors (Fleischmann *et al.*, 1997). Other, less attractive, streams of post-consumer products have been largely ignored by both manufacturers and third party firms and have been landfilled or incinerated (Ferguson *et al.*, 2001).

This situation has begun to change in recent years due to growing environmental issues created by disposed products. Scarcity of landfills, harmful emissions and depletion of nonrenewable resources make both governments and consumers more concerned about proper treatment of products at the end of their life (Thierry *et al.*, 1995; Georgiadis *et al.*, 2004). Manufacturers are under increasing pressure to collect and reuse their old products coming from customers to minimize emissions and recover the residual value of the waste (Krikke, 1998). In addition, extended return policies for new products, warranties, and online sales that have a significantly higher return rate compared to conventional brick and mortar sales are other reasons why companies have to consider reverse flows of products.

The main concerns of reverse logistics are efficient collection, transportation, recovery, proper disposal, and re-distribution of products coming from consumers to maximize economic and environmental value at minimum cost (Krikke, 1998). Reverse logistics is an important component of modern supply chains (Brito *et al.*, 2004) and can be defined as "*the* *process of planning, implementing and controlling flows of raw materials, in process inventory, and finished goods, from a manufacturing, distribution or use point, to a point of recovery or point of proper disposal*" (Brito, 2004).

The combination of several aspects of reverse logistics determines the type of reverse system and consequently the issues that may arise in managing such a system. Four main characteristics of reverse logistics systems are discussed further, including motivation, activities, type of recovered items and entities involved (Fleischmann, 1997). Combinations of different aspects define several typical reverse systems.

2.1.1 Reasons for Product Returns and Motivations for Company Involvement

The question of motivation covers two distinctive characteristics: why products are returned at all and why companies are willing to accept and manage these products. Starting with the former, the reasons for product returns may be classified in three groups that correspond to different stages of the forward supply chain, namely manufacturing returns, distribution returns and customer returns (Brito, 2004; Kumar *et al.*, 2006). Surplus of raw materials, rework of products due to low quality, and production leftovers are typical reasons for manufacturing returns. At the distribution stage, returns to a manufacturer may occur due to product recalls, products being unsold at the end of the season, outdated products, wrong or damaged deliveries, stock adjustment, and functional returns (e.g. packaging). Customers may return products back to manufacturers due to customers' dissatisfaction, the mismatching of products to customers' needs, warranty service, and product end of use or end of life.

Economics and legislation are two main reasons that motivate companies to accept product returns. Recovery of valuable parts or materials from used products and avoidance of disposal costs are direct economic gains that companies can obtain from reverse logistics (Brito, 2004). In-house remanufacturing or recycling of post-consumer products may be used to protect technologies from competitors. Taking responsibility for end-of-life products can improve company/product "green" image and preempt environmental regulation.

In addition to economic benefits, companies have to manage return flows to comply with legislation. Environmental regulation, especially in Europe, makes manufacturers responsible for their products that customers do not need anymore and want to dispose. In the US, this regulation is less strict and tends to encourage recovery instead of mandating it (Guide *et al.*, 2001). De Brito & Dekker (2003) identified corporate citizenship as an additional force driving companies to implement reverse logistics.

2.1.2 Activities Comprising the Reverse Supply Chain

In terms of activities involved, four main steps can be identified in reverse logistics: acquisition and collection of post-consumer products, inspection and grading, value recovery processing, and redistribution (Fleischmann, 2001). These activities connect consumers that want to get rid of their old unneeded goods (also called disposal markets) with re-use markets where collected goods, recovered parts, or materials are used again (Krikke, 1998).

Collection is the only true “reverse” activity (Fleischmann, 2001), because only at this step do products flow from consumers to firms (manufacturers or recyclers). This step involves transportation of small quantities or small numbers of disposed items from many customers to their points of reuse. This results in collection costs that compose a significant part of the total costs of a reverse supply chain, especially in the case of bulky, low-value products (Fleischmann, 2001). Depending on the type of product or material of interest, a collection scheme may utilize a waste management system (e.g. curbside recycling) or drop-off centers where customers bring their discarded products (Srivastava *et al.*, 2006).

Curbside pickup is a relatively expensive scheme because it requires trucks to travel significant distances without being completely loaded. Therefore, this scheme is typically used to collect products made of homogeneous materials that can be easily recycled at low costs (e.g., plastic containers, paper, glass bottles, and aluminum cans). In addition, products that should be kept dry to qualify for recycling can either not utilize this method or require additional expenses to provide households with packaging materials.

Establishing drop-off collection centers allows shifting some of the collection costs to the customers. However, some kind of motivation for the customers must exist, and it should be convenient for customers to carry their recyclables to the points of collection. Customers may be motivated to use drop-off collection points due to environmental consciousness, a ban on disposing the waste at local dumpsters, financial benefits, deposit systems, etc. (Guide, 2001).

Another way to decrease the collection cost is to combine collection with other types of activities (e.g. with distribution of new products, like new for old programs) or to utilize mail delivery services especially for small, high-value items (Fleischmann, 2001). It is also important to take into account that if the recycling process requires high volumes of input to realize significant economies of scale, collection costs may be kept slightly higher (e.g. more collection centers or more frequent pick-up) in favor of better coverage, higher collected volumes and/or more stable flow of recyclables (Fleischmann, 2001).

After collection, products should be graded by wear condition, quality, and type to identify the most value-added recovery option or the most environmentally friendly way of disposal. Early sorting is preferable to avoid unnecessary transportation of unrecyclable products and to direct recyclables to the appropriate recycling facility. Therefore, if this activity is inexpensive and fast, it may coincide with the collection. However, if sorting requires specific expensive equipment or highly skilled labor, centralized sorting facilities may be more economical (Fleischmann, 2001). Consequently, the number and exact locations of sorting facilities in the reverse supply chain depend on the product, and there is a trade-off between transportation costs and the annual operation cost of sorting facilities.

Legislation may impose additional constraints on the location of sorting operations. For example, many states in the US do not accept waste from other states. So waste should be separated from recyclable products within a state, which reduces the possibility of centralization (Fleischmann, 2001). Additional preprocessing operations, like baling or shredding, may be used after grading to compact the materials and reduce transportation costs.

There are many recovery options that may be utilized in the reverse supply chain depending on the type and quality of end-of-life products. Returned products that are new or as good as new can be directly resold to the same market or second-hand markets, which is called direct recovery (Brito *et al.*, 2005). Value-added recovery includes repair and remanufacturing (Guide, 2001), when products are brought to like new conditions and are sold with some discount. Parts recovery is used when the product cannot be repaired to function properly or is outdated, but some of its modules are still working and can be used during manufacturing of new or remanufacturing of similar post-consumer products. Recycling converts post-consumer products to raw materials that can be used for production of the same product (closed-loop recycling) or products that require a lower quality of materials (down cycling). Finally, if any of the described options cannot be used, collected products and leftovers from other options are incinerated to recover energy. Direct, value-added, and parts recovery conserve product/part identity and are usually the most profitable and environmentally friendly because they allow avoiding many production steps in the forward supply chain.

Recovery steps usually require the highest investments (Fleischmann, 2001). Remanufacturing or parts retrieval from complex products that consist of many modules may require a multi-step reprocessing network where different repair or disassembling operations are performed at different stages. While a recycling network may involve one or two tiers, recycling equipment is usually expensive and is built to realize economies of scale when processing high volumes of end-of-life products. When the original manufacturers are responsible for recovery, they may integrate some reverse logistics steps into the forward supply chain to reduce costs (Fleischmann, 2001).

Finally, repaired products, recovered parts, or recycled materials are delivered to the consumers in the redistribution step. In many cases, this step resembles a traditional distribution network, especially when original manufacturers are owners of the reverse activities (Fleischmann, 2001). Problems with redistribution may occur when retrieved parts are outdated or quality of recycled materials is lower than virgin materials. In this case, the most profitable markets should be found or new uses for the materials should be created.

2.1.3 Types of Recovered Items and Product Characteristics

As can be seen from reverse logistics activities, characteristics of the product have a great influence on the possible recovery options, and on the design and profitability of the reverse supply chain. De Brito & Dekker (2003) identified the next important characteristics of returned products: composition, level of deterioration and use-pattern. Depending on the product itself and its characteristics, it can be refurbished, disassembled to retrieve components, recycled to recover the initial materials, or incinerated to recover energy.

The number of modules or materials, as well as the way that they are combined together, defines the complexity of the disassembly operations, the recycling technology required, and the quality of the recycled materials. If a product was designed for remanufacturing or recycling, the costs of these operations should be significantly lower. Some products that are made of different types of materials (especially from different plastics) are difficult or impossible to recycle into separate streams of materials, and the resulting composite materials can be used for low value products only, significantly reducing the profitability of recycling. In some cases, the only recovery option for such products is incineration to produce energy (Wang, 2006). Size and weight of the returned product have a significant influence on transportation costs (Brito, 2005).

The deterioration of products determines if parts or materials retrieved from them may be used in new products. Deterioration can occur due to physical aging, or becoming outdated, where product components and materials are not used in new products anymore. In addition, deterioration can be nonhomogeneous, when a product can no longer perform its function due to problems with some components while other components are still functioning properly (Brito, 2004).

Use-pattern defines the location, intensity and the duration of use. Usually products that were bought for individual use are disposed of in small quantities, which increases collection costs, but products used by institutions may be returned in large volumes that are more economical to collect. Intensity and duration of use have a great influence on the deterioration of products (Brito, 2004).

2.1.4 Entities Involved

Type of returns, type of products, economic benefits, and regulatory requirements define the set of entities involved in the reverse logistics systems for different products. Manufacturing and distribution returns have been a common practice for the forward supply chain for a long time. They occur between or even within one of the players of the forward supply chain, like material suppliers, manufacturers, distributors, and retailers (Brito, 2004).

Customer returns of new products or products for warranty service are also well-established processes. These returns can be dropped-off by customers at retail stores or sent using mail services. Manufacturers or distributors may contract third party logistic companies to handle these returns. In terms of reprocessing, new products can be directly resold or can be sent to discount outlets (Tibben-Lembke *et al.*, 2002). Warranty repair can be handled by the manufacturers themself or they may contract specialized companies (Blumberg, 2005).

Compared to new products and warranty service returns, returns of end-of-life products may involve a higher number of different stages in the reverse supply chain. In the case of end-of-life returns, consumers supply used products, which are “raw materials” for the reverse supply chain. Collection can be conducted by municipal and commercial waste companies (e.g. curbside recycling), specialized independent collectors or collectors affiliated with the owner of the recovery process (Srivastava, 2006). Recovered parts and materials can be sold or sent to the end users of secondary materials in the forward supply chain. These end users may be the traditional entities of the original forward supply chain, second-hand consumers, or other manufacturers.

An important consideration is the owner of the collection and recovery processes. Third party collectors and recyclers can create their own recovery network if the resulting parts or materials can be sold yielding a profit. The original manufacturers may create their own collection networks to gain direct and indirect economic benefits or to be forced to do so by legislation introduced by policy makers. Another way for manufacturers to respond to environmental legislation is to create a branch organization that will handle recovery of post-consumer products for an entire industry (Brito, 2004).

2.1.5 Types of Reverse Networks

Before going into a discussion of typical reverse logistics networks, it is important to distinguish closed-loop recovery systems from opened-loop ones. Many authors define a closed-loop supply chain as a system that includes traditional forward supply chain activities and the additional reverse activities (Guide *et al.*, 2003). De Brito *et al.* (2004) argued that some kind of cycling should exist in the system to be defined as closed-loop. Therefore, the collected products should be returned to the original manufacturer or collected products should be recovered to their original functionality.

The type and specific features of a reverse network are defined by a combination of several factors including type of items to recover, motivation, form of recovery, processes and entities involved, and owner of the recovery process (Fleischmann, 2001; Brito, 2004). Based on these criteria, Fleischmann (2001) identified four generic types of reverse logistic networks, namely networks for mandated product take-back, networks owned by original manufacturers for value-added recovery, dedicated remanufacturing networks, and recycling networks for material recovery.

The first type of reverse networks, networks for mandated product take-back, are initiated by the original manufacturers to comply with environmental regulation and to accept responsibility for the entire life cycle of their products (e.g., electronics, packaging, cars in the EU or batteries in the US). Because such networks are motivated by legislation and not by economic benefits, the value recovered from products (usually through recycling) is small, and manufacturers usually try to minimize their costs instead of maximize their profits. The reverse activities are outsourced to specialized recycling companies with drop-off collection. Customers are charged for disposal through collection fees or via prices of new products. Industry-wide cooperation is common. Testing and grading is not important because separation of materials occurs at the recycling stage.

In contrast to the previous type of reverse systems, a value added recovery network managed by the original manufacturer is designed to recapture value from used products (e.g. auto parts) and to generate profit. It is usually built as an extension of the forward supply chain to reduce investments and transportation costs, and improve coordination of recovery activities with production. Testing and grading play an important role in maximizing the value recovered from used products. Testing is centralized to benefit from economies of scale. The network is a complex, multi-level structure, due to the complex set of interrelated processing steps.

Dedicated remanufacturing networks are managed by third-party recyclers because there is an opportunity to make profit. Examples of such networks are auto parts, equipment, or tire recovery. Acquisition of used products and brokerage are the main activities to find the best matching secondary market for collected products. Recyclers have to build the entire network.

The last type of recovery network is a recycling network for material recovery. Such networks are usually organized to comply with or to prevent legislation (e.g. carpet). Both original manufacturers and material suppliers can play a significant role in the recycling. Material recovery recycling networks are characterized by low profit margins and high investments in recycling equipment. Therefore, the recycling activity is centralized at one facility to create high recycling volumes and to reduce processing costs. Sorting is not very important, but preprocessing is used to reduce transportation costs. The network usually consists of a small number of levels.

2.2 Reverse Logistics Network Design

This section provides a general literature review of facility location problems in application to reverse logistics. More specific reviews relevant to collection and recycling network problems are provided in Chapters 3 and 4, respectively. One of the most important tasks of a reverse logistics network is to efficiently convey used product from a "disposer market" to a "reuse market" (Fleischmann et al., 2001). In this way, returned products go through a set of reverse logistics activities including collection, sorting, reprocessing, and redistribution. Analogous to the forward supply chain, the appropriate location of reverse activities and setting up links between them has a significant influence on the economic viability of the reverse network (Fleischmann, 2001).

During network design, the following decisions should be made (Akçali *et al.*, 2009):

- How many facilities are required and where should they be located;
- What is the capacity of each facility and what tasks should each facility perform;
- How should the flows of materials or products between facilities be allocated?

While these decisions resemble the typical ones that arise during the design of the forward supply chain, some specific questions for reverse logistics are:

- How should returned products be collected to maximize collection rate;
- Where should they be graded to avoid transportation of unrecyclable materials and to minimize investments into sorting equipment;
- What recovery options should be used to recover the maximum value;
- How many levels should be included in the network;
- How centralized should the recovery facilities be to realize economies of scale;
- Should the recovery network be an extension of the forward network or not;
- What links between the forward and reverse networks should exist;
- What are the markets for the recovered products/materials;
- How does the uncertainty of the reverse supply influence the network design?

The growing importance of the effective handling and processing of returned flows of products has resulted in an increasing number of publications on network designs for reverse and closed-loop supply chains. In many cases, these problems are similar to those of the forward supply chain and are often expressed as some modification of forward models. However, multiple recovery options for the returned products and the additional reverse activities, together with high uncertainty of returned volumes and the need for integration of the reverse and forward supply chains, significantly increase the complexity of the reverse network design. There are a series of review papers in the literature concerning network design for reverse logistics. De Brito *et al.* (2003) analyzed reverse network studies with respect to product, recovery activities, entities involved, and reasons and drivers of the recovery systems. As a part of a broader review of facility location decisions in supply chain management, Melo *et al.* (2009) discussed network structures, performance measurements, and solution approaches utilized for reverse network optimization. The paper of Akçali *et al.*

(2009) is focused on the modeling and solution approaches used for network design in reverse logistics. The authors considered more than 30 papers, analyzing network structure and attributes, solution approach, computational testing, types of decisions, including location decisions, and cost elements included in the objective function.

Table 2.1 summarizes studies related to network design for reverse logistics. The reverse activity column specifies for what step of the reverse logistics network or for what recovery option the model was designed. If this information was not specified in the corresponding study or the model developed can be applied to any recovery option, the term "recovery" is used. This column also contains information about the type of products or materials considered, if any. This is given in parenthesis under the activity. The next column "Layers & Location Decisions" specifies the structure of the network. Layers given in regular font were considered to be fixed and facilities in layers given in <u>*underlined italic*</u> font were located to optimize the objective function. If the list of layers for a study starts and ends with a layer of the same name, this means that the network considered was closed-loop. The next column, "Attributes", specifies some characteristics of the model, which include:

- **Fixed Charge** vs. P-median
- **Discrete** vs. Continuous
- **Uncapacitated** vs. Capacitated
- **Single-period** vs. Multi-period
- **Deterministic** vs. Stochastic
- **Single-commodity** vs. Multi-commodity
- **Linear** vs. Nonlinear
- **Single-objective** vs. Multi-objective

The values in the list above given in bold font are the default values and only deviations from these default values are specified in the table.

Table 2.1: Studies of network design for reverse logistics

Reference	Reverse Activity (Case)	Layers & *Location Decisions*	Attributes	Solution approach
(Kroon, 1995)	Redistribution (Returnable containers)	Distribution Center *Container Depot* Distribution Center		Not specified
(Wang C.H., 1995)	Recycling (Paper)	Used paper suppliers *Processing Stations* Markets	Capacitated	MILP-solver Branch & Bound
(Spengler, 1997)	Recycling (Demolition wastes Industrial wastes)	Waste Generators *Reverse Facilities* Markets	Capacitated Multi-commodity	Benders decomposition
(Barros, 1998)	Recycling (Sand)	Demolition projects *Regional Depots* *Treatment Facilities* Construction projects	Capacitated Multi-commodity	Linear relaxation, Branch & Bounds
(Marin, 1998)	Remanufacturing	Consumers *Plants* Consumers		Lagrangian relaxation
(Jayaraman, 1999)	Remanufacturing	Collection Zones *Recovery Facilities* Demand Zones	Capacitated Multi-commodity	MILP-solver
(Louwers, 1999)	Recycling (Carpet)	Sources of used carpet *Regional preprocessing sites* Secondary consumers	Continuous Capacitated Multi-commodity Nonlinear	Nonlinear solver (E04UCF)
(Realff, 1999)	Recycling (Carpet)	Collection Sites *Sorting Sites* *Processing Sites*	Capacitated Multi-commodity	MILP-solver
(Chang, 2000)	Collection (Recyclable wastes)	Consumers *Drop-off Stations*	P-median/Max coverage Capacitated Nonlinear Multi-objective	Genetic algorithm
(Realff, 2000)	Recycling (Carpet)	Collection Sites *Processing Sites* Markets	Capacitated Multi-period Multi-commodity	MILP-solver
(Fleischmann, 2001)	Remanufacturing Recycling (Copiers, Paper)	Consumers *Disassembly Centers* *Plants* *Warehouses* Customers		MILP-solver
(Jayaraman, 2003)	Recovery (Returned products)	Origination Sites *Collection Sites* *Recovery Sites*	Capacitated	Heuristic concentration, MILP-solver
(Realff, 2004)	Recycling (Carpet)	Collection Sites *Processing Sites* Markets	Capacitated Multi-period Stochastic Multi-commodity	MILP-solver

Table 2.1 (continued)

Reference	Reverse Activity (Case)	Layers & *Location Decisions*	Attributes	Solution approach
(Sim, 2004)	Recovery	Consumers *Disassembly Centers* *Plants* *Warehouses* Customers	Capacitated Multi-commodity Multi-period	LP-based Genetic algorithm
(Listes, 2005)	Recovery	Markets *Collection Centers* *Manufacturers* Markets	Capacitated Stochastic	Integer L-shaped decomposition
(Min & Jeungko, 2006)	Collection	Customers *Initial Collection Centers* *Centralized Return Centers*	Nonlinear	Genetic algorithm
(Min & Ko, 2006)	Collection	Customers *Initial Collection Centers* Centralized Return Center	Nonlinear Multi-period	Genetic algorithm
(Salema, 2006)	Remanufacturing (Copiers)	Customers *Disassembly Centers* *Factories* *Warehouses* Customers	Capacitated Multi-commodity	MILP-solver
(Ko, 2007)	Recovery	Consumers *Collection Centers* Manufacturers *Warehouses* Consumers	Capacitated Multi-period Multi-commodity	Genetic algorithm
(Lieckens, 2007)	Recovery	Disposer Markets *Recovery Facilities* Reuse Markets	Capacitated Nonlinear Stochastic	Genetic algorithm
(Listes, 2007)	Recycling (Sand)	Demolition projects *Regional Depots* *Treatment Facilities* Construction projects	Capacitated Stochastic Multi-commodity	MILP-solver L-shaped decomposition
(Lu, 2007)	Remanufacturing	Customers *Collection Centers* *Remanufacturing Centers* *Producers* Customers		Lagrangian relaxation
(Salema, 2007)	Remanufacturing	Customers *Disassembly Centers* *Factories* *Warehouses* Customers	Capacitated Stochastic Multi-commodity	MILP-solver Branch & Bound

Table 2.1 (continued)

Reference	Reverse Activity (Case)	Layers & *<u>Location Decisions</u>*	Attributes	Solution approach
(Üster, 2007)	Remanufacturing (Auto parts)	Retailers *<u>Collection Centers</u>* *<u>Remanufacturing Facilities</u>* Distribution Centers Retailers	Multi-commodity	MILP-solver Benders decomposition
(Wang I.L., 2007)	Recycling (E-waste)	Collection Centers *<u>Storage Sites</u>* *<u>Recycling Plants</u>* Demand Sites	Capacitated Multi-commodity	Heuristic concentration, MILP-solver
(Aras, 2008)	Collection	Consumers *<u>Collection Centers</u>*	P-Median Multi-commodity Nonlinear	Tabu search
(Kumar, 2008)	Recycling (Paper)	*<u>Collectors</u>* *<u>Dealers</u>* *<u>Sorters</u>* *<u>Recyclers</u>* Manufactures	Multi-commodity Multi-objective	MILP-solver
(Lee, 2008)	Recovery (Computers)	Customers *<u>Warehouses</u>* Manufacturers *<u>Warehouses</u>* Customers	Capacitated Multi-commodity	Tabu search
(Cruz-Rivera, 2009)	Collection (Vehicles)	Consumers *<u>Collection Centers</u>*	Multi-period	Lagrangian relaxation
(Woolard, 2009)	Recycling (Carpet)	Collection Centers *<u>Recycling Centers</u>*	Nonlinear	Constructive ADD, Alternative Location Allocation
(Kara, 2010)	Recycling (Paper)	Customers *<u>Collection Centers</u>* *<u>Recycling Centers</u>* Secondary Customers	Capacitated Stochastic	MILP-solver

The table above shows that while there are several papers that consider the collection phase only, the majority of studies are designed to optimize the entire recovery process. The field of application of these models varies from demolition waste to electronic products. The structure of the discussed models varies from simple, open-loop, two-layer models with one optimization layer to complex, closed-loop systems that include four or more interrelated layers, most of which have to be optimally located. In addition to location decisions, all papers also define the allocation of lower level nodes (customers or facilities) to higher level nodes and volumes of product that have to be directed through each path. It is also common for many studies to define a set of reverse logistics tasks that have to be carried out at each facility and to select the best transportation options between facilities.

All models given in the table are discrete location models with one exception (Louwers, 1999), where preprocessing facilities were allowed to be located anywhere within the studied region. In terms of the combination of model attributes, the studies vary from deterministic, uncapacitated, single-period, single-product, linear models with one objective to capacitated, multi-product, multi-period, nonlinear models with stochastic parameters and multiple objectives. The models with relatively small numbers of decision parameters and constraints were optimally solved with standard linear or nonlinear solvers with the possible utilization of branch and bound or decomposition procedures. For larger problem, solutions were obtained using Lagrangian relaxation, heuristic concentration, heuristic expansion, tabu search, genetic algorithms, or combinations of these heuristics.

2.3 Current State of Carpet Recycling in the US

This section briefly discusses the most important economic and technical aspects related to carpet recycling. Section 2.3.1 discusses the technical aspects of carpet recycling as well as potential markets for recycled materials. The reverse activities required for carpet recycling as well as some organizational and regulatory issues are discussed in Section 2.3.2.

2.3.1 Recovery Options for Post-Consumer Carpet

The biggest problem with carpet recycling is its complex structure. Because it has been designed to be used for a long period of time, carpet consists of several layers made of different materials that are tightly bonded together. Some manufacturers are redesigning their carpet to be more recyclable. However, due to the long life-time of carpet, benefits from these efforts will not be seen until ten or more years from the introduction of such carpet to the market.

The majority of carpet sold in the US is broadloom tufted carpet, which consist of face fibers, primary backing, bonding agents and secondary backing (Wang *et al.*, 2003) (see Figure 2.1). The face fibers, which can be made of nylon (N6 or N66), polyester (PET), polypropylene (PP), acrylic fiber, wool, or a mix of polymers, are tufted to the primary backing and secured by latex adhesive by applying it under the primary backing. Finally, the secondary backing is bonded to the primary backing (Mihut *et al.*, 2001). Both primary and secondary backings usually are made from the same polymer (e.g. PP). The most common adhesive is styrene butadiene latex rubber (SBR) filled with calcium carbonate ($CaCO_3$). According to a recent estimate made by the Carpet America Recovery Effort (CARE), the content of face fibers in carpet is 35-40% for residential carpet and 25-30% for commercial carpet (CARE, 2011a). On average, the filler, backing, and adhesive represent 35%, 10%, and 9% of the total weight, correspondingly (Wang, 2006).

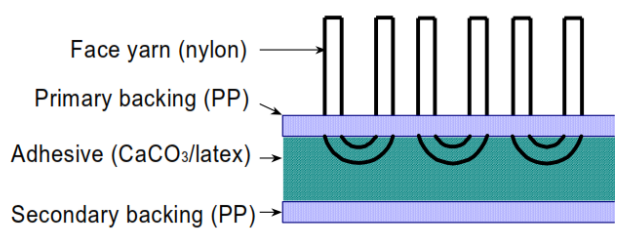

Figure 2.1: Typical carpet construction
Reprinted from Wang, Y. (2006)

Since carpet's composition differs depending on the type of face fiber and carpet end-use, different technologies are required to recover useful materials from post-consumer carpet. In addition, the complex structure of carpet does not permit the recovery of all materials in pure form. Therefore, these materials cannot be used in carpet production again, but have to be marketed for different applications, where the quality of the material is less important.

The recovery options that may help to reduce the volume of carpet going to landfills include reusing it, refurbishing it, recycling it into other products with lower value, and recycling it in a closed-loop manner. Some post-consumer carpets are good enough to be reused again after trimming and cleaning them. Such carpets can be donated to charitable organizations that can resell them at reduced prices or redistribute them for free to low income households.

Another approach is refurbishing or reconditioning of carpet. Some companies accept their old carpet from consumers, clean the carpet, recolor it, and then sell it in secondary markets at reduced prices (Mihut, 2001). Companies that recondition carpet include Milliken and Interface Inc. Both take back their commercial carpet tiles for refurbishing (Colyer, 2005).

While reuse and refurbishing are probably the most economical ways to reduce the volume of landfilled carpet, they are limited in their applications because most carpet is not good enough for reuse, and only a small portion of it can be refurbished. In addition, these options solve the problem only temporarily, just postponing the time when the carpet will be disposed of.

Methods to recycle carpet can be categorized into four groups: depolymerization, material extraction, melt-blending, and energy recovery. Depolymerization is a process to breakdown the used polymer into monomers via chemical reactions. These monomers are then polymerized again to produce the same polymer with virgin-like quality. Due to the high value of nylon, this process is used to recycle nylon fibers from carpet. A detailed discussion of the depolymerization processes for nylon can be found in Mihut (2001) and Wang (2003). While both Nylon 6 and Nylon 6,6 can be broken down to monomeric units, depolymerization of the latter one is more complicated, and as of 2006, was not implemented at commercial scale according to Wang (2006). The recycling of Nylon 6 is run at full scale at the Evergreen Nylon Recycling facility in Augusta, GA, which is currently owned by Shaw Industries Inc. The quality of recycled nylon is high, and it is used in a blend with virgin nylon to produce face fibers for new carpet, forming a closed-loop carpet recycling chain. The plant can recycle 100 million pounds of Nylon 6 carpet into 30 million pounds of caprolactam (monomer for N6) (Delozier, 2006).

Another way to recycle carpet is through extracting separate materials by mechanical methods. In this process carpet is grounded and then the components are separated based on density using air or liquids (Wang, 2006). Alternatively, face fibers can be sheared or shaved from carpet. Fibers are cleaned, and then they are sent to customers as is or pelletized with the possible addition of some filler. While this process can be used on any type of face fiber, the purity of the resulting material is lower. It cannot be used in carpet production again but instead has to be directed to other applications, including different molded products (e.g. automotive parts, drainage systems) or carpet cushions (Colyer, 2005; CARE, 2011b).

The entire carpet can also be shredded without component separation, and the resulting fiber mixture can be used for concrete and soil reinforcement. Molded products (e.g. railroad crossties, fiber blocks), where quality of the resin in not very important, can be produced from composite resin obtained by melting all carpet components together. Some compatibilizer or reinforcing components (like glass fibers) can be added to improve the properties of such melts. In the case of Collins & Aikman, this approach is used in closed-loop production, where their used nylon carpet with PVC backing is melted without separation and is used to produce a new backing called ER3 (Environmentally Redesign, Reused, Recycled) (Fishbein, 2000). When all options described previously cannot be used due to economic reasons, the carpet or residuals from carpet recycling are usually burned with energy recovery.

Examples of some products made of materials recovered from post-consumer carpet can be found on CARE's web site (CARE, 2011b). These include carpet cushions, erosion control systems, chambers for septic and storm water management, fiber blocks, automotive parts, and fuel made in part of carpet binders. However, the markets for these products, as well as for the low quality resins produced by melting carpet or it components, are limited in size or the value of the resulting products is too low to justify investments in recycling equipment and collection networks. De-polymerization of Nylon 6 obtained from face fibers is the most promising option to divert a significant volume of carpet from the landfills.

2.3.2 Reverse Supply Chain of Carpet

Recycling of post-consumer carpet includes many activities in addition to the recycling process itself. Old carpet has to be collected from consumers, delivered to a collection center, graded by quality, condition and carpet type, shipped to a proper recycler, converted to secondary products or materials, and delivered to final customers. All of these activities form a reverse supply chain for carpet recycling. According to the classification of reverse logistics networks proposed by Fleischmann (2001), carpet recycling is a typical material recovery network. The main motivations for organization of such networks are legislation requirements or attempts to preempt possible legislation. In the typical material recovery network discussed by Fleischman, both product manufacturers and material suppliers participate in recycling activities or form an industry-wide organization that is responsible for product recovery. This recycling is characterized by low profit, and it requires significant investments in equipment that can be justified only with high processing volumes. The network usually consists of a small number of levels, and transportation costs are a significant part of total costs.

2.3.2.1 <u>Recycling activities involved</u>

Acquisition of used carpet from consumers is the first step in the carpet reverse supply chain. This stage determines the volume of carpet that goes to recycling. There are several options to collect post-consumer carpet, including sorting from general trash, aggregation at retail sites and collection at specialized centers (Woolard, 2009). Sorting of carpet from general trash is problematic, since it is mixed with other waste and becomes wet and contaminated, making it inappropriate for recycling (Realff, 2006). The issue with retail-based collection is that many retailers do not have enough space to store collected carpet and protect it from the outside environment (Realff, 2006). The option where end-users or installers bring old carpet to specialized collection centers is the most attractive, and many individual companies specializing in carpet collection and recycling utilize this scheme. For example, 111 sites are listed at the CARE web site as Carpet Reclamation Partners. Used carpet can be delivered to their collection centers for a tipping fee.

After collection, carpet has to be sorted and preprocessed. It is often difficult to identify different types of carpet by sight only. However, special equipment exists to sort carpet in manual mode or as an automated process. Sorting can be carried out manually with a portable spectrometer, which is labor intensive (Wang, 2006). If significant volumes are processed at a collection center, more expensive automated sorting equipment can be used (Realff, 2006). Then sorted carpet is baled to increase the amount of carpet that can fit into a truck to be shipped for further processing. The non-recyclable carpet is sent to local landfills or incineration facilities.

The processing steps conducted at a recycling facility depend on the recycling options selected. In most cases, carpet is shredded or grinded to reduce its size. If a processor is interested in the recycling of face fibers only, they can be ripped off or shaved. After size reduction, carpet is used in the recycling processes discussed in the previous sections, which includes caprolactam recovery from Nylon 6 carpet, mechanical separation of carpet to different material streams, melting entire carpet to produce pellets or molded products, and incineration for energy recovery.

2.3.2.2 Organizational and legislation issues

The diversion of post-consumer carpet from US landfills and recycling it into valuable materials has been considered for a long time. In the 1990s, big fiber producers developed processes for the recovery of Nylon 6 (Honeywell) and Nylon 6,6 (DuPont, now Invista and Monsanto, now Solutia) fibers from carpet waste (Peoples, 2006). DuPont and Monsanto invested in pilot facilities only and did not extend their efforts to large scale recycling due to lack of market interest and for economic reasons. Honeywell collaborated with Dutch State Mines (DSM) and built the Evergreen Nylon Recycling plant in Augusta, GA. However, the plant was closed in 2001 due to the low prices of caprolactam and problems with the collection of post-consumer carpet (Peoples, 2006). Later the plant was acquired by Shaw Industries Inc., the biggest carpet manufacturer in the US, and re-launched in 2006.

In 2001, three states, Minnesota, Iowa, and Wisconsin, initiated discussions of carpet diversion. In 2002, these states, the US Environmental Protection Agency, and some non-governmental organizations signed a Memorandum of Understanding (MOU), which set up a schedule of target diversion rate goals of PCC from landfills for the next ten years. To manage this project, a non-profit organization, named the Carpet America Recovery Effort, was created. The goal of this organization was to facilitate the development of a nationwide carpet collection and recycling network to divert 40% of post-consumer carpet from landfills by 2012 (Woolard, 2009). However, due to the recent economic downturn and limited outlets for materials recovered from PCC, the actual recovered volumes are far below the target values. According to the latest CARE report (CARE, 2011c), the diversion rate in 2010 was at 5.6%, which is significantly lower that the planned value of 23%. In April 2011, members of the Carpet Stewardship MOU started the negotiation of a new agreement for the next 12 years (2012-2024).

While negotiation of the new MOU is still in progress, California became the first and only state that passed a carpet stewardship bill (California Assembly Bill No. 2398 “Product stewardship: carpet”). According to the law, all carpet sold in the State of California is subject to a $0.05 fee per square yard, which should be added to the purchase price of all carpet. The fee of $0.05 per square yard will be charged from 2011 to 2013 and will be reassessed, if needed, after 2013. These fees are to be collected by manufacturers or a carpet stewardship organization and redistributed to collection, sorting and recycling businesses to encourage carpet recycling in the state. Carpet manufacturers are required to submit a detailed plan to the California Department of Resource Recycling and Recovery of expected funds and their redistribution to recyclers, which must be approved.

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CHAPTER 3: Logistics of Carpet Recycling in the US – Part I: Collection Network

Abstract

Efficient collection of post-consumer carpet is an important part of the carpet recycling process that helps to reduce the cost of recycled materials and provide sufficient volumes of post-consumer carpet for recycling facilities. This chapter is focused on the design of a collection network for post-consumer carpet in the US. The location set covering optimization model formulated in the chapter allows locating the minimum number of collection centers throughout the US to reach a specific level of population coverage and as a result, a target collection rate. To solve real-scale instances of the problem, a novel randomized greedy heuristic is developed. The heuristic is specifically designed for problems with a large number of points to cover and potential locations for facilities, with sparse coverage matrices. For such problems, the new heuristic performs better than greedy heuristics in the literature. In addition to the heuristic, the chapter presents an estimation of the input parameters and the resulting nationwide carpet collection networks for different levels of population coverage. The results of the study can be used for US carpet recycling policy-making decisions. In addition, problem input parameters can be re-estimated to use the heuristic for design of collection networks for other types of post-consumer products, as well as for location of facilities in forward supply chains.

Keywords

Post-consumer carpet, collection network, location set covering problem, greedy randomized heuristic

3.1 Introduction

In 2010, six billion pounds of post-consumer carpet (PCC) were discarded in the US (CARE, 2011a). Being a bulky product usually composed of synthetic materials, carpet occupies a significant volume of landfill space, does not decompose over time, and does not produce any burnable gases that can be collected from landfills (Fishbein, 2000). In addition, valuable materials that can be recovered from carpet are lost when PCC is landfilled (Realff *et al.*, 1999). Despite these issues, only 5.6% of carpet discarded in the US in 2010 was recovered (CARE, 2011a). There are several problems with carpet recycling that result in such a low diversion rate. The complex structure of carpet makes it difficult to separate individual materials in pure form (Peoples, 2006). Recycling technologies for some carpet components are either absent or economically infeasible (Wang, 2006). Demand for down-cycled products made of PCC or its components is low (CARE, 2011b). Collection, transportation, and recycling of post-consumer carpet add significantly to the cost of recycled materials reducing its attractiveness. Existing recycling technologies require high volumes of carpet to reduce the unit cost of material recovered (Realff, 2006).

Acquisition of used carpet from consumers is the first step in the carpet reverse supply chain. This stage determines the volume of carpet that goes to recycling. There are several options to collect post-consumer carpet, including sorting from general trash, aggregation at retail sites and collection at specialized centers (Woolard, 2009). Sorting of carpet from general trash is problematic, since it is mixed with other waste and becomes wet and contaminated, making it inappropriate for recycling (Realff, 2006). The issue with retail-based collection is that many retailers do not have enough space to store collected carpet and protect it from the outside environment (Realff, 2006). The option where end-users or installers bring old carpet to specialized collection centers is the most attractive. However, collection centers have a limited collection radius, since end-users and installers do not want to travel too far to discard their carpet at collection centers. If there is no collection center nearby, carpet will be disposed of at local landfills. Therefore, collection centers should be carefully located in close proximity to consumers to capture required volumes of old carpet. This chapter is focused on the efficient design of a nationwide carpet collection network that allows reaching target collection rates by opening a minimum number of collection centers throughout the continental US.

The chapter is structured as follows. Section 3.2 presents a review of previous studies on network design for carpet recycling. Then, the problem inputs and the formulation of the optimization model are presented in Section 3.3. In Section 3.4, heuristics from the literature, a novel approach for solving the problem, and computational results are presented. Section 3.5 details the application of the best heuristic to the design of US carpet collection networks for different target collection rates. The last section summarizes the chapter and provides background for further studies.

3.2 Literature Review

The design of reverse networks for post-consumer carpet was previously studied by several authors. Louwers (1999) utilized a quadratic programming model to determine the optimal locations of intermediate preprocessing centers between sources and processors of PCC. The model was applied to carpet recycling in Europe. Post-consumer carpet collected at sources is transported to preprocessing centers where they are sorted and compacted. The recyclable carpet is shipped to processors, and the other carpet is shipped to landfills or incineration facilities. The problem was formulated as a three-layer supply chain model where the locations of facilities at the first and the last layers (sources and processors/disposal sites) are known, and facilities in the intermediate level (regional preprocessing centers) are to be located on a continuous plane. The model objective was minimization of total costs, which included acquisition costs of post-consumer carpet and transportation, storage, preprocessing, and disposal costs. The decision variables were the capacities, the number and locations of preprocessing centers, and the material quantities shipped between facilities. The problem was solved exactly with a sequential quadratic programming method.

Realff *et al.* (1999; 2000a, 2000b, 2004) published a series of papers concerning carpet recycling in the US. In general, the model used for these studies can be described as follows. Post-consumer carpet is collected at predefined locations within the US. The volumes collected at each site are proportional to the population. Reverse logistics tasks include sorting and three types of reprocessing: depolymerization of Nylon 6, depolymerization of both Nylon 6 and Nylon 66, and shoddy production. Two different sets of potential locations for two depolymerization processes are given. Sorting can be set up at any collection or processing site. Both sorting and recycling processes are capacitated and recycling sites can set up a depolymerization process with three different capacities. Carpet collected at processing sites can be sold to another site, converted to secondary materials or disposed.

The model objective was to maximize the net revenue by locating processing sites, selecting sites for sorting operations, defining the transportation modes between sites, and the volumes of carpet shipped. Revenue is generated from sales of recycled materials and costs include the fixed costs (i.e., site opening cost and costs to set up storage, collection, transportation and/or recycling capabilities at a site), variable costs (i.e., volume dependent costs to collect, store and process post-consumer carpet) and transportation costs. The problems in these studies were solved using a commercial mixed-integer programming software.

Recently Woolard (2009) studied a large scale carpet recycling network in the US. The network consisted of two layers: 400 collection centers located in the most populous 3-digit ZIP codes and recycling centers that can be located at any 3-digit ZIP code. The model objective was to minimize cost, which included fixed costs to open recycling centers, transportation costs from collection to recycling centers and recycling costs. The latter was modeled to be volume dependent. The problem was solved using a meta-heuristic developed by Bucci (2009) that allows optimizing large network design problems with economies of scale.

As can be seen from the discussion above, all papers that studied logistics of carpet recycling were focused on the location of recycling facilities assuming that collection networks already exist or that collection centers are located in the most populous areas. For the European case, Louwers (1999) assumed that 60 collection centers are located close to the biggest cities in Germany and the Benelux countries. To design a carpet recycling supply chain in the US, Realff *et al.* (1999, 2004) considered a collection network consisting of 54 sites located throughout the US. In Woolard (2009), the collection centers were assumed to be located in the 400 most populous 3-digit ZIP codes.

The literature on reverse network design for other post-consumer or post-industrial products/materials is extensive. A recent review on this topic that was published by Akçali *et al.* (2009) focused on modeling and solution approaches. Reverse logistics location models were also discussed by Melo *et al.* (2009) as a part of a broader review on facility location and supply chain management. Considering decisions regarding the location of facilities that accept used products or materials from consumers or industry, several approaches can be identified. In some cases, points of aggregation of returns are known a priory (e.g., sand sorting facilities) (Barros *et al.*, 1998; Listes *et al.*, 2005) or it is assumed that collection centers are located in the most populous regions as was discussed above for the case of post-consumer carpet. However, in most of the papers, facilities that receive the reverse flow of products from consumers are located to minimize transportation costs from consumers and the number of facilities opened. These facilities are located separately from other facilities in the reverse supply chain (Aras *et al.*, 2008; Cruz-Rivera *et al.*, 2009) or as a part of multi-echelon reverse logistics models where consumers-facility transportation costs are included into the total cost of the network (Salema *et al.*, 2007; Lee *et al.*, 2008; Kara *et al.*, 2010). Usually, such an approach to locate collection centers is used when a company is responsible for collection of its products due to legislation, or the remaining value of post-consumer products is high enough to make direct collection economically feasible.

However, due to high bulkiness of carpet and a high number of origination points, the cost of direct collection of carpet from end-users is significantly higher compared to the value of carpet collected even if the collection process is optimized. A better objective in this case is to locate collection centers in close proximity to customers to achieve a target coverage of PCC supply points, and as a result, a target collection rate, with a minimum number of collection centers. This problem can be formulated as the location set covering problem that is discussed in more details in the next sections.

3.3 Carpet Collection Network

The Carpet America Recovery Effort (CARE) is a non-profit organization established to facilitate the diversion of post-consumer carpet from US landfills. The CARE web site lists the 110 US facilities as Carpet Reclamation Partners (CARE, 2011c). Locations of these facilities are shown in Figure 3.1 and the complete list is provided in Appendix A.1. Since information about each individual facility in the CARE network is unavailable and only average information is reported by CARE, this analysis assumed that all facilities collect carpet and are identical in terms of the distribution of collected carpet by face-fiber type and collection fees charged.

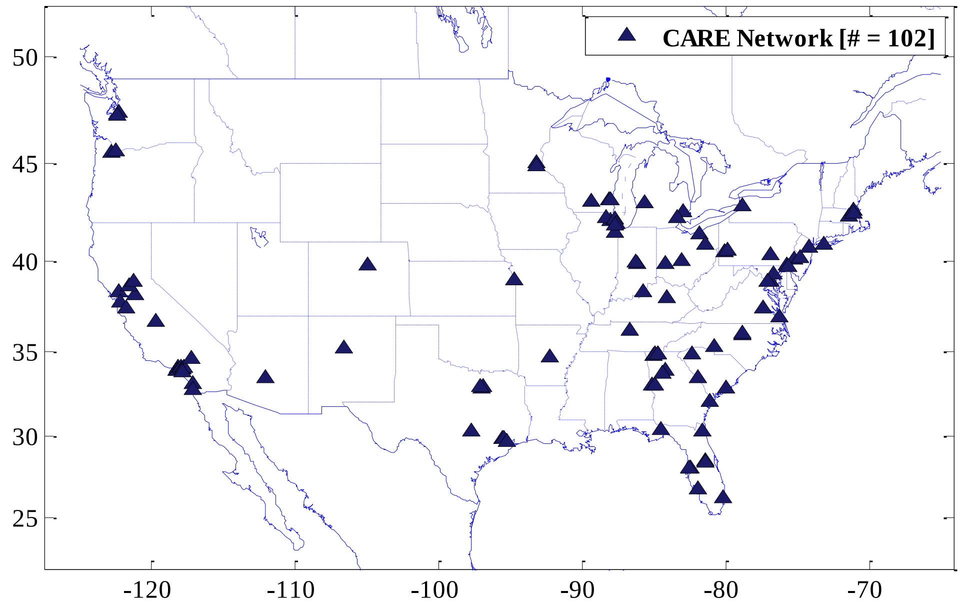


Figure 3.1: Current carpet collection network in the US
Source: (CARE, 2011c)

The collection radius of a center was estimated to be 25.9 miles, as discussed in the next subsection. Given this radius, the CARE network covers 36.39% of the population. However, in 2010, the network diverted only 5.6% of post-consumer carpet. Based on these numbers, the collection efficiency of the network (i.e. percentage of carpet collected from covered population) in 2010 was 15.4%. There are two options to increase the percentage of carpet collected. One option is to try to increase collection efficiency of already existing centers. The second option, which is studied in this chapter, is to open additional collection centers to increase the coverage of end-users. In the remainder of this section, problem parameters and a mathematical formulation of the problem are presented.

3.3.1 Model Parameters

To design a national network for carpet collection, it is assumed that post-consumer carpet is generated at the population centroids of all 5-digit ZIP codes with a population greater than zero. This results in 32,515 supply points of old carpet. The volume of carpet generated at each location is assumed to be proportional to the population. The potential locations for the collection centers are the population centroids of all 5-digit ZIP codes including those with zero population (e.g., industrial areas), resulting in 41,237 potential locations. It is assumed that the cost to open a collection center at any location is the same, disregarding regional differences in space and labor costs. In addition, it is assumed that there are no economies of scale in the collection activities.

The problem requires the estimation of the collection radius and actual road distances between all combinations of supply points and potential locations for collection centers. It is very time consuming to determine the exact traveling distances due to the high number of combinations of origin and destination points (i.e., about 1.4 billion origin-destination distances for the carpet collection problem). Therefore, all distances used in this study are estimated as great-circle distances multiplied by a circuity factor to approximate real-road distances. The circuity factor for long-distance road trips in the US is 1.21 (Kay *et al.*, 2009). However, there is no estimation of this factor for short trips. Therefore, this factor was estimated using the experiment described in Kay & Warsing (2009). One hundred 5-digit ZIP codes within the continental US were randomly selected, and for each, one destination ZIP code located within 25 miles was randomly selected. Great-circle distances were calculated for each pair and compared with the actual road distances between them that were obtained from MapQuest (http://www.mapquest.com). The circuity factor was calculated as a ratio of the actual road distance to the corresponding great circle distance. The complete list of origin-destination ZIP codes sampled, circuity factors for each pair of ZIP codes and the distribution of circuity factor values can be found in Appendix A.2. While there were several high circuity factor values (i.e., 2.6, 2.8 and 4.6), a statistical test for outliers did not reveal any extreme outliers in the sample. Therefore, the average of the circuity factors obtained from the entire sample, 1.45, is used in further analysis.

To estimate the collection radius of a given center, it is assumed that an end-user has two options to dispose old carpet: deliver it to a collection center or dispose it at the local landfill. Both options involve some transportation costs and disposal fees. Since most end-users try to minimize disposal costs, it is assumed that they dispose at a collection center if the corresponding costs are lower compared to landfilling costs. The collection radius of a collection center (r) is the maximum distance that consumers are willing to travel to deliver carpet to a collection center instead of landfilling. This distance depends on the (tipping) fee per ton charged for disposal of carpet at collection centers ($CFee$) and at landfills ($LFee$), the average distance to landfills ($LDist$), the per mile transportation costs ($TrCost$), and the average weight of carpet per trip (W). Using these values, the collection radius is calculated according to Equation (3.1).

$$r = \frac{LDist \times TrCost + (LFee - CFee) \times W}{TrCost} \tag{3.1}$$

The collection radius for this study was estimated based on national averages. It was assumed that used carpet is transported to disposal sites in a thirty-yard roll off dumpster, which has a capacity of 5 tons (Woolard, 2009). In 2008, the national average landfill tipping fees were \$44.09 per ton (Haaren *et al.*, 2010). The average distance to landfills or transfer stations was assumed to be 10 miles as suggested by the US Environmental Protection Agency for location of waste management transfer stations in urban and suburban areas (US EPA, 2002). The assumed transportation costs was \$3 per mile, based on \$2 per mile costs for full long-distance trucks in 2004 (Kay, 2009) adjusted by the Producer Price Index for freight trucking (Series ID=PCU4841214841212: PPI_{2004}=117, PPI_{2011}=136.7) (Bureau of Labor Statistics, 2012) and rounded up to account for smaller loads and shorter distances. It was assumed that the collection fee is \$25 per ton (Lave *et al.*, 1998; Woolard, 2009). Based on these numbers and assuming that transportation costs include two-way travel, the average collection radius estimated from Equation (3.1) is equal to 25.9 miles. This value is close to the 23.82 miles obtained in Woolard (2009) and to the fifty-mile round trip distance to collection centers suggested in Lave (1998).

3.3.2 Optimization Model

With the parameters defined above, the optimization model for collection network design was formulated as a unicost partial location set covering problem (Daskin *et al.*, 1999). There is a known set ($\mathcal{G}$) of discrete locations within the continental United States, where post-consumer carpet is generated (supply points). The number of these locations is $|\mathcal{G}|$ and each location has its own weight (w_g), the fraction of the total annual weight of PCC disposed, which is proportional to population. There is a set ($\mathcal{P}$) of potential locations where collection centers can be opened. Each center has a limited collection radius (r) and the cost to open a collection center at any potential location is the same. If any supply point is within a collection radius of at least one collection center, its weight (w_g) adds to the total network coverage, and post-consumer carpet from this point is delivered to the covering collection centers. Otherwise, carpet is disposed at a landfill and does not enter the collection network. The objective of the model is to open a minimum number of collection centers at the potential locations to reach a specific level of total coverage (c). The specific collection rate of PCC is obtained by multiplying the population coverage of the network by the collection efficiency described earlier.

To formulate the problem mathematically, the notation shown in Table 3.1 is used:

Table 3.1: Collection network model formulation notation

Sets and Indices	
$\mathcal{G}, \mathcal{P}$	sets of known supply points to cover and candidate locations for collection centers
$|\mathcal{G}|, |\mathcal{P}|$	numbers of supply points and candidate locations for collection centers
$g = \{1, \dots, |\mathcal{G}|\}$ $p = \{1, \dots, |\mathcal{P}|\}$	indices of supply points and candidate locations for collection centers
Parameters	
r	collection radius
c	desired coverage of the network
w_g	weight of supply point g
a_{gp}	element of the binary coverage matrix, which is equal to 1 if supply point g is within a collection radius r of potential collection center p, 0 otherwise
Decision variables	
$x_p \in \{0,1\}$	1 if collection center is opened at location p, 0 otherwise
$y_g \in \{0,1\}$	1 if supply point g is covered by at least one collection center, 0 otherwise

Using this notation, the problem can be formulated as:

$$\min \sum_{p=1}^{|\mathcal{P}|} x_p \tag{3.2}$$

$$s.t. \sum_{p=1}^{|\mathcal{P}|} a_{gp} x_p \geq y_g, g = 1 \dots |\mathcal{G}| \tag{3.3}$$

$$\sum_{g=1}^{|\mathcal{G}|} w_g y_g \geq c \tag{3.4}$$

$$x_p \in \{0,1\}, p = 1 \dots |\mathcal{P}| \tag{3.5}$$

$$y_g \in \{0,1\}, g = 1 \dots |\mathcal{G}| \tag{3.6}$$

The objective function (3.2) minimizes the number of opened collection centers. Constraint (3.3) specifies that supply point g is covered ($y_g = 1$) if it is within the collection radius of at least one of the opened collection centers. Constraint (3.4) requires that the total weight of covered supply points should be at least equal to the desired total coverage. The model solution is a binary vector x, non-zero elements of which indicate locations where local collection centers should be opened.

3.4 Heuristic Solution Methods

The formulated model is a binary linear programming problem. It is NP-complete since it can be reduced to the standard set covering problem which is NP-complete (Karp, 1972) by setting the desired coverage (c) equal to one. While simple instances of the set covering problem may be solved with exact algorithms that are mostly based on branch-and-bound and branch-and-cut methods (Haouari *et al.*, 2002), more complex instances of the problem are difficult to solve exactly.

Attempts were made to solve the full-scale collection network problem with CPLEX for desired coverage levels from 40% to 95% in increment of 5%. Two cases for the design of the collection network were considered: one extended the current CARE network and the other did not use the CARE network. CPLEX was only able to solve the extended CARE network with coverage up to 80% and the non-CARE network up to 70% coverage. For higher target coverage levels, “Out of Memory” errors were issued. Therefore, a heuristic was needed to design collection networks for higher target coverage levels. In the remainder of this section, heuristics found in the literature are discussed, a new heuristic is presented and the performance of the new heuristic is compared for some of those found in the literature for smaller test problems.

3.4.1 Heuristics for Set Covering Problems in the Literature

The set covering problem has been used in location science for more than forty years (Farahani *et al.*, 2012). There are many variations of problem formulations and heuristic algorithms proposed in the literature to solve difficult instances of the problem near-optimally, but in reasonable time. Detailed reviews of set covering and related problems, as well as their application and solution techniques, can be found in Caprara *et al.* (2000), ReVelle *et al.* (2008), Fallah *et al.* (2009), Farahani (2012). The earliest heuristics for the covering problem are the deterministic greedy adding algorithm and greedy adding with substitution discussed in Church (1974) and Church *et al.* (1974). While these algorithms are fast and simple to implement, they rarely produce good quality solutions. Therefore, the deterministic greedy approach was later improved by including randomized steps in the solution procedure (Feo *et al.*, 1995; Marchiori *et al.*, 1998; Resende, 1998; Haouari, 2002; Bautista *et al.*, 2007; Lan *et al.*, 2007).

Among other approaches are algorithms that utilize Lagrangian relaxation (Beasley *et al.*, 1992; Lorena *et al.*, 1994; Caprara *et al.*, 1999), tabu search (Kinney *et al.*, 2007), meta-heuristics based on simulated annealing (Jacobs *et al.*, 1993), and genetic algorithms (Beasley *et al.*, 1996; Lorena *et al.*, 1997; Solar *et al.*, 2002). Generally, these algorithms are designed for non-unicost set covering problems. Most of them utilize differences in site opening costs and, as a result, they are not as effective for unicost problems (Kinney, 2007; Lan, 2007).

The greedy approach was selected to solve difficult instances of the collection network problem formulated above. Four greedy heuristics found in the literature were implemented and used. These include the deterministic Greedy Adding with Substitution (GAS) (Church, 1974), and three randomized greedy procedures: the Greedy Randomized Adaptive Search Procedure (GRASP) (Feo, 1995; Resende, 1998), the Iterated Enhanced Greedy (ITEG) (Marchiori, 1998), and the Meta-heuristic for Randomized Priority Search (Meta-RaPS) (Lan, 2007). Details on these heuristics can be found in the references sited. Here, a brief discussion of the algorithms is provided.

The GAS heuristic is an extension of the simple Greedy Adding heuristic and was proposed by Church (1974) to solve the maximal covering location problem, which is closely related to the location set covering problem. The objective of this problem is to maximize the number (or weight) of demand (in our case supply) points covered with a specific number of facilities. The main idea of the deterministic GAS heuristic is to add sites to the solution one by one until all problem constraints are satisfied. Similar to simple Greedy Adding, at each step, the site with the highest coverage gain (i.e., a site that covers the most uncovered demand points) is included in the solution. If there are several candidate sites with the highest gain, the next site to add is defined according to some deterministic rule (e.g., first site in the list). In contrast to simple Greedy Adding, GAS tries to improve the solution each time a site is added, iterating through previously opened sites and moving them to unopened locations if such moves improve the total coverage.

Among randomized algorithms, GRASP has also been used to solve the maximal covering problem, while ITEG and Meta-RaPS were utilized for the set covering problem. All three randomized greedy heuristics consist of a two-phase construction-improvement cycle that is repeated for a user-defined number of iterations. In GRASP and Meta-RAPS, each iteration starts from an empty solution. ITEG starts the next iteration from the sub-set of sites randomly selected from the current best solution.

In the construction phase, sites are added one by one until all constraints are satisfied. However, in contrast to the GAS algorithm, the next site to add is selected randomly among candidate sites. In addition, in randomized heuristics, the list of candidate sites is usually extended by including not only sites with the highest coverage gain, but also sites with gains close to the highest gain. In GRASP, the list of candidates is formed by including all unopened sites with gains higher than the maximum gain multiplied by a restriction parameter (≤ 1), and the next site to add is randomly selected from this list. Meta-RaPS utilizes both approaches: sometimes (with user-defined probability) it selects sites in the same manner as GRASP, and other times sites are selected using the deterministic approach from GAS. ITEG also uses two approaches for site selection: sometime it selects sites similar to GRASP; in other cases, additional criteria is evaluated for sites in the candidate list, and a site with the best value of this criteria is selected.

Different improvement procedures are run after the construction phase of three randomized heuristics. The GRASP swaps sites in the solution with unopened sites that give the biggest increase in coverage. Such swaps are made until no improvement can be gained. In the improvement phase, ITEG removes all inferior sites from the solution and runs the construction step again to reach the desired coverage. The inferior sites are sites that become redundant if any of the unopened facilities are added to the solution. Meta-RaPS utilizes iterative improvement, where some percentage of the sites are randomly removed from the best solution and then the construction step is run again.

3.4.2 IRGAS Heuristic

The greedy heuristics from the literature were adapted to the collection network problem and implemented in MatLab. The solutions obtained from the heuristics were compared to exact solutions for small test problems. This is discussed in more detail later in this section. However, the performance of these heuristics was poor, possibly because these heuristics were initially designed for slightly different problems (i.e., complete or maximal covering) than the problems in this study (i.e., partial covering). To try to improve the quality of the solution, a hybrid heuristic, called the Iterated Randomized Greedy Adding with Substitution (IRGAS), was developed. This heuristic combines some features of already existing heuristics and extends them.

Before discussing the heuristic itself, several definitions are given to simplify the explanation:

- A *coverage* matrix is a binary matrix where rows correspond to supply points and columns correspond to potential locations of collection centers. The intersection of a given row (supply point) and column (collection center) indicates if the supply point is within the collection radius of (i.e., can be covered by) the collection center (one) or not (zero).
- Two collection centers are *overlapping* if they have common supply points within their collection radius (cover common supply points).
- An *overlapping matrix* is a binary symmetric matrix with rows and columns corresponding to potential locations of collection centers. The intersection of a given row and column indicates if a "row" site overlaps with a "column" site (one), or not (zero).

Two functions are extensively called during the algorithm to determine sites to add to ($getSite2Add$) or remove from ($getSite2Rmv$) the solution. Both functions are greedy with some randomness and have two input parameters: *restriction* and *probability of random selection*. To determine a site to add to the solution, the $getSite2Add$ function forms a candidate list of sites to add. This list includes all unopened sites that have coverage gains no less than the maximum coverage gain times the *restriction* parameter. The *restriction* parameter may have values between zero (i.e., all unopened sites are included in the candidate list) and one (i.e., only sites with the highest coverage gain are included into candidate list), which defines the level of randomness during site selection.

The site to add is selected randomly from the list with probability defined by the second parameter (*probability of random selection*). Otherwise, additional fitness values are evaluated for candidate sites, and the site with the highest fitness value is selected. If several sites have the highest fitness value, one site among them is selected randomly. The fitness value of a given site accounts for the entire coverage of a site, including uncovered supply points and supply points already covered by other sites. Therefore, a candidate site with highest fitness value not only has high coverage gain, but also overlaps with already opened sites as much as possible. This increases the possibility that already opened sites overlapping with the site just added can be moved to other locations during the improvement phase with an increase in the total coverage.

Two types of fitness values are used in the algorithm. At the beginning of each iteration, one type is randomly selected and is used for the entire iteration. The first type of fitness value is just a sum of weights of supply points that can be covered with a site at a candidate location that are already covered by other sites. The second type adjusts (divides) these weights by the number of opened sites that covers each supply point. Therefore, in the latter case, preference is given to candidates that have overlapping supply points with high weights, but that are covered by fewer already opened sites.

A site to remove from the solution is found analogously. The remove candidate list is formed with opened sites with coverage losses no more than the minimum loss divided by the restriction parameter. When fitness values are used for evaluation, the site with the lowest fitness value is selected.

Since gains and losses depend on the current solution, their values are updated each time the current solution changes (a site is added or removed from the solution). The calculation intensity of these updates depends on the coverage and overlapping matrix densities. A site added to (removed from) the solution has an effect on gains or losses of only sites that overlap with it. Therefore, if the problem has a low overlapping matrix density, then the number of sites that requires update of gains or losses is small compared to the total number of potential locations. In addition, updating the gain (loss) of any site requires evaluation of states (i.e., covered/not covered) of supply points within its collection radius and adjusting the gain (loss) by the weights of those points that changed their states. Therefore, problems with low-density coverage matrix have on average a lower number of supply points to evaluate for each site during the update, which results in a lower computational intensity.

Figure 3.2 shows the pseudo-code of the IRGAS heuristic. The algorithm utilizes an iterative approach similar to ITEG (Marchiori, 1998). The main inputs to the heuristic are the coverage matrix ($\mathcal{A}$), weights of supply points ($\mathcal{w}$), the desired coverage (c), and six parameters. The heuristic runs $niter$ iterations (line 03) and returns the best solution found among all iterations (line 22). The first iteration starts from an empty solution (line 02) and all subsequent iterations start from a randomly selected sub-set of the current best solution ($getFractSol$) (line 20) that contains from $rfrLow$ to $rfrHigh$ percentage of already located sites. In turn, each iteration has two main steps: construction (lines 04-12) and "global" improvement (lines 13-16). If the iteration results in a solution that has a lower number of sites or the same number of sites, but higher coverage than the current best solution, the best solution (S^*) is updated (lines 17-19). The total coverage is used as a secondary criterion to select the best solution since multiple solutions may have the same number of sites.

During the construction phase, sites are added to the solution one-by-one until the desired coverage is reached. The next site to add is selected using the $getSite2Add$ function (line 05). In contrast to the randomized heuristics from the literature, the "local" improvement procedure ($swapOverlapping$) runs after each addition of a site (line 07). The experimentation shows that construction with local improvement results in better solutions compared to construction without it.

The local improvement tries to move opened sites that overlap with the most recently added site to other locations to get better coverage with the same number of sites. While local improvement may increase computational time for coverage problems with high densities of coverage and overlapping matrices, it does not have a significant effect on the execution time for the collection network problem studied here, since we have low matrix densities (i.e., 0.12% and 0.34% for coverage and overlapping matrices respectively). Therefore, the local improvement step tries to move a relatively low number of sites after each add and evaluates a relatively low number of supply points.

The solution formed by the construction phase is passed to the improvement phase (lines 13-16). The "global" improvement ($swapAll$) tries to move all sites in the solution one by one to other locations to improve the total coverage. Such swapping repeats until no improvements can be gained. After this, the improved solution is passed through the function ($rmvRedundand$) that closes all redundant sites in the solution.

```
S = FUNCTION IRGAS(𝒜, 𝓌, c, restr, pRndSel, pRndRmv, rfrLow, rfrHigh, niter)[1]
    S* = {1, … , |𝒫|}
    S = ∅
    FOR i = 1, … , niter
//---CONSTRUCTION---
        WHILE cov(S) < c
//------Add site to the solution
            s = getSite2Add(restr, pRndSel, 𝒫/S)
            S = S ∪ {s};
//------"Local" Improvement
            S = swapOverlapping(S, s);
//------Randomly remove one or more sites among the "worst" opened sites
            WHILE rand() ≤ pRndRmv
                s = getSite2Rmv(restr, pRndSel, S);
                S = S\{s};
            END WHILE
        END WHILE
//---"GLOBAL" IMPROVEMENT---
        WHILE No improvement
            S = swapAll(S);
        END WHILE
        S = rmvRedundant(c, S);
//---Update the best solution and generate an initial solution for the next iteration
        IF (|S| ≤ |S*|) AND (cov(S) > cov(S*))
            S* = S;
        END IF
        S = getFractSol(rfrLow, rfrHigh, S*);
    END FOR
    RETURN S*;
END FUNCTION
```

Figure 3.2: Main body of the IRGAS heuristic in pseudo-code

[1] $|S|$ is a number of elements in the set S; $\emptyset$ is an empty set; cov(S) returns total weight of supply points covered by sites in S

3.4.3 Comparison of Heuristics on Test Problems

The performance of the IRGAS heuristic was benchmarked against CPLEX and the four heuristics from the literature that were previously described using three small instances of the collection network problem. For all test problems (TP), it was assumed that the locations of the supply points and the potential locations of collection centers coincide. For the first test problem (TP 880), the three-digit ZIP codes of the continental US with non-zero population (880 locations) were used. For the second test problem (TP 1K), one thousand, five-digit ZIP codes with non-zero population located in the southeastern states were randomly selected. For the third problem (TP 2K), two thousand, five-digit ZIP codes were randomly selected among all five-digit ZIP codes with non-zero population in the continental US. The weights of the supply points were assumed to be proportional to the population. Population centroids of the corresponding ZIP codes were used as locations of the supply points and potential locations of the collection centers. The test problem parameters are summarized in Table 3.2. The parameters of the full-scale collection network problem (FULL) are given for reference.

Table 3.2: Test problems for comparison of heuristics

Problem	**Size**	**Collection Radius**	**Desired Coverage**	**Density of Coverage Matrix**	**Density of Overlapping Matrix**
TP 880	[880x880]	100	95%	2.02%	5.00%
TP 1K	[1,000x1,000]	35	95%	0.96%	2.02%
TP 2K	[2,000x2,000]	50	95%	0.62%	1.34%
*FULL**	[32,515x41,237]	25.9	-	0.12%	0.34%

* For reference

The desired total coverage was set to 95% for all problems, and collection radii of 100, 35, and 50 miles were used for the three problems. These values were selected to keep the coverage and overlapping matrix densities low, but at the same time allow potential sites to cover at least 10 supply points on average. The coverage and overlapping matrix densities for these problems are higher compared to the densities of the matrices in the full-scale problem.

However, due to a relatively low number of locations in the test problems, further reduction of densities (by means of reduction in collection radii) would result in a very low number of supply points covered by each site and a low number of overlapping sites. For example, setting the coverage matrix density of the second problem to 0.12% would result only in 1.2 supply points being covered by each potential location, on average.

The test problems were solved with CPLEX and with each heuristic. Since the covering problem may have several optimal solutions in terms of number of sites opened, all problems solved in this study with CPLEX were optimized in two steps. First, the covering problem was solved to find the minimum number of centers. Then, the corresponding maximum coverage problem was solved, where the total number of centers was set to the optimum number of centers from the first step.

Since all randomized heuristics are parameterized and different combinations of parameters may be better for different problems, each heuristic was run multiple times with different combinations. In addition, three different random seeds were used for each combination of parameters for each randomized heuristic. Table 3.3 summarizes the number of experiments run for each problem. In total, each test problem was solved 1,079 times.

Table 3.3: Numbers of experiments for each small test problem

Solution Method	**# of Parameters**	**# of Parameters Combinations**	**# of Random Seeds**	**# of Experiments**
CPLEX	-	-	-	1
GAS	-	-	-	1
GRASP	1	9	3	27
Meta-RaPS	3	27	3	81
ITEG	4	108	3	324
IRGAS w/o local improvement	4	108	3	324
IRGAS with local improvement	4	108	3	324

Two versions of the IRGAS heuristic were used for these test problems: with and without "local" improvement. In each experiment, GRASP, ITEG and IRGAS were run for 1000 iterations and Meta-RaPS was run for 50 main iterations each, with 200 iterations in the improvement step. 200 improvement iterations were selected because this was the number used by the author (Lan, 2007) for testing the heuristic on the unicost set covering problems, and 50 main iterations were used to allow Meta-RaPS to run longer than IRGAS.

The best solutions for the test problems obtained with CPLEX and the heuristics are summarized in Table 3.4. It can be seen from the table that the best solutions obtained with the IRGAS heuristic with local improvement are the same as that of CPLEX in terms of both the number of opened sites and the actual coverage reached. The best solutions obtained from IRGAS without local improvement also have the same number of opened nodes as CPLEX for all problems, but the total coverage for the third problem is slightly lower. For the heuristics from the literature, Meta-RaPS was the only heuristic that found the optimum number of sites for the first two problems. In all other experiments, the heuristics tested from the literature resulted in a higher number of sites than optimal.

Table 3.4: Comparison of best solutions found by heuristics

	Minimum # of Sites Opened			**Total Coverage**		
Solution Method	**TP 880**	**TP 1K**	**TP 2K**	**TP 880**	**TP 1K**	**TP 2K**
CPLEX	**58**	**92**	**136**	**95.22%**	**95.21%**	**95.08%**
GAS	62	96	141	95.11%	95.11%	95.06%
GRASP	60	93	139	95.09%	95.05%	95.07%
Meta-RaPS	**58**	**92**	137	95.12%	95.07%	95.01%
ITEG	59	93	139	95.15%	95.04%	95.08%
IRGAS w/o local improvement	**58**	**92**	**136**	**95.22%**	**95.21%**	95.06%
IRGAS with local improvement	**58**	**92**	**136**	**95.22%**	**95.21%**	**95.08%**

Figure 3.3 demonstrates how close solutions obtained by the randomized heuristics are to the optimal solution. The figure shows the distribution of the deviations of number of sites from the optimal solutions for each randomized heuristic. It can be seen that GRASP, Meta-RaPS and ITEG have a high percentage of solutions that deviate from the optimal solutions by nine or more sites. GRASP and ITEG did not yield the optimum number of sites for any

problem, and Meta-RaPS had only about 8% of experiments with the optimum number of sites. In contrast, both IRGAS without local improvement and IRGAS with local improvement resulted in better solutions, with more than 60% and 80% of the solutions yielding the optimal number of sites, respectively.

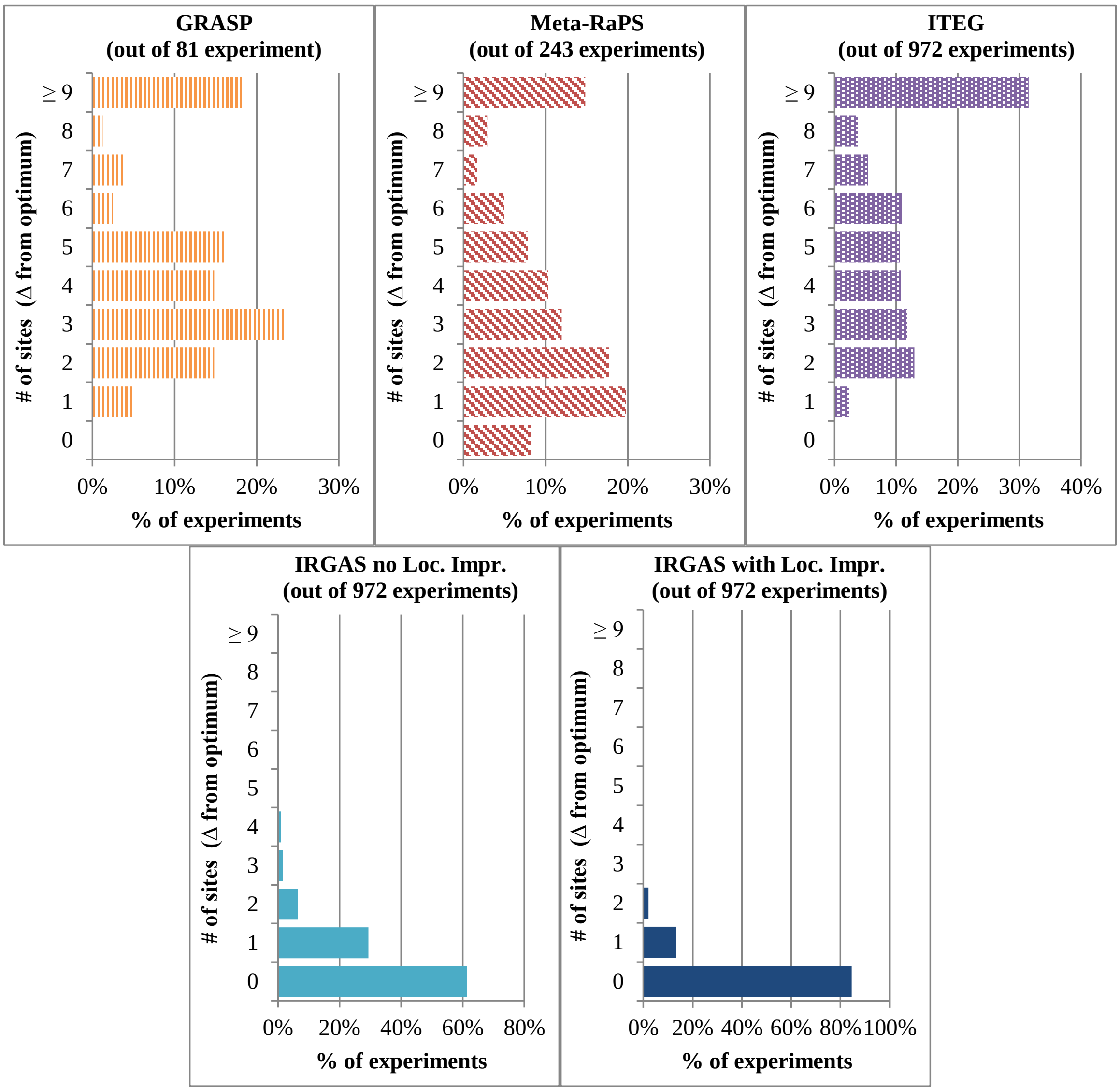


Figure 3.3: Deviations of number of sites in solutions found by the randomized heuristics from the optimum numbers of sites
(combined for the three test problems)

Table 3.5 compares heuristics in terms of robustness to selection of parameters. The table shows the percentage of parameter sets that resulted in solutions with the optimum number of sites for all three random seeds. In contrast to IRGAS, none of the heuristics from the literature that were tested yielded the optimum number of sites for all three seeds and three problems. Meta-RaPS had one set of parameters that resulted in the optimum number of sites for all seeds for the first two problems, but not for the last one. It also can be seen that IRGAS with local improvement is more robust in terms of the parameter selection compared to IRGAS without local improvement, yielding a higher percentage of optimal solutions in terms of number of sites for all seeds.

Table 3.5: Performance comparison of heuristics

Solution Method	**# of Parameter Sets per Problem**	**% of Parameters Combinations that Yielded Optimum # of Sites for All Seeds**		
		TP 880	**TP 1K**	**TP 2K**
GAS	-	0%	0%	0%
GRASP	9	0%	0%	0%
Meta-RaPS	27	4%	4%	0%
ITEG	108	0%	0%	0%
IRGAS w/o local improvement	108	48%	93%	11%
IRGAS with local improvement	108	86%	98%	47%

Figure 3.4 compares the average computational time per experiment required to run the randomized heuristics for 1,000 iterations (for Meta-RaPS, 50 iterations each with 200 improvement iterations). Both versions of the IRGAS heuristics were the fastest heuristics for all three problems. The figure shows that IRGAS with local improvement had a slightly higher computational time compared to IRGAS without local improvement for the first problem, but for the last two problems, the computational times of this heuristic were slightly lower. This is because IRGAS with local improvement finds a better solution at earlier iterations (i.e., lower number of opened sites and less overlapping among opened sites), so fewer sites are moved during improvements (both “local” and “global”).

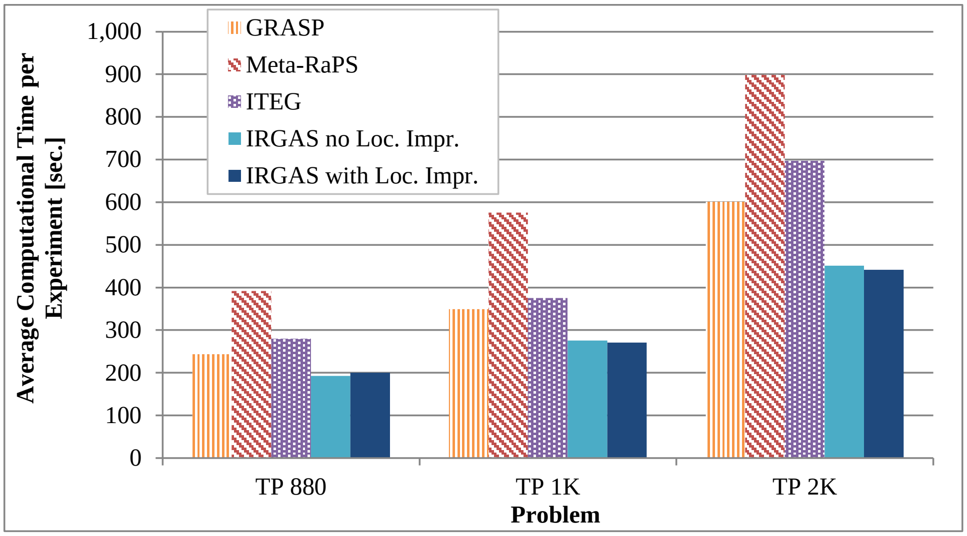


Figure 3.4: Average computational time for small test problems

While GRASP has a less complex logic of site selection and does not have random removal of sites, it requires more calculation time compared to IRGAS because it constructs a new solution for each iteration. ITEG has an even higher solution time since its improvement procedure is very computationally intensive for the problems tested. During improvement, it removes inferior sites and then runs the construction procedure again starting from the partial solution to reach a target coverage. Since collection centers were allowed to be located at any supply point, almost all opened sites, except sites that cover itself only, were inferior and were removed from the solution. Meta-RaPS has the longest computational time, since this heuristic requires a high number of improvement iterations.

Figure 3.5 shows the best and average number of sites for each heuristic as a function of a number of iterations for all the experiments. To reflect the fact that Meta-RaPS requires a smaller number of iterations (i.e., 50) compared to other heuristics (i.e., 1000), but each Meta-RaPS iteration is significantly longer (i.e., in 25-40 times), the x-axis of the graphs was scaled by the average computational time required by each heuristic for one iteration. The lines that represents the optimal solution are drawn for references and do not reflect CPLEX computational time.

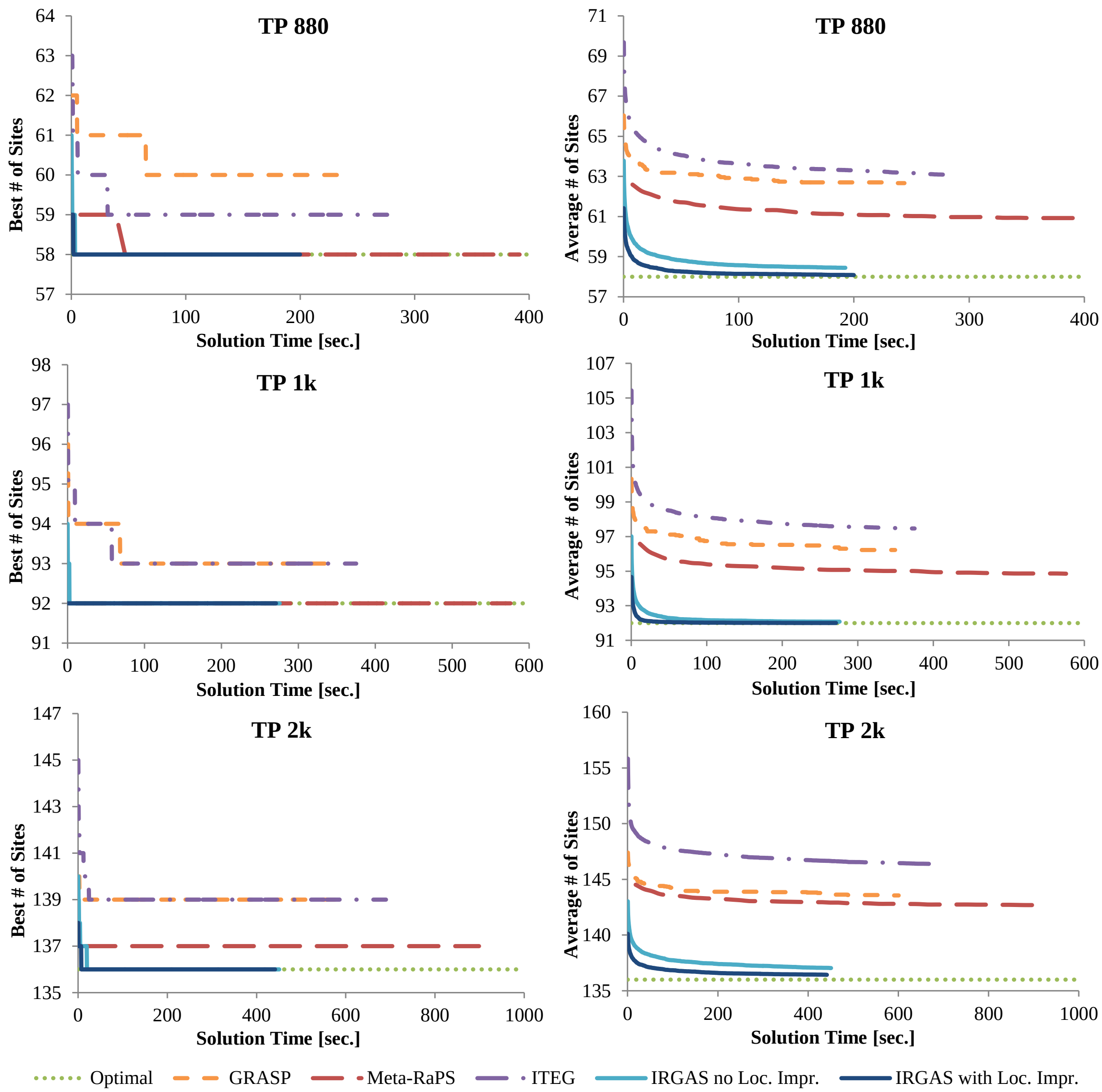


Figure 3.5: Best and average heuristic solutions vs. computational time

As can be seen from the figure, the best IRGAS solutions quickly reach the optimal number of sites for all three problems. In addition, the average IRGAS solutions become very close to the optimal solutions after about a quarter of the computational time, which shows that a significant portion of experiments found optimal solutions at early iterations and that IRGAS is not very sensitive to the selection of parameters. The best solutions for the first two problems found by Meta-RaSP also reached the optimal values at early iterations, but for the third problem, even the best solution has two more sites compared to the optimal solution despite the fact that the computational time of Meta-RaSP is longer by about two times compared to IRGAS. The average Meta-RaPS solutions have a significantly higher number of sites meaning that there were only a few experiments with good solutions. The number of sites obtained by both GRASP and ITEG heuristics are higher compared to IRGAS despite the fact that both heuristics have longer computational times.

Table 3.6 and Figure 3.6 show the variability of the solutions obtained by the heuristics after the first iteration, 50% of iterations (i.e., 25 iterations for Meta-RaPS and 500 iterations for other heuristics) and after completion (i.e., 50 iterations for Meta-RaPS and 1000 iterations for other heuristics). It can be seen that the IRGAS heuristic has a lower standard deviation and range of solutions compared to other heuristics starting from the first iteration. Increases in the number of iterations reduce both the standard deviation and range of the IRGAS solutions significantly faster than other heuristics.

Table 3.6: Statistics of heuristic solutions after one, 50% and 100% of iterations

Solution Method	**After Iter. #**	**# of Sites in Solution (Among All Experiments)**								
		TP 880			TP 1k			TP 2k		
		Min	Avg.	Std. Dev.	Min	Avg.	Std. Dev.	Min	Avg.	Std. Dev.
Optimal		58		-	92		-	136		-
GRASP	1	62	66.0	3.8	96	100.3	5.3	140	147.4	8.7
	500	60	62.9	2.7	93	96.5	3.7	139	143.9	6.7
	1000	60	62.7	2.4	93	96.2	3.5	139	143.6	6.4
Meta-RaPS	1	59	62.6	2.7	92	96.6	3.5	137	144.5	6.1
	25	58	61.1	2.4	92	95.1	3.0	137	142.9	5.3
	50	58	60.9	2.4	92	94.9	2.8	137	142.7	5.1
ITEG	1	63	69.7	4.5	97	105.4	6.5	145	155.8	9.0
	500	59	63.4	2.9	93	97.8	3.3	139	146.8	6.0
	1000	59	63.1	2.9	93	97.5	3.1	139	146.4	5.9
IRGAS w/o local improvement	1	61	63.8	1.6	94	97.0	1.8	140	143.0	2.3
	500	58	58.6	0.8	92	92.1	0.5	136	137.4	1.0
	1000	58	58.4	0.7	92	92.1	0.4	136	137.0	1.0
IRGAS with local improvement	1	59	61.4	1.1	92	94.7	1.4	138	140.1	1.6
	500	58	58.1	0.4	92	92.0	0.1	136	136.6	0.7
	1000	58	58.1	0.3	92	92.0	0.1	136	136.4	0.6

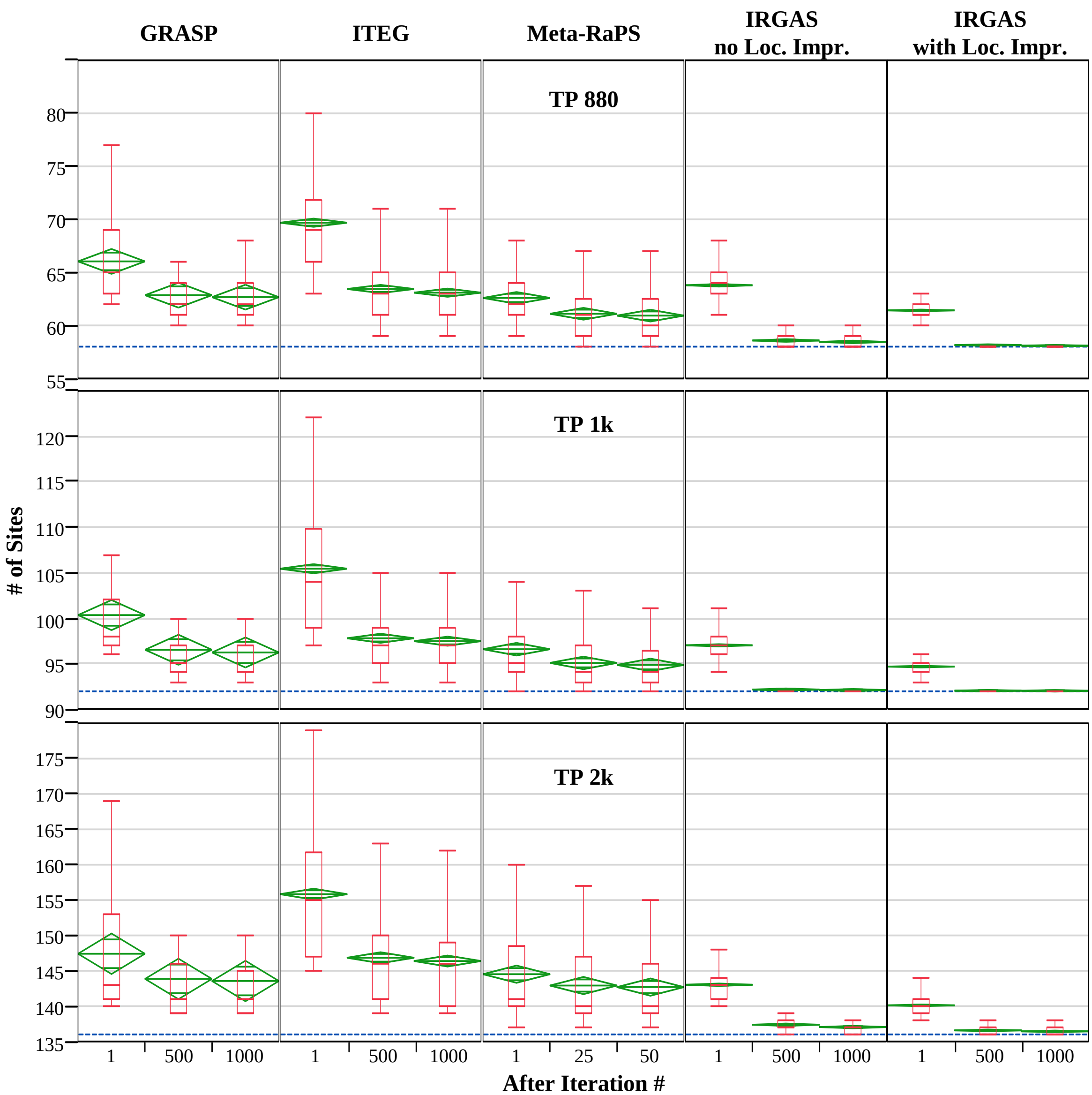
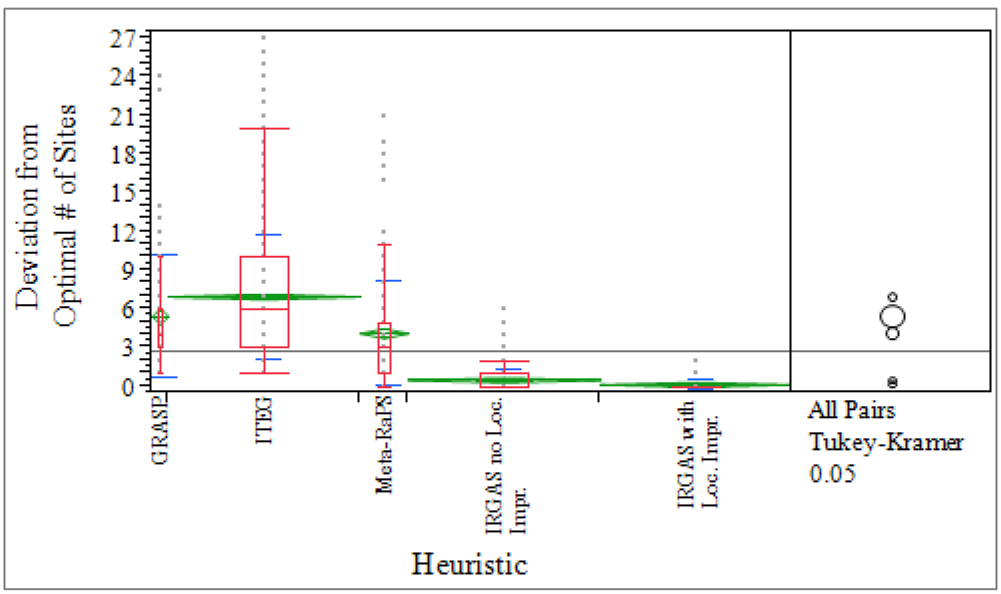


Figure 3.6: Statistics of heuristic solutions after one, 50% and 100% of iterations

To check if the IRGAS heuristic produces significantly better results compared to other heuristics, the final solutions were tested for differences among the means. Since different problems have a different number of sites, the analysis was conducted on the absolute deviations of the heuristic solutions from the optimal solutions. The results are shown in Figure 3.7. As can be seen from the plot, the variances of the results of each heuristic are not homogeneous, which was also confirmed with Levene's Test (p-value < 0.0001). Therefore, the one-way ANOVA F test cannot be used to test the differences in the means of each group, and the Kruskal-Wallis rank test was used instead. The test p-value of 0.0001 is lower than 0.05, which means that there is a significant difference in the deviation from optimum between heuristics. To identify heuristics that differs significantly from each other, a pairwise comparison with the Tukey-Kramer HSD test was conducted. As can be seen from the report, all heuristics, except both versions of IRGAS, produce statistically different results. Since the mean deviations of the IRGAS results are lower compared to other heuristics, it can be concluded that IRGAS produces significantly better results.



Wilcoxon / Kruskal-Wallis Tests (Rank Sums)

Level	Count	Score Sum	Expected Score	Score Mean	(Mean-Mean0)/Std0
GRASP	81	200697	131261	2477.73	8.766
ITEG	972	2559927	1575126	2633.67	42.355
Meta-RaPS	243	533682	393782	2196.22	10.469
IRGAS no Loc. Impr.	972	1104060	1575126	1135.86	-20.260
IRGAS with Loc. Impr	972	852055	1575126	876.60	-31.099

1-way Test, ChiSquare Approximation

ChiSquare	DF	Prob>ChiSq
2396.4040	4	<.0001 *

Comparisons for all pairs using Tukey-Kramer HSD

Connecting Letters Report

Level					Mean
ITEG	A				6.9773663
GRASP		B			5.4814815
Meta-RaPS			C		4.1563786
IRGAS no Loc. Impr.				D	0.5236626
IRGAS with Loc. Impr				D	0.1748971

Levels not connected by same letter are significantly different

Figure 3.7: Statistical comparison of heuristics

To test the IRGAS heuristic on larger problems, three additional test problems were created by randomly selecting 5000 (TP 5K), 7500 (TP 7.5K), and 10000 (TP 10K) population centroids of five-digit ZIP codes as locations for supply points and potential locations for collection centers. Collection radii for the problems were set to 100, 25, and 20 miles, correspondingly. Characteristics of the test problems, as well as the full-scale problem for reference, are summarized in Table 3.7. While the first problem has higher coverage and overlapping matrix densities, the second and third problems have almost the same characteristics in terms of densities as the full-scale problem.

Each test problem was solved exactly with CPLEX and IRGAS for 75% and 95% coverage. To reduce the number of experiments, combinations of IRGAS parameters that yielded an optimum number of sites for all three seeds for all "small" test problems were ranked by solution coverage, and the twenty best parameter combinations were tested for larger problems, each with three different random seeds (360 experiments in total). The number of iterations was set to 1000. The best solutions obtained with IRGAS for each problem among all experiments are contrasted with the CPLEX solutions in Table 3.8.

Table 3.7: Test problems for IRGAS heuristics

Problem	**Size**	**Collection Radius**	**Desired Coverage**	**Density of Coverage Matrix**	**Density of Overlapping Matrix**
TP 5K	[5000x5000]	100	75%, 95%	1.80%	5.44%
TP 7.5K	[7500x7500]	25	75%, 95%	0.18%	0.41%
TP 10K	[10000x10000]	20	75%, 95%	0.13%	0.30%
*FULL**	[32,515x41,237]	25.9	-	0.12%	0.34%

* For reference

Table 3.8: Best solutions for test problems obtained with IRGAS heuristic

Problem	**Desired Coverage**	**# of Sites**			**Total Coverage**	
		CPLEX	**IRGAS**	**% deviation**	**CPLEX**	**IRGAS**
TP 5K	75%	26	**26**	0.00%	75.14%	75.14%
TP 5K	95%	56	**56**	0.00%	95.19%	95.18%
TP 7.5K	75%	167	**167**	0.00%	75.06%	75.06%
TP 7.5K	95%	499	503	0.80%	95.01%	95.00%
TP 10K	75%	220	**220**	0.00%	75.03%	75.03%
TP 10K	95%	711	719	1.13%	95.00%	95.01%

IRGAS solutions were the same as CPLEX solutions for problems with relatively low number of sites in optimal solution (TP 5K, TP 7.5K 75%, and TP 10K 75%). However, IRGAS solutions for more difficult problems (TP 7.5K 95% and TP 10K 95%) had slightly higher number of sites (by 0.8% and 1.13%, respectively). To check if any improvements could be obtained by running the heuristic longer, the last test problem (TP 10K 95%) was optimized for 15,000 iterations with the three best combinations of parameters. These parameters were selected by ranking all the parameter sets considered by deviation from the optimal solution for all six problems. The parameters selected are summarized in Table 3.9. The sets have the same restriction parameter and restore fraction boundaries, but they have a different probability of random selection and random removal of sites during construction.

Table 3.9: Best parameters sets after IRGAS testing on large problems

Parameters\Set Name	IRGAS 1	IRGAS 2	IRGAS 3
Restriction on candidate lists (*restr*)	75%	75%	75%
Probability of random selection (*pRndSel*)	0%	15%	0%
Probability of random removal (*pRndRmv*)	25%	10%	0%
Restore fraction boundaries (*rfr*)	[70%; 90%]	[70%; 90%]	[70%; 90%]

To account for the randomized nature of the heuristic, each set of parameters was run five times with different random seeds. Figure 3.8 shows the average final solution as a function of the number of iterations for the three sets of parameters. A significant improvement in the number of sites occurs during the first 1,000 iterations (on average the number of sites is reduced from about 739 to about 721). After 5,000 iterations, the number of sites is improved by about three sites (to about 718). An additional 10,000 iterations improved solutions only by one site. The figure also shows that the second set of parameters yielded better results starting from 3,000 iterations. In addition, in this set, the probability of random selection among the candidates and random removal of sites is higher than zero, which means that this set utilizes both of these “features” of the IRGAS heuristic. Therefore, 5,000 iterations and the “IRGAS 2” set were selected for optimization of full-scale problems.

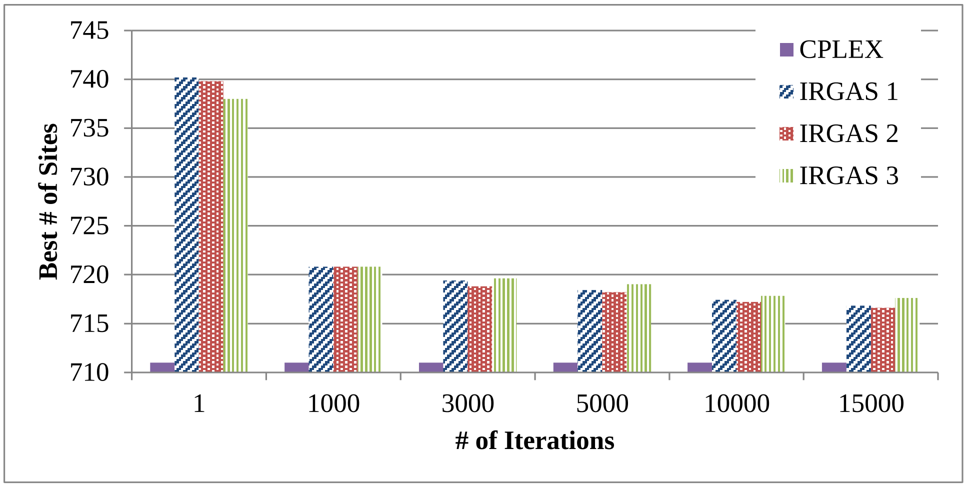


Figure 3.8: Average IRGAS solutions versus number of iterations for "TS 10K 95%" problem

3.5 Applying IRGAS to the Carpet Collection Network

Two options of network design were considered in the study: construction of a new collection network and extension of the current CARE network. Since the potential locations for collections sites are assumed to be in the population centroids of 5-digit ZIP codes, the collection centers in the CARE network that are located in the same 5-digit ZIP code are considered as one site. This results in 102 5-digit ZIP codes for the existing CARE centers.

The IRGAS heuristic with the parameter set identified in the previous section was used to design carpet collection networks for different levels of population coverage. The results are compared to the solutions obtained with CPLEX for those problems it could solve. In addition, to benchmark the quality of the heuristic solutions, especially for the cases where CPLEX solutions are not available, an additional simple "By Region" heuristic was used. In this heuristic, the continental states are grouped into regions (i.e., West, Rocky Mountains, Southeast, etc.) and the exact solution of a covering problem for each region is obtained individually using CPLEX. These solutions are combined into a solution for the entire country, and the "*swapAll*" and "*rmvRedundant*" procedures are used to improve its quality.

The problems were solved on a machine with 64-bit four-core processor and 8 GB of memory. All code was implemented in the 64-bit version of MatLab R2011a, and CPLEX solutions were obtained using the 64-bit version of CPLEX 12.2 through CPLEX for MatLab API. Figure 3.9 compares solution times as a function of the number of sites in the solution for the full-scale collection network problem built from scratch for a desired coverage from 40% to 95%. The solution times of IRGAS were computed after 5,000 iterations.

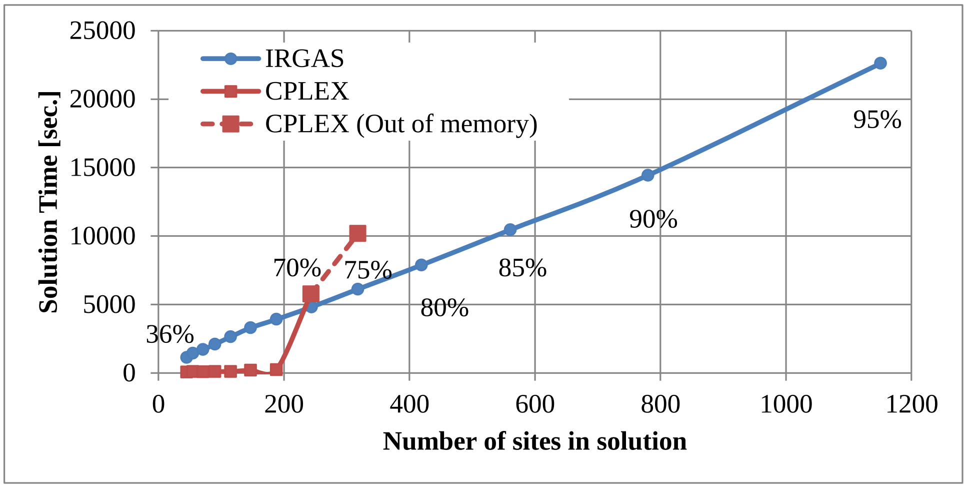


Figure 3.9: Comparison of CPLEX and IRGAS solution times for full-scale problems

It can be seen from the figure that for a low number of sites, CPLEX solves the problems quickly. However, when the number of sites in the solution increases above 200 (i.e., for 70% desired coverage), the CPLEX solution time jumps to about 1.5 hours. For 75% coverage problems, which CPLEX was unable to solve, CPLEX was working for about three hours before issuing an "Out of memory" error. In contrast, IRGAS requires more time to solve problems with a low number of sites, but the computational time increases linearly with the number of sites in the solution.

The number of sites required to reach the desired coverage obtained with CPLEX, the IRGAS heuristic and the benchmark heuristic for both options are shown in Table 3.10 and Table 3.11, respectively[2]. As can be seen from these tables, the number of collection centers

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[2] Collection networks for each level of target coverage can be found in figures provided in Appendix A.3.

obtained with IRGAS is the same for almost all problems that were solved with CPLEX. The exceptions are 75% coverage for the CARE network extension and 70% coverage for the new network, where the heuristic results in one more site compared to the optimal solutions. Comparison of the IRGAS heuristic with the "By Region" heuristic shows that the IRGAS generates better solutions, especially for high coverage.

Table 3.10: Number of collection centers for the CARE network extension

Coverage	# of Sites			Difference in # of sites	
	CPLEX	IRGAS	By Regions	IRGAS-CPLEX	By Regions-IRGAS
36.39%	102	102	102	0	0
40.00%	107	107	107	0	0
45.00%	118	118	118	0	0
50.00%	136	136	137	0	1
55.00%	161	161	162	0	1
60.00%	194	194	196	0	2
65.00%	236	236	239	0	3
70.00%	292	292	294	0	2
75.00%	366	367	373	1	6
80.00%	465	465	476	0	11
85.00%	-	607	619	-	12
90.00%	-	820	836	-	16
95.00%	-	1,188	1,213	-	25

Table 3.11: Number of collection centers for the new network

Coverage	# of Sites			Difference in # of sites	
	CPLEX	IRGAS	By Regions	IRGAS-CPLEX	By Regions-IRGAS
36.39%	45	45	47	0	2
40.00%	55	55	57	0	2
45.00%	71	71	73	0	2
50.00%	90	90	94	0	4
55.00%	115	115	119	0	4
60.00%	147	147	152	0	5
65.00%	188	188	195	0	7
70.00%	243	244	251	1	7
75.00%	-	318	329	-	11
80.00%	-	419	433	-	14
85.00%	-	561	572	-	11
90.00%	-	780	788	-	8
95.00%	-	1,151	1,160	-	9

Figure 3.10 compares the number of opened sites required to reach different levels of population coverage for both cases, with and without the CARE network. The figure shows that the number of sites in both networks grows exponentially with the desired coverage. For example, an increase of coverage from 40% to 60% requires the number of sites to approximately double for the CARE case and to approximately triple for the network without CARE sites. In contrast, coverage growth from 40% to 95% leads to increase in the number of sites that is about eleven times for the CARE case and almost 21 times for the second case.

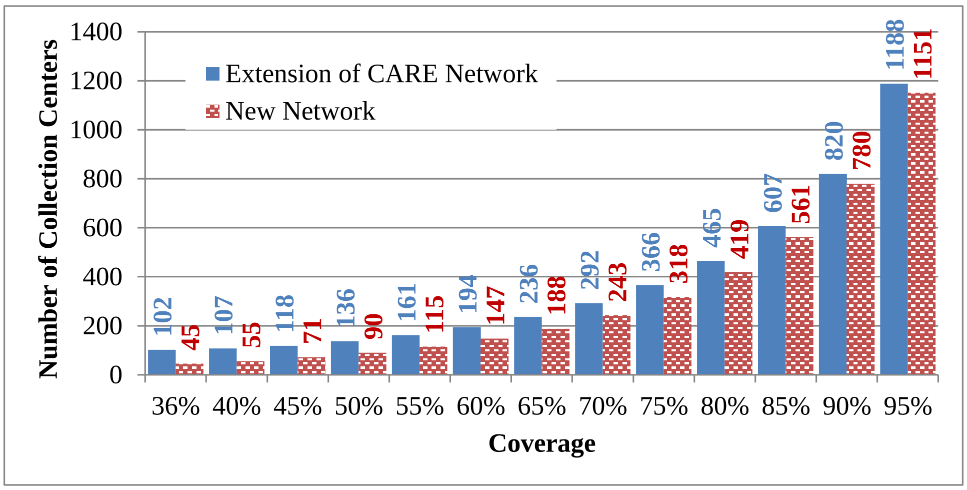

Figure 3.10: Number of collection centers for different levels of population coverage

Figure 3.11 compares locations of collection centers in the current CARE network with the optimal network with the same coverage (36.39%). It can be seen that the optimal network requires only 45 collection centers in contrast to the 102 collection centers in the CARE network. Many collection centers in the CARE network are located close to the corresponding optimal location. The main exception are the southeastern states that have a high number of CARE sites, but only a few sites in the optimal network. This is because most carpet manufacturers are located in the southeastern states, and many carpet mills accept used carpet directly or have collection centers in close proximity. While the relative difference in the number of sites for the network built as an extension of CARE network and the network built from scratch is significant with low desired coverage, this difference diminishes with the growth of the network. For example, for 40% coverage, the number of sites in the amended CARE network is nearly twice the number for the "from scratch" network, but for 80% coverage, this difference is only about 11%.

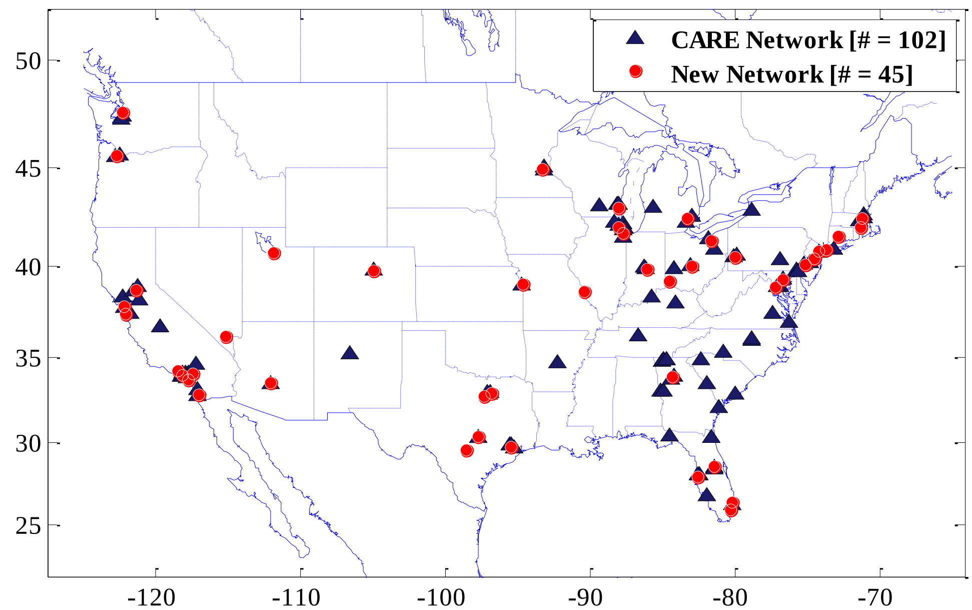

Figure 3.11: Current CARE and optimal collection networks for 36% coverage

On average, a collection center in the current CARE network covers 0.357% of population. To extend the network to 50% coverage, only 24 additional collection centers have to be opened (see Figure 3.12). This extension improves the average coverage per center to 0.368%, because the CARE network is not optimally located and there are regions with high population, but without collection centers. However, a further increase in coverage to 75% requires opening 366 centers as shown in Figure 3.13 or almost triple the number of collection center compared to 50% coverage. This decreases the average coverage per center significantly to 0.205%.

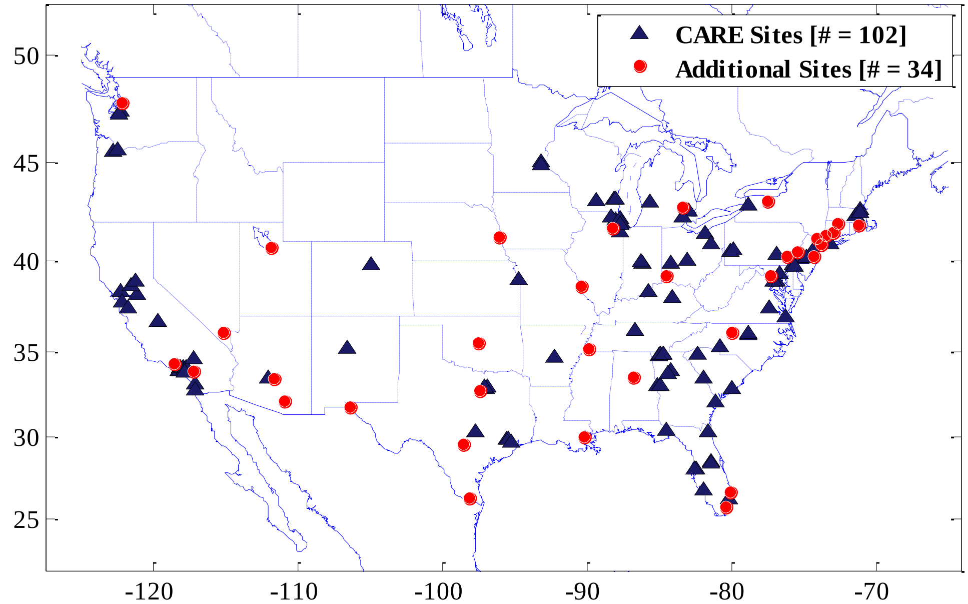

Figure 3.12: CARE network extended to 50% coverage

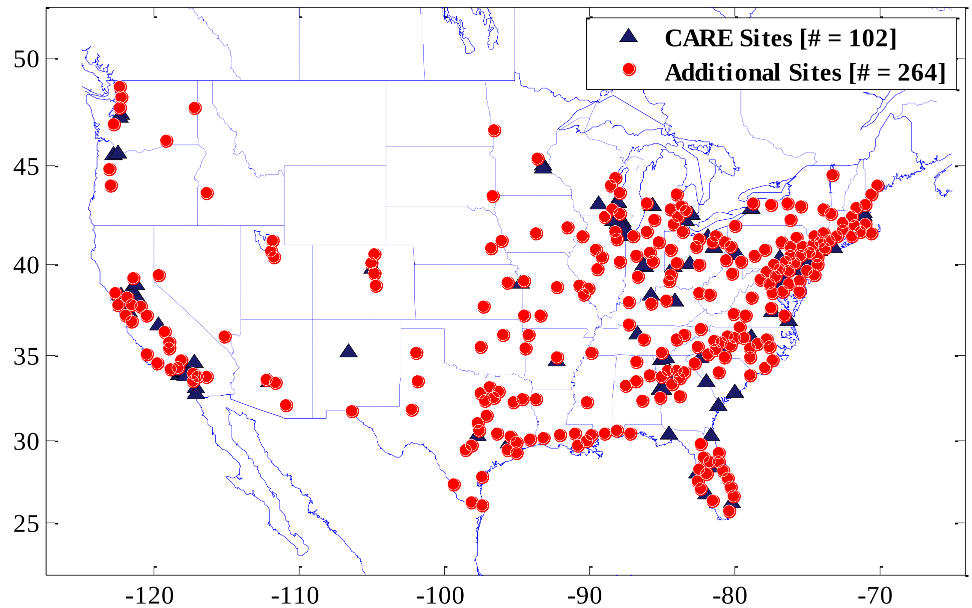

Figure 3.13: CARE network extended to 75% coverage

3.6 Conclusions and Future Research

This chapter presented a procedure to determine where to locate carpet collection centers to achieve a target collection level. This collection network design problem was formulated as a unicost location set covering problem. To solve difficult instances of the problem that cannot be solved exactly with CPLEX, a specialized, randomized greedy heuristic method was developed. The heuristic is designed to work efficiently with large unicost covering problems that have low coverage and overlapping matrix densities. Computational results showed that the heuristic performed better than other greedy heuristics proposed in the literature for similar types of problems.

In the application section, the design of the nationwide carpet collection network in the US was discussed. Two options were considered in the study: one network extended the current CARE network and other network was built from scratch. The minimum required number of sites as well as their locations were identified and compared for both options with a target coverage from 36% to 95%. From this experimentation, it was determined that as the target coverage (collection rate) is increased, the required number of collection centers grows exponentially. This relationship can be used to establish the appropriate target collection rate considering the effort and investment required to build the corresponding collection network.

The results of this chapter can be used in further studies to determine appropriate fees charged by collectors for post-consumer carpet. These fees are required to cover the expenses of the collectors, but they have a significant effect on the collection radius. Lowering collection fees will reduce the collectors' revenue, but at the same time increase the collection radius and as a result, decrease the number of collection centers required to reach a target collection rate. Applying the analysis described in the chapter with different levels of collection fees and comparing the total fees collected with investments required to establish new collection centers allows determining the optimum level of collection fees.

In addition, both the problem formulation and the heuristic can be modified in further studies. Considering the assumptions made during the model development, several recommendations can be given for further extension of this study. The optimization model used in this study assumes that the cost to open any collection center is the same regardless of the exact location of a center and the volume of carpet collected. This model can be extended by including regional differences in space and labor rates and by introducing volume dependent site opening costs (i.e., economies of scale). In this way, the problem can be reformulated as a non-unicost set covering problem with partial coverage, and the solution heuristic should be revised to capture differences in costs. The estimation of the collection radius was done using national average landfilling fees. However, landfilling fees differ significantly among states from as low as $25 to as much as $85 per ton of waste (Haaren, 2010). This can have an effect on the collection radius of sites located in different states. This aspect can be easily incorporated into the modeling by recalculating the corresponding coverage matrix. Finally, the collections sites were allowed to be located in any 5-digit ZIP code. However, the location of collection centers in some ZIP codes may be prohibited due to zoning issues. Therefore, the set of potential locations for collections sites should be revised.

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CHAPTER 4: Logistics of Carpet Recycling in the US – Part II: Recycling Network

Abstract

Transportation of post-consumer carpet from collection points to recycling facilities and then to the end-users of the recycled materials contributes significantly to the final costs of recycled materials. Efficient location of facilities in the reverse supply chain can significantly reduce transportation costs and improve the economics of recycling. In addition, such operations as sorting, baling, and material recovery can be carried out at different stages of the reverse supply chain, which has an influence on the costs of the carpet recycling network. In this chapter, several alternative network designs for nationwide carpet recycling systems are developed and compared in terms of network costs. In two scenarios, these networks include layers of local collection centers, recycling plants, and markets for recycled materials. In the third scenario, a layer of regional collection centers is added before the recycling plants to aggregate carpet for more efficient sorting and transportation. To find the optimal number and locations of recycling plants and regional collection centers as well as the optimal flows among network facilities, a hierarchical facility location model is formulated that can be used for the different network configurations considered. To solve large-scale instances of the problem, a heuristic method based on the alternative location-allocation procedure is developed, and a computational study is conducted to assess its performance. The results of the study can be used by organizations involved in carpet recycling in the US to establish reverse networks. In addition, the optimization model and the solution heuristic can be used for similar problems in forward or reverse logistics.

Keywords

Post-consumer carpet, reverse supply chain, hierarchical facility location, discrete location-allocation heuristic

4.1 Introduction

The high volume of post-consumer carpet that is disposed in the US requires a significant amount of landfill space and leads to the loss of the valuable materials from which carpet is made. Recycling of post-consumer carpet reduces pressure on the landfills and has the potential to direct materials back into production. The majority of carpet sold in the US is broadloom tufted carpet, which has a complex structure and consists of face fibers, primary backing, bonding agents and secondary backing (Wang *et al.*, 2003). These carpet components are usually made from different materials, which make it difficult to separate individual materials in pure form during recycling.

There are several methods to recycle used carpet. Material extraction by mechanical methods involves grinding and separation of components based on density (Wang, 2006). Alternatively, face fibers can be sheared (FCW, 2012) or shaved (Van der Voo, 2011) from carpet. However, due to complex carpet structure and contamination of old carpet, materials obtained with mechanical methods have significantly lower quality compared to virgin materials. The entire carpet can also be shredded without component separation, and the resulting fiber mixture can be used for concrete and soil reinforcement. In addition, molded products, where the quality of the resin in not very important, can be produced from the composite resin obtained by melting all carpet components together. While mechanical recycling and melt-blending can divert some portion of PCC from landfills, the demand for low quality secondary materials produced with these methods or down-cycled products made of these materials is very limited.

In contrast, polymers with virgin-like quality can be recycled from carpet components using depolymerization. Depolymerization is a process aimed to breakdown a polymer into monomers and polymerize it again to produce the same polymer. Due to the high value of nylon and the availability of depolymerization technology, this process is used to recycle nylon fibers from carpet. A detailed discussion of the depolymerization processes for nylon can be found in Mihut *et al.* (2001) and Wang (2003). While both Nylon 6 and Nylon 6,6 can be broken down to monomeric units, depolymerization of the latter one is more complicated, and as of 2006 was not implemented on a commercial scale according to Wang (2006). Full scale recycling of Nylon 6 is carried out at the Evergreen Nylon Recycling facility in Augusta, GA, which is currently owned by Shaw Industries Inc. The recycling of Nylon 6 from PCC back to virgin-like materials is the most preferable option since it recovers materials in the most valuable form, enables their reuse for a long time in a closed-loop manner, and reduces the requirements for virgin materials. However, to make recycled materials competitive with virgin materials, the cost of recycled materials should be kept as low as possible. At the recycling plant level, processing costs can be minimized by building large plants that take advantage of economies of scale. However, such plants require significant capital investments and high volumes of carpet to be collected and transported to them. Therefore, carpet-recycling networks should be carefully designed to minimize transportation costs and capital investments in facilities.

In this chapter, several alternative recycling network configurations for Nylon 6 recovered from post-consumer carpet are discussed and compared in terms of costs. A three-layer collector-recycler-market reverse supply chain is contrasted with a four-layer layout, where an intermediate layer of regional collection centers is used to centralize sorting and baling as well as to aggregate carpet for railroad transportation instead of trucking. In addition, the effect of different collection volumes that enter the reverse supply chain is studied.

The chapter is structured as follows. In Section 4.2, previous studies on network design for carpet recycling are discussed. Then in Section 4.3, definitions of specific scenarios considered in the study and estimations of input information are presented. In the following sections, an optimization model for the reverse carpet supply chains studied is formulated, and a solution algorithm and results of testing it on small networks are presented. Section 4.6 applies the solution algorithm to the proposed configurations of the full-scale carpet-recycling network and analyzes the results. The last section summarizes the chapter and provides direction for future studies.

4.2 Literature Review

Several authors studied the design of reverse networks for post-consumer carpet. Louwers (1999) utilized a quadratic programming model to determine the optimal locations of intermediate preprocessing centers between sources and processors of PCC. The model was applied to carpet recycling in Europe. Post-consumer carpet collected at sources is transported to preprocessing centers where they are sorted and compacted. The recyclable carpet is shipped to processors while the remaining carpet is shipped to landfills or incineration facilities. The problem was formulated as a three-layer supply chain model where locations of facilities at the first and the last layers (sources and processors/disposal sites) are known, and facilities in the intermediate level (regional preprocessing centers) are to be located on a continuous plane. The model objective was minimization of total costs, which included acquisition costs of post-consumer carpet and transportation, storage, preprocessing, and disposal costs. The decision variables were the capacities, the number and locations of preprocessing centers, and the material quantities shipped between facilities. The problem was solved exactly with a sequential quadratic programming method.

Realff *et al.* (1999, 2000a, 2000b, 2004) published a series of papers concerning carpet recycling in the US. In general, the model used for these studies can be described as follows. Post-consumer carpet is collected at predefined locations within the US. The collected volumes at each site are proportional to the population. Reverse logistics tasks include sorting and three types of reprocessing: depolymerization of Nylon 6, depolymerization of both Nylon 6 and Nylon 66, and shoddy production. Two different sets of potential locations for two depolymerization processes are given. Sorting can be set up at any collection or processing site. Both sorting and recycling processes are capacitated and recycling sites can set up a depolymerization process with three different capacities. Carpet collected at processing sites can be sold to another site, converted to secondary materials or disposed.

The model objective was to maximize the net revenue by locating processing sites, selecting sites for sorting operations, defining the transportation modes, and the volumes of carpet shipped. Revenue is generated from sales of recycled materials, and costs include fixed costs (i.e., site opening cost and costs to set up storage, collection, transportation and/or recycling capabilities at a site), variable costs (i.e., volume dependent costs to collect, store and process post-consumer carpet) and transportation costs. The problems in these studies were solved using a commercial mixed-integer programming software.

Recently Woolard (2009) studied a large scale carpet recycling network in the US. The network consisted of two layers: 400 collection centers located in the most populous 3-digit ZIP codes and recycling centers that can be located at any 3-digit ZIP code. The model objective was a cost minimization, which included fixed costs to open recycling centers, transportation costs from collection to recycling centers and recycling costs. The latter was modeled to be volume dependent. The model was solved using a meta-heuristic developed by Bucci (2009) that allows optimizing large network design problems with economies of scale.

Woolard (2009) considered only a two-layer recycling network with known collection centers locations and optimized the locations of the recycling plants. Louwers (1999) discussed a three-layer network. The optimization located facilities at the middle layer only and assumed the locations of the collection centers and recycling plant were known. Realff *et al.* (Realff, 1999, 2000a, 2000b, 2004) utilized a more complex model that simultaneously located two types of recycling facilities as well as assigned sorting and shredding capabilities to facilities in the network. However, the problems studied in these papers were relatively small in terms of the number of potential facility locations and the number of collection sites.

There are many publications in the literature concerning the reverse network design problems for other post-consumer products. Reviews of these studies can be found in Fleischmann (2001), Jayaraman *et al.* (2003), and Akçali *et al.* (2009). Many different models are proposed that consider reverse flows of products only or integrate forward and reverse supply chains, locate up to four types of facilities simultaneously, account for different types of fixed and variable costs, as well as, different problem specific assumptions (e.g., multi-period optimization, stochastic supply of used products, multiple products).

Wang *et al.* (1995) studied the three layer reverse supply chain for paper recycling. The purpose was to minimize the total network cost by opening processing centers among 20 potential locations that accept used paper from 90 suppliers and ship recycled paper to nine markets. A similar study was conducted by Schultmann *et al.* (2003) for the case of battery recycling. There were 450 sources of old batteries and 29 treatment facilities. An objective of the optimization model used in the study was to locate sorting facilities at some sources to minimize the total network cost. Both problems were solved with commercial MILP-solvers.

Simultaneous location of several layers of reverse facilities was considered by Barros *et al.* (1998) for the case of sand recycling. A layer of sorting facilities supplies contaminated sand to treatment facilities through regional depots, and treatment facilities ship recycled sand to construction projects. Locations of 33 sorting facilities and 10 construction projects were known, and locations of regional depots and treatment facilities had to be selected among 86 and 21 potential locations, respectively. The problem was formulated as a multi-stage supply chain model and solved with a heuristic based on the LP-relaxation of integer constraints. Jayaraman (2003) studied a reverse network for refurbishing returned products. The problem consisted of returned product origination sites (100 known locations), potential locations for collection sites (40 locations) and refurbishing sites (30 locations). The heuristic concentration was used to find the numbers and locations of collection and refurbishing sites that minimize the total network cost.

Examples of closed-loop networks designs include the work of Fleischmann (2001) that used a commercial MIPL-solver to simultaneously locate manufacturing plants (20 potential locations), warehouses and disassembly centers (50 potential locations for each layer) that distribute new products and receive used products for remanufacturing from 50 customer zones. Similar problems with comparable sizes were also considered by Sim *et al.* (2004) (solved with Genetic algorithms based on the LP relaxation of integer constraints), Salema *et al.* (2006) (MILP-solver), and Lu *et al.* (2007) (Lagrangian heuristic).

In contrast to previous studies for carpet recycling, this chapter considers the simultaneous location of facilities at several layers of the carpet reverse network and includes the final consumers of recycled materials to model the closed-loop supply chain. Several network configurations are studied, and their effect on the cost of recycled Nylon 6 is quantified. In addition, problems considered in this study are significantly larger (i.e., more than 1000 supply points of used carpet and more that 2000 potential locations for regional collection centers and recycling plants) than problems in the literature.

4.3 Definition of Scenarios and Input Information

The analysis conducted in this chapter is focused on the reverse supply chain for recycling Nylon 6 from post-consumer carpet. Four types of facilities, organized in layers are considered in the study: local collection centers (LCC), regional collection centers (RCC), recycling plants (RP), and markets (M) for recycled Nylon 6. The reverse activities considered during modeling include sorting, baling, and transportation of post-consumer carpet collected, as well as recovery of Nylon 6 and delivery of recycled Nylon 6 to final customers. Several alternative recycling network configurations are studied. The configurations differ by the number of layers used and the reverse activities performed at each layer. These designs are compared in terms of annual costs required to run the corresponding network. At the beginning of this section, the input parameters common for all scenarios are defined. Later they are combined to produce scenario specific inputs.

The first set of inputs is the weight of carpet/materials that flow through the network. These values are summarized in Table 4.1. The weight of post-consumer carpet that enters the recycling network (collected weight) is defined by the total annual weight of PCC generated by the end-users, population coverage of the collection network and its collection efficiency. It is assumed that collection centers accept all types of carpet, but only carpet with Nylon 6 face fibers are shipped to the next stage after sorting (i.e., sorting yield). Similarly, only recycled Nylon 6 is shipped to markets from recycling plants, and its weight is equal to the weight of face fibers in the total carpet weight (i.e., recycling yield).

Table 4.1: PCC flow parameters in the reverse supply chain

Parameter	Value
Annual weight of PCC generated	3 million tons[1]
Collection efficiency	15.43%[2]
Collection network population coverage	36.39%[3]-95%
Annual collected weight of PCC	0.17-0.44 million tons
Sorting yield (share of Nylon 6 carpet in PCC collected)	36%[4]
Recycling yield (share of Nylon 6 face fibers in Nylon 6 carpet)	35%[5]

[1] Weight of PCC generated in 2010 (CARE, 2011a)
[2] The collection efficiency of the CARE network in 2010 (see Chapter 3 for details)
[3] The current coverage of CARE collection network in 2010 (see Chapter 3 for details)
[4] Estimated based on carpet collected in 2010 (CARE, 2011a)
[5] Obtained from CARE (2011b)

The total annual cost of any scenario is composed of the transportation costs of post-consumer carpet and recycled materials and the fixed annual cost of operating reverse facilities. The transportation costs are calculated based on shipment weights, delivery distances, and corresponding rates per ton-mile of the transportation mode used (i.e. full truckloads or intermodal deliveries). All distances in this study are estimated as great-circle distances adjusted by circuity factors to convert them to actual road distances. The circuity factors as well as transportation rates are summarized in Table 4.2.

Table 4.2: Transportation cost parameters

Parameter	**Value**
Circuity factors[1]:	
- truck shipments	1.21
- intermodal shipments	1.25
Transportation rates ($/ton-mile):	
- truck shipments (loose carpet)	$0.103
- truck shipments (baled carpet)	$0.093
- intermodal shipments	$0.040

[1] Obtained from Kay & Warsing (2009)

Two types of transportation modes, full truckloads and full rail boxcars, are used in this study depending on the scenario considered. Since LCCs collect a relatively low weight of carpet, it is assumed that all shipments for LCCs are made using full truckloads. In contrast, regional collection centers and recycling plants process significantly larger weights of carpet. Therefore, it is assumed that all shipments from these facilities use intermodal transportation, where trucks are used to deliver materials to (from) railroad stations and railroad is used to transport them for long distances. It is assumed that in 5% of the delivery distance a truck is used, and the remaining part is railroad, as was found in Zhang *et al.* (2004).

It was assumed that the transportation costs are equal throughout the US, and national average costs per ton-mile for the corresponding transportation modes are used. For road transportation, it was assumed that PCC is shipped in a standard forty-eight foot semi-trailer with dimensions of 570 x 98.5 x 108 inches (Woolard, 2009). The maximum payload weight of a trailer is 50,000 lbs. (25 tons) (Kay, 2009). Realff (2006) estimated that the typical dimension of a PCC bale is 60 x 32 x 48 inches, which results in a volume of 53.3 ft^3. The weights of such a bale depend on the baling equipment used and are 1100 lbs. for vertical baling and 1200 lbs. for horizontal baling. Using these numbers, the average density of the two types of bales are estimated to be $\rho_V = 20.6$ lbs/ft^3 and $\rho_H = 22.5$ lbs/ft^3. Realff (2006) also mentioned that the capacity of a truck for loose (not baled) carpet is 25,000 lbs. and for baled carpet is 40,000 lbs. Assuming that baled carpet is from a vertical baler, the density of loose carpet is $\rho_L = 12.9$ lbs/ft^3. Based on the weight (W_{cap}) and cube (V_{cap}) capacities of the trailer and estimated densities, the maximum weight of carpet in tons that can fit into a forty-eight foot semi-trailer can be estimated from the Equation (4.1) (Kay, 2009) and is equal to 25 tons for baled carpet and 22.6 tons for loose carpet.

$$w_{max} = \min\left\{W_{cap}, \frac{\rho V_{cap}}{2000}\right\} \tag{4.1}$$

Kay & Warsing (2009) estimated that the average transportation rate per loaded-truck-mile was \$2 in 2004. Adjusting this value by the TL Producer Price Index (Bureau of Labor Statistics, 2012b) (Series ID=PCU4841214841212), the average transportation rate per loaded-truck-mile in 2011 was \$2.34. Transportation of baled and loose carpet was estimated to cost 9.347¢ and 10.332¢, respectively, per ton-mile by dividing the loaded-truck-mile rate by the corresponding weight capacities of a truck.

An estimate of the average rail carload rate per ton-mile was made based on the total revenue and total ton-miles transported by railroad intercity freight traffic. In 2003, the revenue from this freight service in the US was \$36.6 billion, and in the same year, about 1.6 trillion ton-miles were carried (The US Congressional Budget Office, 2006). By dividing the freight revenue by the total ton-miles, an average rate of 2.288¢ per ton-mile in 2003 was obtained. This value was adjusted by the Producer Price Index for carload freight transportation (Bureau of Labor Statistics, 2012b) (Series ID=PCU4821114821111), and in 2011, it was equal to 3.662¢. Using the per ton-mile rates for baled carpet transportation by trucks and railroad, and the proportion of trucking to rail distances traveled of 5% to 95%, the transportation rate of intermodal transportation was estimated as 3.952¢ per ton-mile.

The fixed annual costs of opening a facility at any potential location was assumed to be independent of the exact location, but depends on the activities performed at this facility, its capacity and the equipment required. The fixed costs consist of the annualized purchase cost of the equipment and/or the construction cost of the recycling plant, as well as the annual cost of space and labor required. Two types of sorting and baling equipment (i.e., small-capacity and large-capacity) were considered in the study. The Evergreen Recycling Facility was used as a model for recycling plants. Capacities and costs of sorters, balers and the recycling plant are shown in Table 4.3.

Table 4.3: Plant and equipment capacities and costs

	Annual capacity [Tons]	**Total cost**	**Assumed life-time [years]**	**Annualized cost[4]**
Manual sorter1	3,500	$80,000	7	$15,736
Automated sorter1	14,000	$150,000	7	$29,504
Vertical baler1	1,850	$10,000	7	$1,967
Horizontal baler1	15,200	$300,000	7	$59,008
Recycling plant	50,000[2]	$120,000,000[3]	30	$11,370,913

[1] Data obtained from Realff (2006)
[2] Capacity of Evergreen Nylon Recycling plant (Delozier, 2006),
[3] Total construction cost of Evergreen Nylon Recycling plant (Peoples, 2006)
[4] Based on capital recovery factor with cost of capital of 8.7% (an average value for chemical industry at the beginning of 2012 (Damodaran, 2012))

The annual cost of labor for each type of equipment and recycling plant was estimated based on the number of employees (operators) required, annual hours paid per employee and the hourly labor rate adjusted by the indirect payroll cost. Annual cost of space was estimated based on the area required to process one million pounds of PCC and an average annual rate of renting manufacturing space. The cost of space at LCCs with sorting equipment is calculated proportionally to the weight of carpet collected. For other facilities, it is calculated proportionally to capacities. This information is summarized in Table 4.4.

Table 4.4: Labor and space cost parameters

Parameter	Value
Labor cost	
Number of employees required[1]:	
- manual sorter	1
- automated sorter	2
- vertical baler	1
- horizontal baler	1
- recycling plant	60
Annual hours paid per employee[2]	2,080 hrs. per year
Adjusted hourly labor rate[3]	$23.27 per hr.
Space cost	
Space required per million pounds of PCC[4]	1,000 sq. ft.
Average annual rental rate[5]	$4.71 per sq. ft.

[1] Labor requirements for balers and sorters were obtained from Realff (2006) and the number of employees at Evergreen Nylon Recycling plant was obtained from Emerson (2009)
[2] 8 hours per day, 5 days per week, 52 weeks per year
[3] An hourly labor rate of $16.05 for Waste Collection industry in May 2011 (Bureau of Labor Statistics, 2012a) adjusted by indirect payroll cost of 45% (Humphreys, 2004)
[4] Rough estimation based on information from Realff (2006)
[5] An average annual rental rate of manufacturing space in 2011 (Cushman & Wakefield, 2011)

The last set of inputs required are the locations of fixed facilities (LCCs and markets) and potential locations for RCCs and recycling plants. Locations and weights of carpet collected at local collection centers are obtained from Chapter 3, where carpet collection networks for different levels of population coverage were constructed. Three markets for recycled Nylon 6 shown in Figure 4.1, as well as their relative demands were defined based on the biggest carpet production clusters in the US and their weights in the total carpet production. To define the markets, it was assumed that recycled Nylon 6 is used in closed-loop production by carpet manufacturers. According to the industry report for carpet mills in the US (IBISWorld, 2011), there were three regions in 2011 in the US where 95.7% of carpet by value was produced. This included the southeastern United States (i.e., GA, AL, SC, NC, and TN) (86.2%), California (5.7%), and Pennsylvania (3.8%). Locations of carpet mills in these regions were obtained from the U.S. Census Bureau database (U.S. Census Bureau, 2010). The weight of each mill in the total demand for recycled Nylon 6 was set in proportion to the number of employees as a proxy for production size. Based on this information, three market locations were defined as centroids of carpet mills in each region. Relative market demands for recycled Nylon 6 were set proportionally to region weights in the total carpet production.

It was assumed that regional collection centers and recycling plants could be located at the population centroids of three-digit ZIP codes within the continental US, at local collection centers and markets. In addition, the Evergreen Nylon Recycling plant was explicitly included into the solutions of all problems by fixing one recycling plant at the population centroid of the corresponding 5-digit zip code (i.e., Augusta, GA 30901).

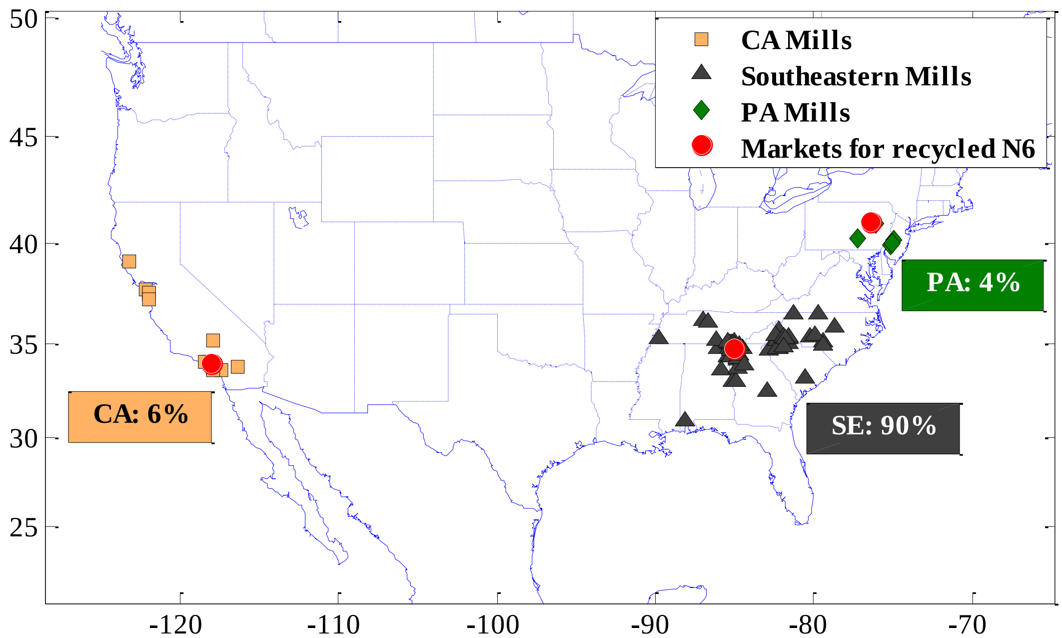


Figure 4.1: Locations of markets and relative demand for recycled Nylon 6

Three alternative recycling network configurations as well as corresponding input parameters are defined below. In all scenarios, the objective is to find the optimum number and locations of regional collection centers and/or recycling plants, and weights of carpet/materials shipped between facilities at different layers to minimize the total cost of the network. Scenarios do not include all possible costs of reverse activities, but they are used to compare the costs of different network designs. Therefore, costs that are common to all scenarios and are not relevant to the location and allocation decision are not considered. This includes collection costs, disposal costs, and variable costs of sorting, baling and recycling.

4.3.1 Scenario 1

The first scenario assumes that there are only two types of reverse facilities in the network: local collection centers and recycling plants. Collection centers do not perform any preprocessing and ship all of the carpet that is collected to recycling plants. Since each local collection center aggregates a relatively low weight of carpet, it is assumed that carpet is shipped to recycling plants in trucks. Since recycling plants receive all types of carpet and Nylon 6 carpet has to be separated from other types before recycling, the recycling plants have high-capacity sorting equipment in addition to recycling equipment. Recycled Nylon 6 is recovered from Nylon 6 face-fibers, and other types of carpet and recycling by-products are disposed. Recycled Nylon 6 is delivered to final consumers using intermodal transportation (truck + railroad). This scenario is shown in Figure 4.2.

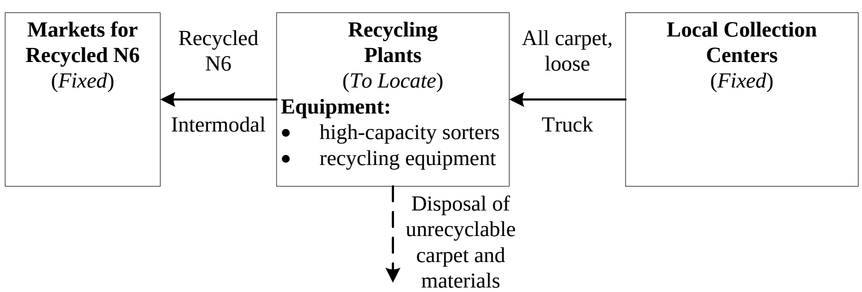


Figure 4.2: Two-tier recycling network with markets (late sorting)

The plant recycling equipment can process 50,000 tons of Nylon 6 PCC per year. To obtain such a volume of Nylon 6 PCC, the plant has to sort about 139,000 tons of all carpet, which requires 10 automated sorters to be installed, 20 additional operators and about 280,000 square feet of additional space. In this scenario, local collection centers do not have any sorting or baling equipment. The estimation of fixed costs for the first scenario is summarized in Table 4.5. Note that the number of operators, space requirements and the total annual cost of LCCs are zero because in this scenario LCCs perform collection only. Since the cost of collection is not relevant for comparison of scenarios, it is not considered.

Table 4.5: Estimation of cost parameters for the first scenario

	LCC	RP
Equipment	-	10 Automated Sorters 1 Recycling Plant
Capacity	-	138,889 tons
Yield	100.0%	12.6%[1]
Operators for Sorting/Baling and/or Recycling	0	80[2]
Space for Sorting/Baling	0 sq. ft.	277,778 sq. ft.
Total Annual Cost	$ 0	$16,846,833
Transportation Cost per ton-mile	$0.103	$0.040

[1] Sorting yield times recycling yield (36%*35%)
[2] 60 operators for recycling plant and 20 operators for sorting equipment

4.3.2 Scenario 2

The network in the second scenario also has two types of reverse facilities (LCCs and recycling plants), but in this case, local collection centers perform carpet sorting and baling. Baled Nylon 6 carpet is sent to recycling plants in trucks and the remaining unrecyclable fraction of carpet is disposed locally. In this case, recycling plants receive Nylon 6 carpet only. The second scenario is depicted in Figure 4.3.

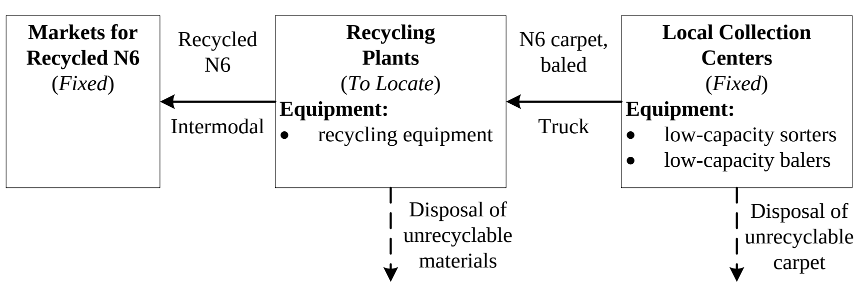


Figure 4.3: Two-tier recycling network with markets (early sorting and baling)

In this scenario, there is no need for sorting equipment at recycling plants. However, each local collection center is equipped with manual sorters and vertical balers. The exact numbers of these machines are defined by the annual weight of PCC collected at a local collection center, which was defined based on the collection network optimization in the first part of the series. If a LCC collects less than 3,500 tons of carpet per year, it requires 1 sorter and 1 baler, 2 operators and 7,000 square feet of space. The estimation of fixed costs for the second scenario is summarized in Table 4.6.

Table 4.6: Estimation of fixed cost for the second scenario

	LCC[1]	**RP**
Equipment	1 Manual Sorter 1 Vertical Baler	1 Recycling Plant
Capacity	3,500 tons	50,000 tons
Yield	36.0%	35.0%
Operators for Sorting/Baling and/or Recycling	2	60
Space for Sorting/Baling	7,000 sq. ft.	0 sq. ft.
Total Annual Cost	$147,486	$14,275,321
Transportation Cost per ton-mile	$0.093	$0.040

[1] For LCC with annual collection of 3,500 tons (capacity of one manual sorter)

4.3.3 Scenario 3

In contrast to the previous two scenarios, the third scenario assumes that there is an additional intermediate layer of regional collection centers in the reverse supply chain. The main function of regional collection centers is to centralize sorting and baling and to aggregate enough Nylon 6 carpet to utilize intermodal transportation instead of trucking. In this scenario, all carpet is shipped in full truckloads from the local collection centers to the regional collectors that have high-capacity sorting and baling equipment. Then sorted and baled Nylon 6 carpet is shipped to recycling plants via intermodal transportation, and the unrecyclable fraction is disposed. Carpet cannot be shipped directly to the recycling plants from the local collection center, since recycling plants do not have sorting equipment. Figure 4.4 shows this design option.

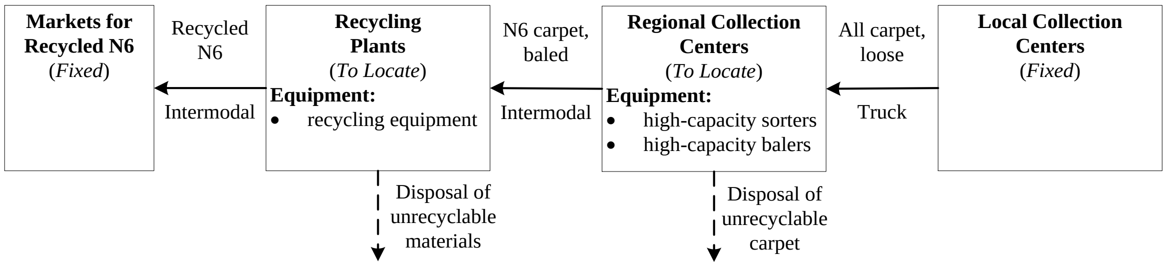


Figure 4.4: Three-tier recycling network with markets (intermediate sorting and baling)

In this case, local collection centers do not require any equipment, as in the first scenario, and the recycling plant does not require any sorters as in the second scenario. However, each regional collection center is equipped with one horizontal baler that can bale 15,000 tons of Nylon 6 carpet. To support this capacity, regional collection centers have to sort about 42,000 tons of all carpet, which requires three automated sorters. This results in seven operators employed at each RCC and about 83,000 square feet of space required. The estimation of fixed costs for the third scenario is summarized in Table 4.7.

Table 4.7: Estimation of fixed cost for the third scenario

	LCC	RCC	RP
Equipment	-	3 Automated Sorters 1 Horizontal Baler	1 Recycling Plant
Capacity	-	41,667 tons	50,000 tons
Yield	100.0%	36.0%	35.0%
Operators for Sorting/Baling and/or Recycling	0	7	60
Space for Sorting/Baling	0 sq. ft.	83,334 sq. ft.	0 sq. ft.
Total Annual Cost	$ 0	$878,872	$14,275,321
Transportation Cost per ton-mile	$0.103	$0.040	$0.040

4.4 Formulation of Optimization Model

In general, optimization models for all three scenarios can be formulated as hierarchical capacitated facility location models using mixed-integer linear programming. Since the third scenario has four layers and is the most complex, the mathematical formulation of the optimization model and solution heuristic discussed below are based on this scenario. Optimization models for the first two cases can be obtained by removing unnecessary variables and constraints from the model and by altering model parameters. The notation used in the model formulation is summarized in Table 4.8. In the table, superscripts indicate layers, and parameters with superscripts are common to all facilities at this layer. Subscripts indicate location specific parameters or variables.

Table 4.8: Recycling network model formulation notation

Sets and Indices	
$\mathcal{L}, \mathcal{M}$	sets of known locations of local collection centers and markets for recycled Nylon 6
$\mathcal{R}, \mathcal{P}$	sets of candidate locations for regional collection centers and recycling plants
$\ell = \{1, \dots, \lvert\mathcal{L}\rvert\}$ $r = \{1, \dots, \lvert\mathcal{R}\rvert\}$ $p = \{1, \dots, \lvert\mathcal{P}\rvert\}$ $m = \{1, \dots, \lvert\mathcal{M}\rvert\}$	corresponding indices of LCCs, RCCs, RPs and markets, respectively
Parameters	
w_ℓ, w_m	weight of post-consumer carpet collected at the local collection center ℓ and weight of recycled Nylon 6 demanded by the market m
$c^{(\mathcal{R})}, c^{(\mathcal{P})}$	inbound capacities of regional collection centers and recycling plants, correspondingly
$\varphi^{(\mathcal{L})}, \varphi^{(\mathcal{R})}, \varphi^{(\mathcal{P})}$	processing yields of local collection centers, regional collection centers and recycling plants, correspondingly (i.e., percentage of received weight that is shipped to the next layer for further processing)
f_ℓ, f_r, f_p	annual fixed costs to operate local collection center, regional collection center and recycling plant at corresponding locations
$T_{\ell r}, T_{rp}, T_{pm}$	costs to transport a ton of material between facilities at different layers
M	large number (e.g., equal to $\sum_{\ell}^{\lvert\mathcal{L}\rvert} w_\ell$)
Decision variables	
$y_r, y_p \in \{0,1\}$	1 if a regional collection center (recycling plant) is opened at the potential location r (p), 0 otherwise
$Q_{\ell r}, Q_{rp}, Q_{pm} \geq 0$	weight of materials shipped between facilities at different layers

Using the notation defined, the optimization model is formulated as follows:

$$\sum_{\ell=1}^{|\mathcal{L}|} f_\ell + \min\left[\sum_{r=1}^{|\mathcal{R}|} f_r y_r + \sum_{p=1}^{|\mathcal{P}|} f_p y_p + \sum_{\ell=1}^{|\mathcal{L}|}\sum_{r=1}^{|\mathcal{R}|} T_{\ell r} Q_{\ell r} + \sum_{r=1}^{|\mathcal{R}|}\sum_{p=1}^{|\mathcal{P}|} T_{rp} Q_{rp} + \sum_{p=1}^{|\mathcal{P}|}\sum_{m=1}^{|\mathcal{M}|} T_{pm} Q_{pm}\right] \tag{4.2}$$

$$\textbf{\textit{s.t.}}\ Q_{\ell r} \le M y_r, \forall \ell, r \tag{4.3}$$

$$Q_{rp} \le M y_r, \forall r, p \tag{4.4}$$

$$Q_{rp} \le M y_p, \forall r, p \tag{4.5}$$

$$Q_{pm} \le M y_p, \forall p, m \tag{4.6}$$

$$\varphi^{(\mathcal{L})} w_\ell = \sum_{r=1}^{|\mathcal{R}|} Q_{\ell r}, \forall \ell \tag{4.7}$$

$$\varphi^{(\mathcal{R})} \sum_{\ell=1}^{|\mathcal{L}|} Q_{\ell r} = \sum_{p=1}^{|\mathcal{P}|} Q_{rp}, \forall r \tag{4.8}$$

$$\varphi^{(\mathcal{P})} \sum_{\ell=1}^{|\mathcal{L}|} Q_{rp} = \sum_{m=1}^{|\mathcal{M}|} Q_{pm}, \forall p \tag{4.9}$$

$$\sum_{p=1}^{|\mathcal{P}|} Q_{pm} = w_m, \forall m \tag{4.10}$$

$$\sum_{\ell=1}^{|\mathcal{L}|} Q_{\ell r} \le c^{(\mathcal{R})} y_r, \forall r \tag{4.11}$$

$$\sum_{r=1}^{|\mathcal{R}|} Q_{rp} \le c^{(\mathcal{P})} y_p, \forall p \tag{4.12}$$

$$y_r, y_p \in \{0,1\} \tag{4.13}$$

$$Q_{\ell r}, Q_{rp}, Q_{pm} \ge 0 \tag{4.14}$$

The objective function shown in Equation (4.2) consists of two parts. The first part is the annual cost of equipment installed at local collection centers. This term does not have any effect on and does not depend on the optimization decisions, but is included into the model to make different scenarios comparable. This term is equal to zero for the first and third scenarios, which assume that there is no sorting and baling equipment at local collection centers, and is equal to the total annualized cost of low-capacity sorting and baling equipment installed in the local collection centers in the second scenario. The equipment required by each local collection center can be defined based on the carpet weight collected (w_ℓ) and annual capacities of sorters and balers installed. The second part of the objective function is the sum of the fixed costs of regional collection centers and recycling plants and the sum of the costs required to ship carpet and recycled materials between facilities.

The decision variables of the objective function are subject to constraints (4.3)-(4.14). Constraints (4.3)-(4.6) prohibit flow to and from RCCs and RPs that are not opened. Constraints (4.7)-(4.10) balance material flow between facilities, taking into account processing yields. Constraints (4.11)-(4.12) are capacity constraints on the RCCs and RPs. Finally, equations (4.13)-(4.14) restrict the possible values of the decision variables.

4.5 Solution Heuristic and Computational Results

The model defined in the previous section is a discrete hierarchical facility location problem with capacity constraints. The problem is an extension of the classical capacitated facility location problem which is known to be NP-hard (Mirchandani *et al.*, 1990). Therefore, the carpet recycling network problem is also NP-hard and while small instances of the problem can be solved with exact methods, large instances require significant computational time or resources. As will be discussed later in this section, CPLEX was able to solve the problems with 60 potential locations for facilities at the second and third layers of the recycling network. For higher numbers of potential locations, CPLEX issues the “Out of Memory” error after about four hours of computation time. Since the number of potential locations in the full-scale problems is significantly larger (from 1000 to 2100), a heuristic is necessary to provide a solution to these problems.

4.5.1 Solution Approaches in the Literature

Hierarchical locations of facilities have been studied by many authors. Reviews of hierarchical location models can be found in Narula (1986), Serra *et al.* (1994), Sahin *et al.* (2007), and Bastani (2009). A review of network design problems for reverse logistics, most of which are hierarchical, can be found in Akçali (2009). Many solution approaches proposed in the literature include exact algorithms using Branch and Bound procedure (Kaufman *et al.*, 1977; Ro *et al.*, 1984; Tcha *et al.*, 1984; Gao *et al.*, 1992, 1994; Barros, 1998; Hindi *et al.*, 1998; Tragantalerngsak *et al.*, 2000) or Lagrangian relaxation based algorithms (Pirkul *et al.*, 1996, 1998; Tragantalerngsak *et al.*, 1997; Marín *et al.*, 1999; Lu, 2007; Litvinchev *et al.*, 2012). Heuristic approaches are mostly based on the Interchange improvement procedures initially proposed by Teitz & Bart (1968) for the p-median problem. The Interchange procedure is used in combination with Add/Drop heuristics (Scott, 1971; Bloemhof-Ruwaard *et al.*, 1994; Yeh, 2004; Berman *et al.*, 2005) or as a sub-routine in meta-heuristics, like GRASP (Montoya-Torres *et al.*, 2010), Tabu Search (Berman, 2005; Ignacio *et al.*, 2008), Simulated Annealing (Berman, 2005) and Genetic Algorithms (Yeh, 2005).

In the Interchange heuristic, facilities in the current solution are moved one by one to other locations when such movements improve the objective function (Mladenović *et al.*, 2007). This procedure requires the constant evaluation of the benefits from each move. For conventional p-median problems many efficient implementations of this procedure have been proposed (Mladenović, 2007). However, in the context of hierarchical networks, estimation of benefits from a facility movement on any layer is more complex since it may affect transportation patterns on all layers. Therefore, evaluation of each move requires solving a transportation problem (often formulated as a LP model) (Scott, 1971; Yeh, 2004, 2005; Montoya-Torres, 2010) or estimation of savings by considering all possible paths in the network (Bloemhof-Ruwaard, 1994; Berman, 2005; Ignacio, 2008). Owing to the large size of the recycling network problems considered in this study, the use of the Interchange procedure would be too time consuming (i.e., solving the transportation problem for each move with about 2000 potential locations of facilities for two layers) or resource consuming (i.e., storing and updating costs, flows and available capacities for each of about sixteen billion possible paths). Therefore, the heuristic used in this study is based on another classical improvement routine for p-median problems proposed by Maranzana (1964), the Alternative Location-Allocation (ALA) heuristic for discrete problems (ReVelle *et al.*, 2005).

In the ALA procedure, the location of facilities and allocation of customers are separated into two different steps. The procedure starts with some initial feasible solution that defines the locations of *p* facilities. Customers are allocated to opened facilities to minimize transportation costs (e.g., by solving transportation problem if facilities are capacitated). Customers allocated to each facility become its neighborhood. After allocation, the 1-median problem is solved for each opened facility considering its neighborhood. Each facility is relocated to the optimal 1-median location resulting in the new solution, which is used again to allocate customers. This location-allocation cycle is repeated until there are no further changes in the locations of the facilities or the allocation of customers (Current *et al.*, 2002). In contrast to the Interchange heuristic, relocation of facilities in the ALA procedure does not require solving transportation problem after each move and it is solved only once per cycle after re-location of all facilities is made.

To solve fixed charge location problems, which determine the optimum number of facilities in addition to their locations, the ALA procedure is applied several times with different numbers of opened facilities, and the solution with minimum cost is selected as the best. In addition, since the objective function of the location-allocation problems may have many local minima, the ALA procedure is usually applied several times with different initial facility locations, and the best solution found is recorded (Houck *et al.*, 1996).

4.5.2 Multi-Start Hierarchical Alternative Location-Allocation Heuristic

The ALA procedure for the p-median problem was adapted and used as an improvement step in the heuristic for the hierarchical facility location problems. The general procedure of the hierarchical ALA heuristic (HALA) is depicted in Figure 4.5. For a given set of opened RCCs and RPs, the allocation of facilities at all layers is optimized by solving the hierarchical transportation problem. Re-location of facilities is done layer by layer. First, regional collection centers are re-located assuming that recycling plants are fixed, and then recycling plants are re-located assuming that regional collection centers are fixed. This layer-by-layer re-location is run repeatedly until there are no further changes in plant locations. The neighborhood of any facility opened includes facilities that are connected to it at both lower and upper layers (i.e., 1-median problem for each facility is solved to minimize sum of both inbound and outbound transportation costs). If for some layer, two (or more) facilities were re-located to the same location, the facility with the lower increase in cost between its best and second best locations is moved to its second best location. If the re-location step results in the movement of any facility to another location, the allocation-location cycle is run again. Otherwise improvement stops.

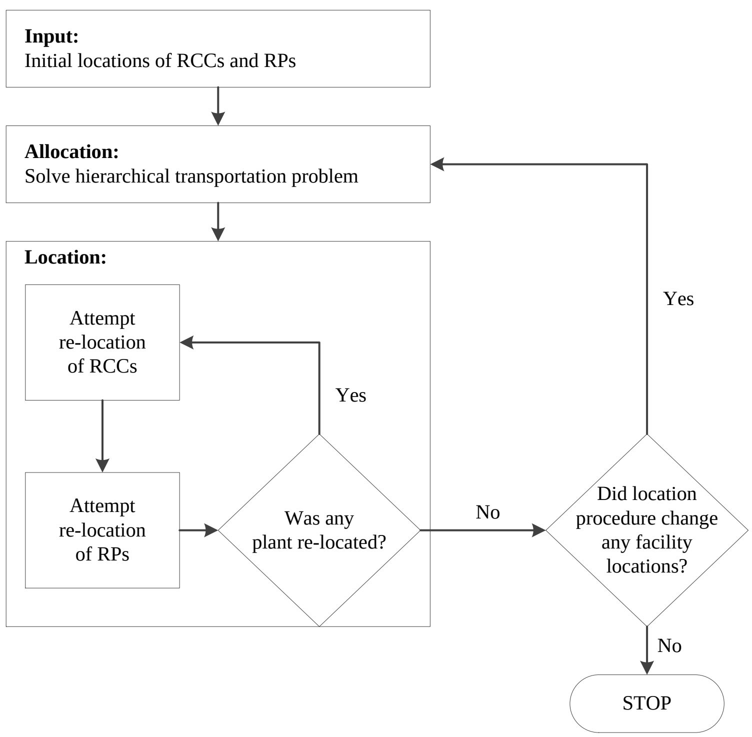


Figure 4.5: Hierarchical ALA improvement procedure

To find the optimum number of facilities to open at each layer, the improvement heuristic is combined with randomized add and drop steps (RAD+HALA). Figure 4.6 depicts the general procedure of this heuristic. The heuristic runs in two loops. The first loop adds regional collection centers to the current solution one by one, keeping the number of opened recycling plants constant and runs HALA to improve the solution after each add. This loop stops when no further cost reduction can be gained from opening additional RCCs. The second loop takes the best solution from the first loop, randomly closes RCCs leaving the minimum required number opened, randomly opens an additional recycling plant, and passes this solution to the first loop. The second loop stops if no further cost reduction can be obtained by opening additional plants. The heuristic starts by randomly opening the minimum required number of facilities at each layer to satisfy capacity constraints. The lower bound on the number of facilities opened at any layer is a rounded up ratio of the inbound flow of the layer to the capacity of one facility at this layer.

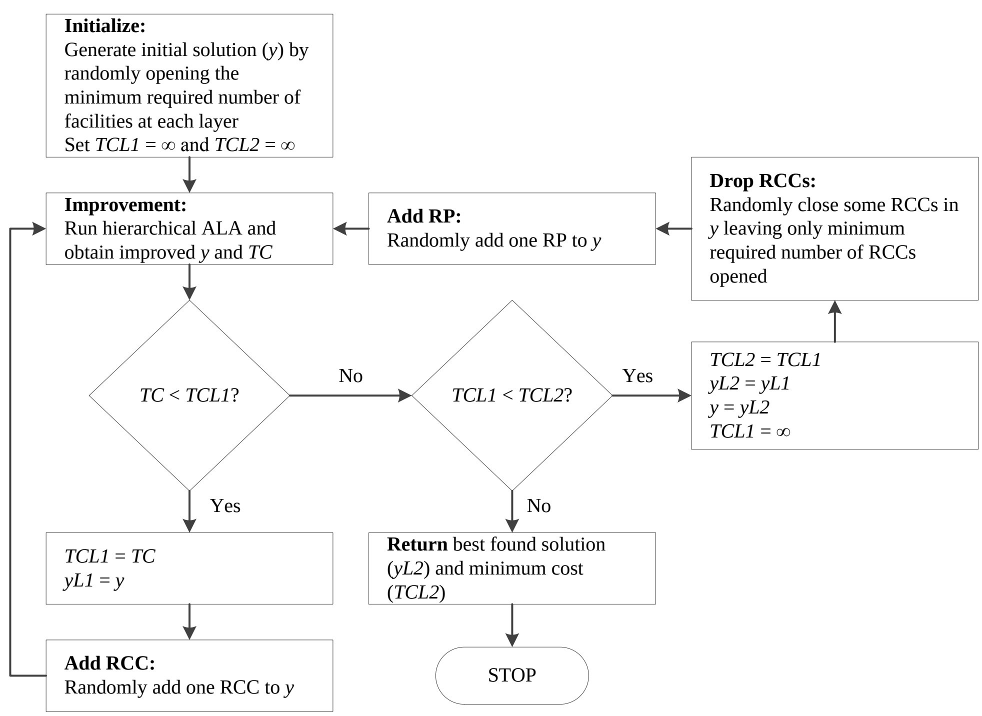


Figure 4.6: RAD+HALA procedure

To avoid local minima, the RAD+HALA heuristic is embedded into the multi-start heuristic, which applies RAD+HALA multiple times for a user-defined number of iterations. Each iteration starts with a new initial solution and facilities are opened/closed at different locations during add/drop steps. The solution with the lowest total cost is returned as the best solution found by the multi-start heuristic.

4.5.3 Computational Results

To assess the algorithm performance, two sets of testing problems were generated. The problems in the first set were generated based on actual data for the carpet recycling network with four layers. The local collection center locations and corresponding collected carpet weights for 40%, 50%, 75% and 95% coverage were used, which correspond to 107, 194, 366 and 1188 facilities in the first network layer. Locations of the three markets defined in Section 3 with corresponding demands were used as the fourth network layer. Potential locations for RCCs and RPs were randomly selected among the population centroids of three-digit ZIP codes. The minimum number of potential locations used was 20, and this was increased by 20 sites for each set of LCCs until CPLEX issued an “Out of Memory” error. Three instances of each problem were generated and solved with CPLEX and the multi-start RAD+HALA heuristic with 100 iterations. This resulted in 42 problems, 30 of which were solved by CPLEX. The results of the first set of problems are summarized in Table 4.9.

As can be seen from the table, the maximum number of potential locations for facilities at the second and third layers that CPLEX could solve was 60 for networks with up to 366 facilities at the first layer. For test problems with 1188 facilities at the first layer, only problems with 20 potential locations were solved without “Out-of-Memory” errors. Among the 30 problems solved to optimality with CPLEX, the heuristic solutions differ from optimal in four instances only. The average deviation was 0.0022%. The maximum solution error of 0.0369% was for one instance of the 1188x20x20x3 problem. By comparing the last two columns of Table 4.9, it can be seen that an increase in the number of potential locations dramatically increases the CPLEX solution time, while the solution time of the heuristic increases very slowly.

Table 4.9: Results for the first set of test problems

Problem Size	**# of Variables**		**% Deviation From Optimal**		**Average # of Opened Facilities**[1]		**Average Solution Time** [sec.]	
LCCxRCCxRPx**M**	Loc.	Flow	Avg.	Max.	RCCs	RPs	CPLEX[2]	ALA
107x20x20x3	40	2,600	0%	0%	6.0	2.0	4	28
107x40x40x3	80	6,000	0%	0%	6.0	2.0	171	32
107x60x60x3	120	10,200	0.0005%	0.0014%	6.0	2.0	605	39
107x80x80x3	160	15,200	Out of memory		6.0	2.0	714	41
194x20x20x3	40	4,340	0%	0%	7.7	3.0	8	29
194x40x40x3	80	9,480	0%	0%	7.7	3.0	142	38
194x60x60x3	120	15,420	0.0044%	0.0133%	8.0	3.0	1,138	39
194x80x80x3	160	22,160	Out of memory		8.0	3.0	1,833	40
366x20x20x3	40	7,780	0%	0%	9.0	3.0	11	43
366x40x40x3	80	16,360	0.0049%	0.0146%	9.0	3.0	370	47
366x60x60x3	120	25,740	0%	0%	9.0	3.0	2,839	54
366x80x80x3	160	35,920	Out of memory		9.0	3.0	3,526	58
1188x20x20x3	40	24,220	0.0123%	0.0369%	11.0	4.0	238	109
1188x40x40x3	80	49,240	Out of memory		11.0	4.0	13,797	124
Total			**0.0022%**	**0.0369%**				

[1] Numbers of opened facilities were the same for CPLEX and ALA for all problems
[2] Solution time or time of "Out of Memory" error

The second set of test problems was generated to assess the performance of the heuristic with different proportions of transportation costs to fixed costs and facility capacities to the total inflow into the network. A summary of the input parameters is shown in Table 4.10. For these problems, facility locations were randomly selected from the nodes of a 1000 by 1000 grid. The Euclidian distances between the facilities were calculated and scaled to 3000 miles (i.e., approximately the largest distance between ZIP codes in the continental US). Two problem sizes, two levels of inflow, and three levels of opening costs for regional collection centers and recycling plants were used resulting in 36 problems. Processing yields and of facility capacities were set at the same levels as for the third scenario. Transportation costs per ton-mile were randomly sampled from a uniform distribution with bounds of ± 20% of corresponding transportation costs in the third scenario described in Section 4.3.3. The percent of the total supply of PCC collected at each local collection center and the percent of the total demand for recycled nylon incurred by each market were randomly generated.

Table 4.10: Input parameters for the second set of test problems

Parameter	Value		
Transportation cost per ton-mile ($/ton-mile)	**Truck**		**Intermodal**
	~U(0.08, 0.12)		~U(0.03, 0.05)
Yield	**Sorting**		**Recycling**
	36%		35%
Capacity (tons)	**RCC**		**RP**
	41,666		50,000
	Levels		
Problems size	100x60x60x5		200x40x40x5
Total Inflow (tons)	200,000		400,000
RP opening cost ($M)	10	15	20
RCC opening cost ($M)	0.5	1.0	2.0

Ten instances of each problem were generated and solved with CPLEX and the heuristic. For three problems, CPLEX issued an "Out of Memory" error, resulting in 357 test problem instances left for comparison. The results are summarized in Table 4.11. The table contains the average and maximum relative deviation of the heuristic solution from the optimal solution for each combination of inputs, as well as a comparison of the average number of facilities opened in the heuristic and optimal solutions. Among 357 instances, 52% were solved to optimality. On average, the total network costs of heuristic solutions were 0.046% higher compared to the optimal solutions. The maximum deviation from the optimal was 0.596%. The number of recycling plant opened was the same for both the heuristic solution and the optimal solutions for all problems. The number of regional collection centers opened differs slightly, especially for problems with a low RCC opening cost. Figure 4.7 shows the improvement in the heuristic's average deviation from the optimal solution as the number of iterations increases. For the first test set, the average deviation drops about 20 times when the number of iterations increases from 20 to 100, from 0.04% to 0.0022%. For the second test set, it drops about 3.5 times, from 0.16% to 0.046%.

Table 4.11: Results for the second set of test problems

Size	Total Inflow [k tons]	Fixed Costs [M$] RP	RCC	% Deviation From Optimal Avg.	Std. Dev.	Max.	Average # of Opened Facilities RCCs[1] CPLEX	ALA	RPs[2]
100x60x60x5	200	10	0.5	0.088%	0.121%	0.293%	6.1	6.2	2
			1.0	0.002%	0.004%	0.011%	5.1		2
			2.0	0%	0%	0%	5.0		2
		15	0.5	0.116%	0.113%	0.364%	6.3	6.2	2
			1.0	0.016%	0.036%	0.100%	5.3	5.1	2
			2.0	0.001%	0.003%	0.009%	5.0		2
		20	0.5	0.041%	0.087%	0.281%	6.6	6.4	2
			1.0	0.005%	0.010%	0.025%	5.1		2
			2.0	0%	0%	0%	5.0		2
	400	10	0.5	0.147%	0.121%	0.376%	11.4	11.2	3
			1.0	0.025%	0.051%	0.156%	10.0		3
			2.0	0.032%	0.067%	0.205%	10.0		3
		15	0.5	0.082%	0.065%	0.216%	11.9	11.4	3
			1.0	0.051%	0.070%	0.184%	10.0		3
			2.0	0.005%	0.008%	0.020%	10.0		3
		20	0.5	0.063%	0.070%	0.195%	11.5	11.3	3
			1.0	0.013%	0.024%	0.070%	10.0		3
			2.0	0.029%	0.045%	0.121%	10.0		3
200x40x40x5	200	10	0.5	0.105%	0.148%	0.451%	6.5	6.7	2
			1.0	0%	0%	0%	5.0		2
			2.0	0%	0%	0%	5.0		2
		15	0.5	0.073%	0.048%	0.142%	6.3	6.1	2
			1.0	0.002%	0.008%	0.025%	5.0		2
			2.0	0.005%	0.014%	0.045%	5.0		2
		20	0.5	0.021%	0.024%	0.056%	6.4	6.3	2
			1.0	0%	0%	0%	5.0		2
			2.0	0.005%	0.015%	0.048%	5.0		2
	400	10	0.5	0.186%	0.172%	0.596%	10.8	10.7	3
			1.0	0.039%	0.053%	0.157%	10.0		3
			2.0	0.036%	0.047%	0.125%	10.0		3
		15	0.5	0.115%	0.095%	0.264%	10.9		3
			1.0	0.089%	0.077%	0.231%	10.0		3
			2.0	0.057%	0.066%	0.207%	10.0		3
		20	0.5	0.099%	0.042%	0.152%	11.1	10.5	3
			1.0	0.059%	0.047%	0.128%	10.0		3
			2.0	0.047%	0.052%	0.153%	10.0		3
				0.046%	**0.079%**	**0.596%**			

[1] One number for both cells is shown when numbers of opened RCCs are equal in CPLEX and ALA solutions
[2] Numbers of opened plants were the same for CPLEX and ALA for all problems

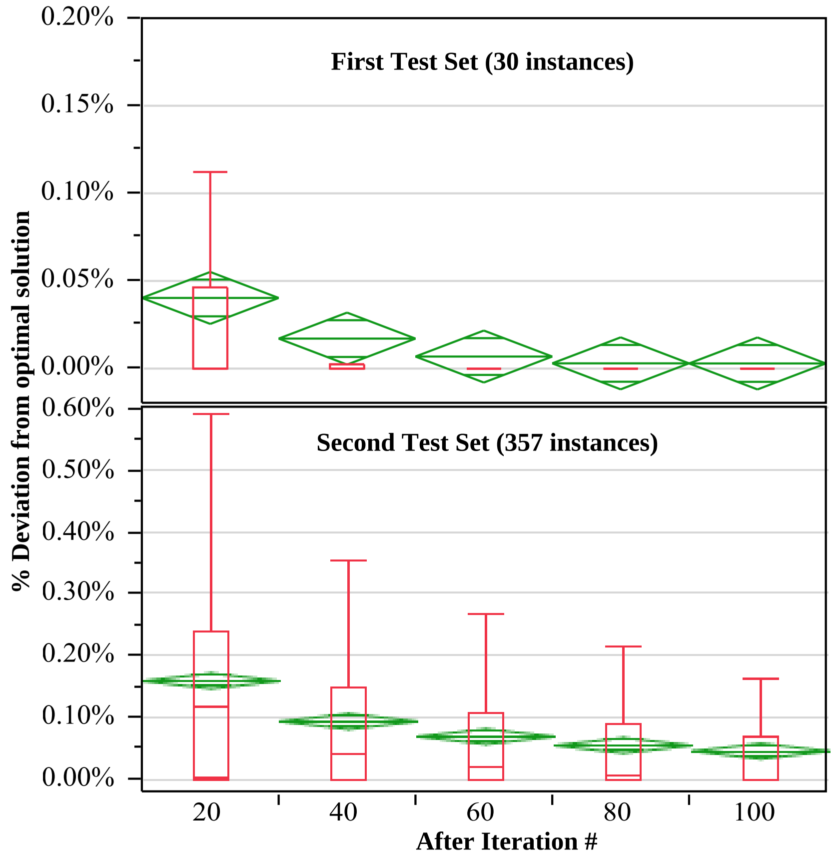


Figure 4.7: Deviation of heuristic solution from optimal as a function of the number of iterations

4.6 Comparing Design Alternatives for Carpet Recycling Network

In this section, the heuristic was used to solve the carpet recycling network problems for the three scenarios discussed, each with the 13 sets of local collection centers identified in Chapter 3. The collection networks used are shown in Table 4.12. The smallest collection network represented the current CARE collection network, and consisted of 102 centers with 36% population coverage and collected carpet weight of about 170 thousand tons. The largest network had 95% coverage with 1188 centers and about 440 thousand tons of PCC collected.

Table 4.12: Collection networks used

	# of LCCs	Population Coverage	Collection Rate	PCC Weight Collected [tons]
1	102	36.39%	5.62%	169,017
2	107	40.54%	6.25%	188,265
3	118	45.23%	6.98%	210,060
4	136	50.17%	7.74%	232,978
5	161	55.12%	8.50%	255,985
6	194	60.06%	9.27%	278,943
7	236	65.01%	10.03%	301,932
8	292	70.05%	10.81%	325,331
9	366	75.02%	11.57%	348,384
10	465	80.04%	12.35%	371,729
11	607	85.00%	13.12%	394,770
12	820	90.00%	13.89%	417,981
13	1,188	95.01%	14.66%	441,219

Since real-scale problems had a significantly larger number of potential locations for RCCs and RPs compared to the test problems, the number of iterations of the multi-start heuristic was increased to 1,000. The solutions obtained for all 39 problems are provided in Appendix B.1. Figure 4.8 depicts the solution times as a function of the total number of location variables in the problem (i.e., total number of potential locations for facilities at all not-fixed layers).

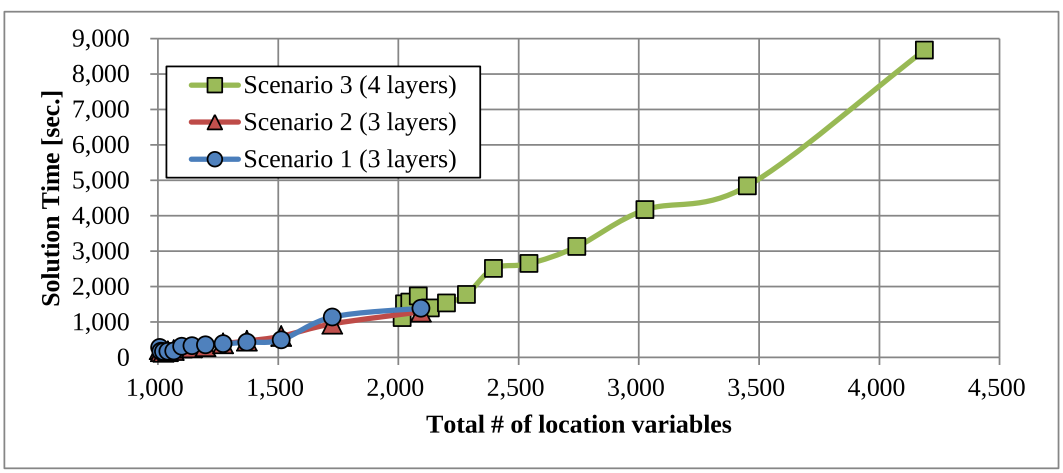


Figure 4.8: Heuristic solution times for 1000 iterations

As can be seen from the figure, in the first two scenarios, only one layer of facilities was located (i.e., recycling plants), and the solution time for the largest problem instances for these scenarios was about 1.3-1.4 seconds per iteration. In the third scenario, two layers were located, which doubles the number of location variables and significantly increased the number of flow variables (i.e., 10.6 times for the smallest collection network and 2.8 times for the largest one). The solution time for the largest problem in the third scenario was about 8.7 seconds per iteration.

Figure 4.9 summarizes the total network costs for all scenarios as a function of the total weight of post-consumer carpet entering the recycling network. While differences in network costs for the first and third scenario are relatively small for all collection levels, the network costs of the second scenario growth exponentially with an increase in collected weight.

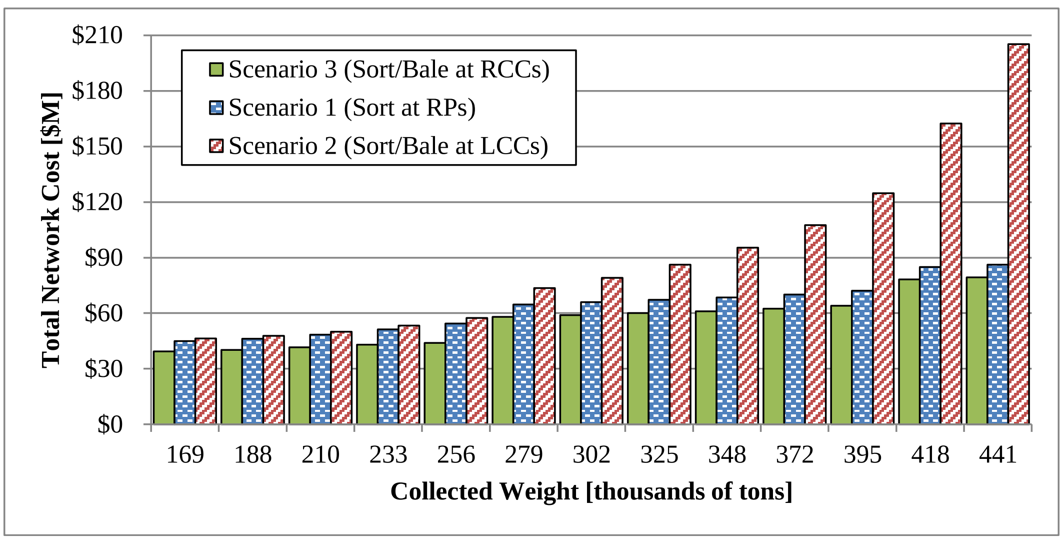


Figure 4.9: Comparison of total scenario costs with different collection weights

As is shown in Figure 4.10 (A), the main contributor of the cost growth in Scenario 2 is the cost of sorting and baling equipment installed at the local collection centers. To increase the weight of the PCC collected, more and more "small" collection centers are included into the collection network. These centers do not collect enough carpet to use the sorters and balers at full capacity, which results in a sharp drop in the total equipment utilization at the LCCs as is shown in Figure 4.10 (B).

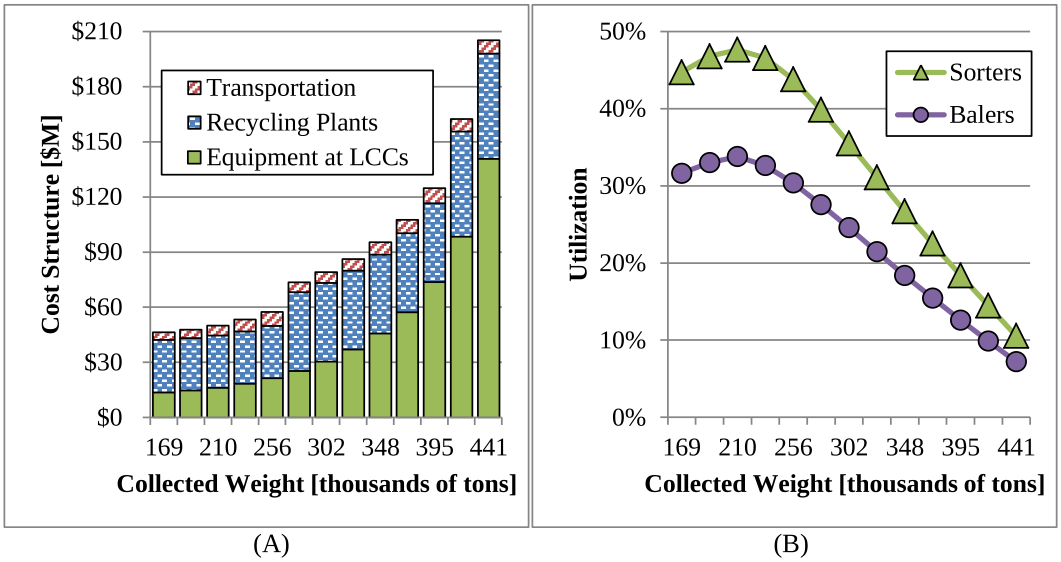


Figure 4.10: Cost structure (A) and utilization of LCC equipment (B) for Scenario 2

Figure 4.11 depicts differences in fixed, transportation and total costs between the first and third scenarios. As can be seen from the figure, the difference in fixed costs oscillates around zero (plus/minus one million). In contrast, transportation costs in Scenario 3 are lower by $5-$11 million due to the intermediate layer of regional collection centers that shortens transportation distances of unrecyclable carpet and allows utilizing cheaper intermodal transportation for the Nylon 6 carpet shipped from the RCCs. This improvement in the transportation costs results in a reduction in the network costs of the third scenario by 8%-19% compared to the first scenario.

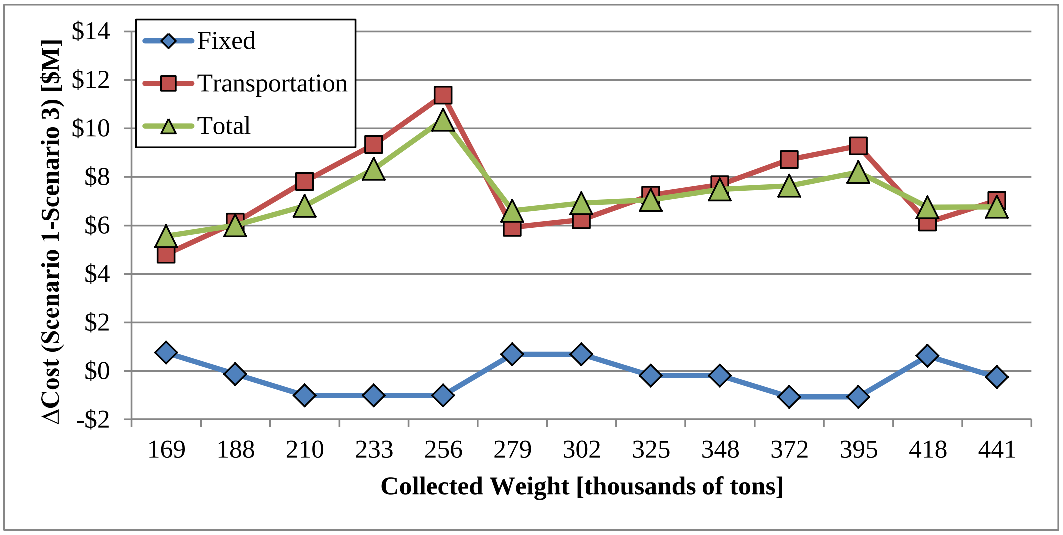
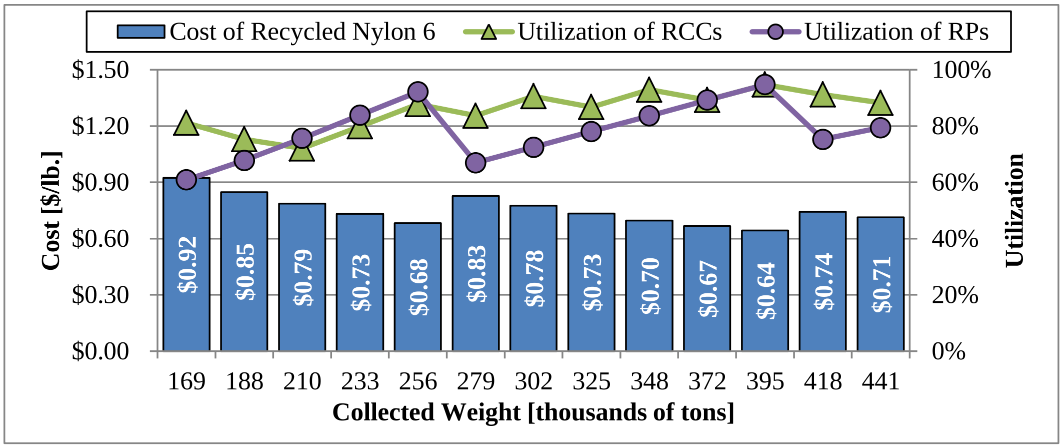
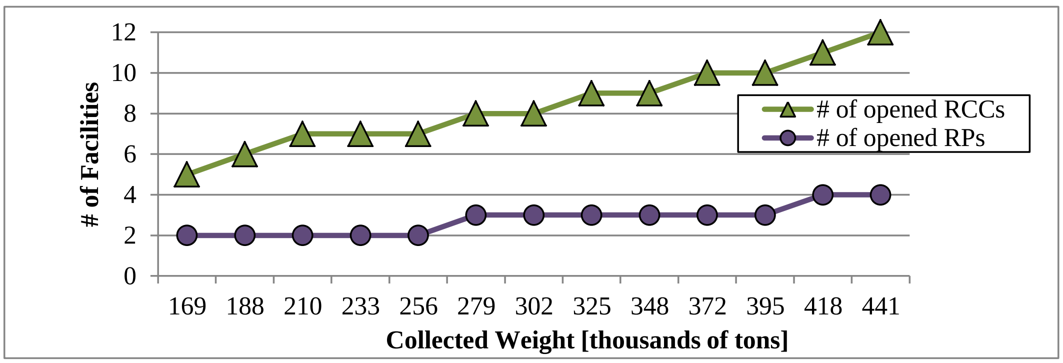


Figure 4.11: Cost differences between Scenarios 1 and 3

Figure 4.12 depicts the logistics cost per pound of recycled Nylon 6 and the facility utilization for different collection levels for Scenario 3. For the current CARE collection network, this cost is $0.92 per pound. This recycling network consists of two recycling plants and five regional collection centers (see Figure 4.13). Utilization of the recycling plants is about 60%, and RCCs are utilized by about 80%. It can be seen from the Figure 4.12 that the logistics costs of recycled Nylon 6 are very sensitive to the utilization of the recycling plants. The utilization increases with an increase in the weight of carpet that enters the recycling network, which reduces the recycled Nylon cost to $0.68 per pound. A further increase in the weight of the PCC collected requires an additional plant to be opened, which drops the plant utilization and leads to a jump in the unit cost. Utilization of regional collection centers does not have such a significant effect on unit cost, since a RCC is about 16 times less expensive compared to a recycling plant and has lower capacity.



(A)



(B)

Figure 4.12: Logistics costs per lb. of recycled Nylon 6, utilization, and number of facilities in Scenario 3

The lowest logistics cost of $0.64 per pound of recycled Nylon 6 was obtained for a collected weight of 395 thousand tons of PCC. This weight of carpet is supplied by the collection network that consists of 607 local collection centers and covers 85% of population. For the current collection network, the same unit cost can be obtained by solving the problem with improved local collection center efficiency to provide enough carpet to utilize the recycling plants completely. The recycling network for this case is shown in Figure 4.14. In contrast to the network in Figure 4.13, two additional regional collection centers were opened to be able to sort all PCC, and the California recycling plant was moved closer to the southeastern market.

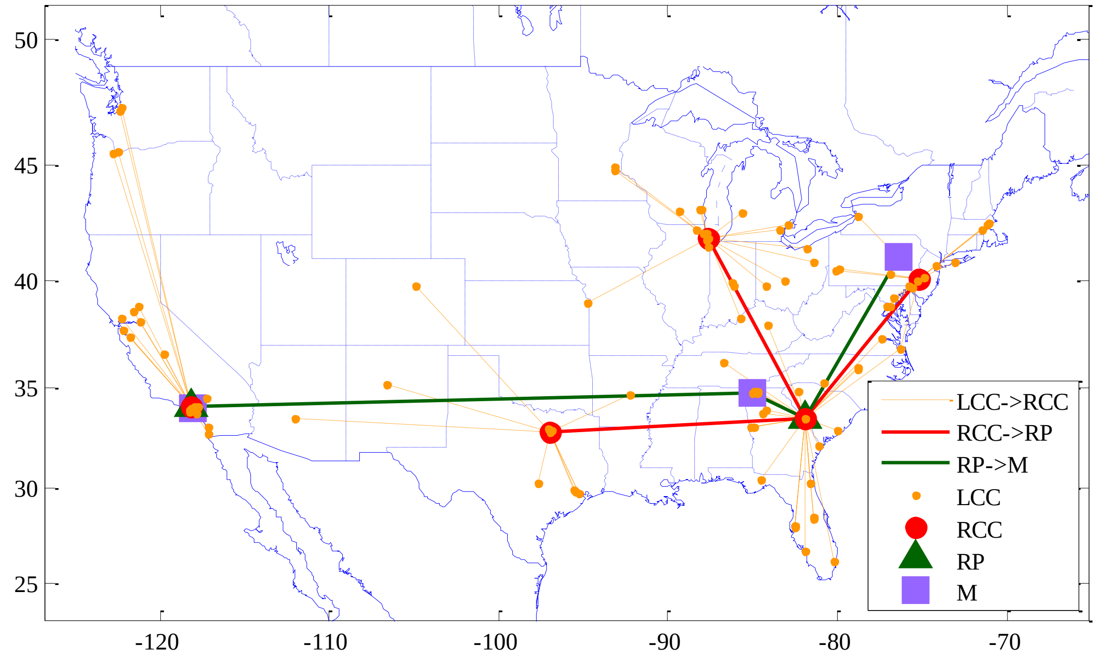


Figure 4.13: Recycling network for the current collection network

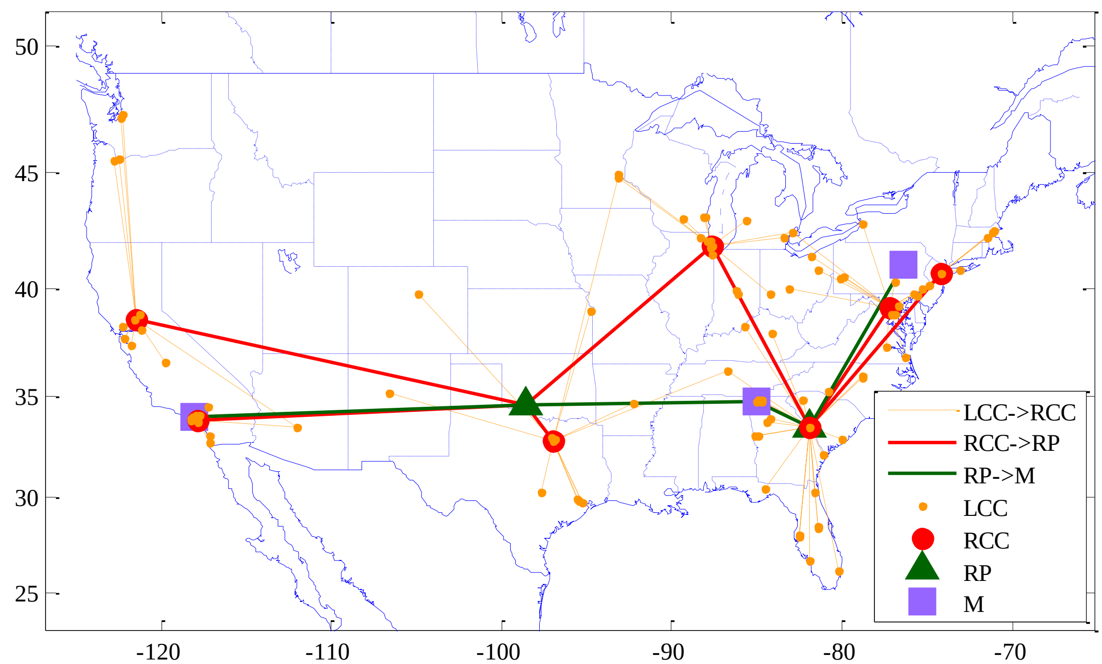


Figure 4.14: Recycling network for the current collection network with improved collection efficiency

4.7 Conclusions and Future Research

The objective of this chapter was to quantify the effect of the intermediate layer of regional collection centers on the logistics cost of Nylon 6 recycled from PCC and to identify the best allocation of the reverse logistics tasks to network layers. For this purpose, a hierarchical facility location model for carpet recycling networks was formulated that is easily adaptable for optimization of networks with different numbers of layers. To solve large instances of the problem that cannot be solved with CPLEX, a heuristic that combines the random add/drop of facilities with the hierarchical ALA improvement procedure was developed. The performance of the heuristic was assessed using about 400 test problems, comparing optimal solutions with solutions obtained from the heuristic. The average deviation of the objective function from its optimum was 0.046%, the maximum deviation was 0.596%, and more than 50% of test problems were solved by the heuristic to optimality.

Three design scenarios for closed-loop carpet recycling network were formulated. In the first two scenarios, post-consumer carpet was directly shipped to recycling plants from local collection centers. In the first scenario, all carpet was delivered to recycling plants that performed carpet sorting in addition to recycling. The second scenario assumed that low capacity sorters and balers were installed at local collection centers, and only Nylon 6 carpet was shipped to recycling plants. Finally, the third scenario considered an intermediate layer of regional collection centers that was responsible for centralized sorting and baling of carpet and its aggregation for intermodal transportation instead of trucking. The heuristic was used to find the number and locations of facilities in all three scenarios for 13 sets of local collection centers that represented collection networks with different levels of population coverage and provided different volumes of PCC carpet to the recycling network.

It was shown that for collection networks with low coverage, that mostly consist of a small number of collection centers each collecting high volumes of carpet, the cost of all scenarios are not considerably different. However, for collection networks with higher coverage, the cost of equipment at the local collection centers in the second scenario grows exponentially. Therefore, it may be concluded that centralized high-capacity sorting (and baling) of carpet is preferable to local sorting (and baling). Comparison of the first and third scenarios showed that the layer of regional collection centers led to an 8%-19% reduction in the total cost due to lower transportation costs.

The lowest logistics cost for recycled Nylon 6 of $0.92 per pound for the current collection network was obtained for Scenario 3. However, the utilization of recycling plants is this case was only about 60%. Due to the high sensitivity of unit cost to the utilization of the recycling plants, the unit cost can be reduced by providing more carpet into the recycling network. This can be done by extending the collection network to increase population coverage (e.g., collection network with 55% coverage provides enough carpet to increase plant utilization to more than 90% and reduce the logistics cost to $0.68 per pound). Alternatively, the collection efficiency of the current collection network can be improved (e.g., increasing collection efficiency from its current 15% level to 25% will provide enough carpet to completely utilize two recycling plants and reduce unit costs to $0.64 per pound).

The results of this study may be used to support decisions for the design of the carpet recycling infrastructure in the US. Logistics cost of recycled Nylon 6 combined with variable sorting, baling and recycling costs, can be compared with market prices of virgin or recycled Nylon 6 to check the economic feasibility of Nylon 6 carpet recycling. The optimization model and the solution heuristic can be used to solve similar problems for the design of reverse logistics networks for other products.

Considering the assumptions used in the study, several recommendations can be made for further research in this area. During the estimation of the parameters, it was assumed that the cost to open a regional collection center (or recycling plant) is the same regardless of the exact location. This analysis can be extended by including regional differences in space and labor rates. In addition, regional collection centers and recycling plants were assumed to have predefined capacities and the annual facility costs did not change with the actual volume that they processed. Facility capacities may be included in the decision variables, so the model will optimize not only numbers and location of facilities at each level, but also the capacity required by each facility.

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CHAPTER 5: Conclusions and Directions for Future Work

5.1 Conclusions

This research was focused on logistics issues in carpet recycling in the US. To make large-scale carpet recycling economically feasible, recycling plants have to receive sufficient volume of post-consumer carpet provided by the collection network. This network has to be designed to collect the volume of carpet required with the minimum number of collection centers opened in order to minimize the collection costs. In addition, location of facilities in the carpet recycling network has a significant impact on transportation cost of PCC and recycled materials. These two logistics problems were considered in this dissertation.

Owing to the high bulkiness of carpet and a high number of locations where old carpet may be generated, carpet collectors have to rely on the drop-off collection scheme, where consumers and carpet installers bring old carpet to collection centers. Since a collection radius of such centers is limited, they have to be located in close proximity to highly populated areas to maximize collection. The development of the collection network was studied in Chapter 3. The mathematical representation of the problem was formulated as a location set covering model with partial coverage. This model located the minimum number of local collection centers throughout the continental US to reach a target level of population coverage and, as a result, a target collection rate. Large instances of the problem cannot be solved with exact methods. Therefore, a novel heuristic was developed, which combined and extended features of greedy randomized heuristics found in the literature for similar problems. The heuristic was specifically designed to solve problems with sparse coverage and overlapping matrices, like the carpet collection network problem, efficiently. A computational study was conducted to assess performance of the heuristic against CPLEX and heuristics from the literature. It showed that the heuristic developed provided optimal or near-optimal solutions and outperformed the heuristics from the literature. Finally, the heuristic was used to design carpet collection networks for 13 levels of target population coverage, from the current coverage of 36% to almost complete coverage of 95%. Such networks were designed for two cases: an extension of the current CARE network and a new network. The relationship between the target collection rate and the number of collection centers required was identified. This can be used to establish an appropriate target collection rate considering the effort and investment required to build the corresponding network.

Chapter 4 was focused on the location of reverse facilities in the network for recycling Nylon 6 from post-consumer carpet. The objective of the chapter was to quantify the effect of an intermediate layer of regional collection centers on the cost and to identify the best allocation of the reverse logistics tasks to network layers. For this purpose, a hierarchical facility location model was formulated that is easily adaptable for optimization of networks with different numbers of layers. For large-instances of the problem that cannot be solved with CPLEX, a heuristic that combines the random add/drop of facilities with a hierarchical alternative location-allocation improvement procedure was developed. The performance of the heuristic was assessed on a series of test problems. It was shown that for more than 50% of test problems, the heuristic yielded optimal solutions, and for non-optimal solutions, the deviation of the objective function from optimal was no more than 0.6%.

Three design scenarios for closed-loop carpet recycling network were formulated. In the first two scenarios, post-consumer carpet was directly shipped to recycling plants from local collection centers. In the first scenario, all carpet was delivered to recycling plants that performed carpet sorting in addition to recycling. The second scenario assumed that low capacity sorters and balers were installed at local collection centers, and only Nylon 6 carpet was shipped to recycling plants. Finally, the third scenario considered an intermediate layer of regional collection centers that was responsible for centralized sorting and baling of carpet and its aggregation for intermodal transportation instead of trucking. The heuristic was used to find the number of facilities as well as their locations in all three scenarios for 13 sets of local collection centers that represented collection networks with different levels of population coverage and provided different volumes of used carpet. Comparison of the scenarios showed that the third scenario yielded the minimum network costs for all collection networks considered. It was also shown that the cost of recycled Nylon 6 is very sensitive to the utilization of the recycling plants. In order to minimize the cost of recycled Nylon 6, the plants need to operate at full capacity.

5.2 Future Work

This research considered and demonstrated the importance of the strategic location of facilities for collection and recycling of post-consumer carpet in the US. The problems studied can be extended and modified in many ways. Future research areas are as follows.

- Collection network:
    - The analysis of carpet collection networks in Chapter 3 can be extended by considering the difference in landfilling fees by states, which has an effect on the collection radius of centers located in different states. In addition, the set of potential locations for collection centers can be revised to exclude locations prohibited due to zoning issues.
    - The optimum level of collection fees can be determined by applying the analysis described in Chapter 3 with different levels of collection fees and comparing the total fees collected with the investments required to establish new collection centers. Collection fees are required to cover the expenses of the collectors, but they have a significant effect on the collection radius. Lowering collection fees will reduce the collectors' revenue. But at the same time, it will increase the collection radius and as a result, decrease the number of collection centers required to reach a target collection rate.
    - The model and heuristic from Chapter 3 can be modified to account for differences in the opening cost of collection centers at different potential locations. Opening costs may differ due to differences in space and labor rates. In addition, volume-dependent site opening costs can be included in the model by considering several types of centers with different cost-capacity ratios (i.e., economies of scale).
- Recycling network
    - The analysis in Chapter 4 can be extended by including regional differences in space and labor rates to model differences in site opening costs at different locations.
    - Facility capacity, as well as capacity-dependent, site-opening costs, may be included in the decision variables. Therefore, the model will optimize not only the number and location of facilities at each layer, but also the capacity required by each facility.

- In several cases, recycling networks developed in Chapter 4 had local collection centers connected to two facilities on the next layer, with a significant portion of PCC allocated to one facility and a smaller portion (sometimes less than one truckload per year) allocated to another facility. Since the weight of carpet collected at any local collection center is significantly smaller than the capacity of a regional collection center or recycling plant, it may be assumed that any local collection center will ship all carpet to only one facility at the next layer. This restriction may be included into the recycling network problem by incorporating single-sourcing constraints in the optimization model in Chapter 4. However, with single-sourcing constraints, the allocation problem in the ALA procedure becomes a NP-hard mixed-integer problem, which will require an allocation heuristic to be developed and used instead of the LP allocation used in the this study.
- In this study, collection networks in Chapter 3 were constructed to reach a target collection rate with the minimum number of local collection centers opened, disregarding the locations of markets for recycled Nylon 6. For the recycling networks in Chapter 4 that were built on top of these collection networks, this resulted in the transportation of some carpet throughout the entire country to reach destination markets. The total fixed facility location and transportation costs of opening two smaller local collection centers closer to a market may be less that opening one center with the same coverage that is further from the market. A model that accounts for such decisions can be developed by combining the models from Chapter 3 and Chapter 4. The objective function of the recycling network model could be extended to include the costs of opening local collection centers, and all required coverage-related variables and constraints could be added to the model. This model will simultaneously locate local collection centers, regional collection centers and recycling plants to minimize the network cost and to reach a target collection rate.

APPENDICES

Appendix A: Supplementary Information for Chapter 3

A.1 List of CARE Reclamation Centers

Table A.1.1: CARE reclamation centers

#	Company	Location	ZIP Code	Lon.	Lat.
1	Conigliaro Industries	Boston, MA	01702	-71.422	42.284
2	ERCS	North Reading, MA	01864	-71.098	42.583
3	Allegheny Contract Flooring	Boston, MA	01890	-71.143	42.452
4	CarpetCycle	Elizabeth, NJ	07206	-74.192	40.653
5	Long Island Carpet Recycling	Long Island, NY	11779	-73.119	40.819
6	WNY Professional Flooring	Buffalo, NY	14220	-78.819	42.846
7	Steinberger Flooring	Heidelberg, PA	15106	-80.090	40.404
8	Capital Carpet Recycling	Pittsburg, PA	15215	-79.916	40.498
9	Harrisburg Carpet Recycling	Harrisburg, PA	17102	-76.891	40.273
10	Capital Carpet Recycling	Philadelphia, PA	19004	-75.233	40.013
11	Foam Recycle Center	Philadelphia, PA	19007	-74.855	40.109
12	EZ Carpet Recycling	Newark, DE	19711	-75.743	39.701
13	Modular Carpet Recycling	New Castle, DE	19720	-75.590	39.669
14	Waste Carpet Depot	New Castle, DE	19720	-75.590	39.669
15	Foam Recycle Center	Forestville, MD	20747	-76.886	38.855
16	Foam Recycle Center	Baltimore, MD	21227	-76.677	39.242
17	Foam Recycle Center	Alexandria, VA	22304	-77.117	38.813
18	RM Brokerage	Alexandria, VA	22304	-77.117	38.813
19	Foam Recycle Center	Norfolk, VA	23510	-76.290	36.853
20	Ace Recycling	Chester, VA	23836	-77.346	37.343
21	Foam Recycle Center	Raleigh, NC	27560	-78.839	35.846
22	Foam Recycle Center	Durham, NC	27703	-78.840	35.966
23	Blue Ridge Recycling	Charlotte, NC	28205	-80.792	35.222
24	Southeastern Plastic Recovery Inc.	Charleston, SC	29405	-79.982	32.857
25	Atlanta Foam Recycle	Greenville, SC	29607	-82.341	34.826
26	Atlanta Foam Recycle	Atlanta, GA	30084	-84.220	33.854
27	Dixie Mill Enterprises, Inc.	LaGrange, GA	30240	-85.075	33.030
28	Interface Americas	LaGrange, GA	30241	-84.989	33.037
29	Georgia Recycling	Atlanta, GA	30315	-84.384	33.710
30	CLEAR	Dalton, GA	30705	-84.775	34.753
31	Columbia Recycling	Dalton, GA	30720	-84.987	34.766
32	Lofty's Textile Waste, Inc.	Dalton, GA	30720	-84.987	34.766
33	Dalton-Whitfield SWMA	Dalton, GA	30721	-84.940	34.781
34	Tandus Flooring, Inc.	Dalton, GA	30722	-84.951	34.760
35	Mohawk's Greenworks	Eton, GA	30724	-84.760	34.822
36	Evergreen Nylon Recycling	Augusta, GA	30901	-81.973	33.461
37	Foam Recycle Center	Savannah, GA	31401	-81.093	32.069
38	Foam Recycle Center	Jacksonville, FL	32217	-81.621	30.244
39	Paved Recycling, INC.	Tallahassee, FL	32310	-84.348	30.400
40	United Carpet Recyclers of Florida	Orlando, FL	32809	-81.388	28.463
41	Carpet Recycling, Inc.	Orlando, FL	32837	-81.412	28.386
42	Foam Recycle Center	Fort Lauderdale, FL	33309	-80.172	26.185
43	Recyc-Carpets of South Florida	Fort Lauderdale, FL	33309	-80.172	26.185
44	Carpet Recycling Services	Tampa, FL	33603	-82.463	27.984
45	Florida Carpet & Pad Recycling	Tampa, FL	33614	-82.506	28.006
46	Cantrell's Flooring Services	Tampa, FL	33634	-82.549	28.005
47	Cantrell's Flooring Services	Cape Coral, FL	33909	-81.950	26.687
48	Southeastern Recycling	Nashville, TN	37210	-86.744	36.141
49	CLEAR	Louisville, KY	40202	-85.751	38.253
50	Champion Polymer	Lexington, KY	40391	-84.170	37.982

Table A.1.1 (continued)

51	Reclamation LTD	Columbus, OH	43204	-83.082	39.958
52	ServiceMasters by AmeriSteam	Brook Park, OH	44142	-81.821	41.400
53	CLEAR	Canton, OH	44702	-81.375	40.799
54	CLEAR	Dayton, OH	45423	-84.269	39.750
55	CLEAR	Indianapolis, IN	46204	-86.156	39.772
56	Kruse Carpet Recycling	Indianapolis, IN	46268	-86.225	39.898
57	Great Lakes Recycling	Roseville, MI	48066	-82.939	42.503
58	CLEAR	Romulus, MI	48174	-83.372	42.212
59	CLEAR	Grand Rapids, MI	49503	-85.659	42.964
60	Lippert Tile Company, Inc.	Menomonee Falls, WI	53051	-88.110	43.151
61	CLEAR	Milwaukee, WI	53218	-87.994	43.111
62	Sergenians Floorcoverings	Madison, WI	53713	-89.392	43.038
63	Bro-Tex Co.	St. Paul, MN	55114	-93.196	44.965
64	CLEAR	Eagan, MN	55122	-93.199	44.805
65	CLEAR	Elk Grove Village, IL	60005	-87.985	42.069
66	Exceed Flooring	Chicago, IL	60014	-88.331	42.227
67	Foam Recycle Center	Chicago, IL	60022	-87.763	42.131
68	CLEAR	Markham, IL	60466	-87.688	41.473
69	Kruse Chicago	Chicago, IL	60602	-87.629	41.883
70	Exhibitors Carpet Service	Chicago, IL	60632	-87.711	41.809
71	Design Source Flooring	Lenexa, KS	66219	-94.772	38.964
72	Balcones Resources	Little Rock, AR	72206	-92.269	34.691
73	Carpet Again Recycling	Dallas, TX	75061	-96.961	32.827
74	Mezquite Carpets	Dallas, TX	75220	-96.863	32.868
75	Texas Carpet Recycling	Grapevine, TX	76051	-97.085	32.932
76	Carpet Recovery International, Inc.	Houston, TX	77041	-95.572	29.859
77	Natural Transitions	Houston, TX	77055	-95.496	29.799
78	Texan Floor Service	Houston, TX	77055	-95.496	29.799
79	Southeast Carpet & Recycling	Houston, TX	77087	-95.304	29.687
80	Foam Recycle Center	Houston, TX	77587	-95.231	29.662
81	Balcones Resources	San Antonio, TX	78702	-97.719	30.265
82	Re:Volve Recycling	Lakewood, CO	80220	-104.917	39.734
83	A1 Planet Recycle	Phoenix, AZ	85004	-112.071	33.451
84	Green Planet Recycling	Albuquerque, NM	87107	-106.641	35.134
85	Los Angeles Fibers Company	Los Angeles, CA	90058	-118.226	34.000
86	Waste Management Carson	Gardena, CA	90248	-118.288	33.870
87	The Carpet Recyclers	La Mirada, CA	90638	-118.010	33.902
88	Waste Management	Los Angeles, CA	90810	-118.215	33.816
89	Bentley Prince Street	City of Industry, CA	91746	-117.985	34.047
90	Oceanaire International, Inc.	Diamond Bar, CA	91765	-117.817	34.004
91	Mission Recycling	Pomona, CA	91766	-117.753	34.046
92	Planet Recycling	San Diego, CA	92029	-117.116	33.088
93	A+	San Diego, CA	92113	-117.120	32.697
94	Don Farraese Charities	Victorville, CA	92395	-117.270	34.258
95	Padworks	Santa Ana, CA	92701	-117.862	33.747
96	SoEx Group	Fresno, CA	93725	-119.741	36.659
97	Napa Recycling Service	Napa, CA	94559	-122.287	38.291
98	Waste Management	San Leandro, CA	94577	-122.157	37.722
99	The Carpet Recyclers	Oakland, CA	94603	-122.173	37.738
100	Carpet Collectors	San Jose, CA	95127	-121.821	37.369
101	Waste Management Central Valley	Lodi, CA	95240	-121.250	38.125
102	Bentley Prince Street ReEntry	West Sacramento, CA	95605	-121.528	38.592
103	Carpet Collectors	Rocklin, CA	95765	-121.263	38.818
104	Carpet Collectors	Beaverton, OR	97005	-122.804	45.491
105	East County Recycling	Portland, OR	97230	-122.505	45.539
106	Again	Kent, WA	98032	-122.259	47.388
107	Recovery 1, Inc.	Tacoma, WA	98421	-122.412	47.251

A.2 Identification of Road Distance Circuity Factor for Short Trips

Table A.2.1: Road distance circuity factors for sampled ZIP code pairs

#	ZIP Code Origin	ZIP Code Destination	Distance (miles)	Circuity Factor
1	32084	32092	19.74	1.38
2	52590	63565	22.50	1.40
3	65746	65632	30.45	1.30
4	14024	14714	21.52	1.04
5	94618	94588	27.30	1.25
6	67337	67347	24.53	1.34
7	36695	36603	14.11	1.25
8	96118	89501	45.53	1.82
9	34498	34433	20.48	1.52
10	62338	62325	8.63	1.39
11	16157	44512	24.49	1.25
12	82001	82060	21.49	1.24
13	68975	68452	22.24	1.43
14	64082	66202	25.89	1.38
15	29530	29069	34.73	1.47
16	23504	23464	8.14	1.24
17	61471	61480	7.12	1.41
18	62918	62884	26.55	1.20
19	87124	87004	12.20	1.31
20	90012	90019	7.83	1.34
21	15546	15560	14.80	1.28
22	66609	66431	29.01	1.39
23	31065	31021	15.68	1.17
24	16725	16333	26.01	1.40
25	74001	74073	16.55	1.30
26	11804	10457	30.24	1.28
27	49927	54121	30.99	1.56
28	17049	17005	49.45	2.17
29	20853	22209	14.84	1.10
30	36564	36561	33.16	1.35
31	96126	96118	16.15	1.77
32	73015	73006	27.86	1.48
33	79561	79537	28.70	1.71
34	45833	45851	25.70	1.36
35	21902	21645	40.94	2.50
36	17963	17003	20.17	1.21
37	93235	93646	21.43	1.26
38	49404	49456	15.84	1.26
39	97864	97825	39.25	1.63
40	4290	4276	11.71	1.68
41	33981	33903	38.42	1.55
42	62665	62611	11.01	1.12
43	98579	98572	38.20	1.92
44	46825	46797	16.65	1.26
45	48831	48848	16.81	1.14
46	43767	43734	15.63	1.63
47	17016	17041	9.92	1.26
48	32258	32256	8.03	1.88
49	81044	81057	10.66	1.43
50	80530	80621	10.12	1.37

#	ZIP Code Origin	ZIP Code Destination	Distance (miles)	Circuity Factor
51	30019	30005	26.63	1.31
52	95420	95437	9.55	1.75
53	37841	38504	29.71	2.10
54	39060	39202	7.08	1.18
55	38568	38501	20.91	1.28
56	68960	68966	22.98	1.32
57	42088	42023	33.36	1.53
58	1803	1923	18.95	1.38
59	71245	71028	23.38	1.18
60	55417	55076	13.96	1.31
61	43517	43555	25.62	1.03
62	30294	30013	21.46	1.31
63	81419	81428	13.24	1.48
64	95247	95257	30.70	1.92
65	73560	73526	22.50	1.38
66	61356	61424	30.45	1.33
67	30677	30648	24.82	1.23
68	22460	20684	107.79	4.55
69	30641	30638	15.38	1.77
70	54895	54732	30.19	1.36
71	15361	15021	12.07	1.35
72	55321	55363	14.98	1.13
73	83523	83522	19.55	1.46
74	29075	29127	14.28	1.88
75	98039	98040	7.77	1.97
76	24441	22973	29.44	1.49
77	49079	49008	15.93	1.06
78	65802	65809	9.73	1.37
79	20140	20186	18.95	1.27
80	48140	43412	32.59	1.50
81	63565	64655	17.38	1.15
82	42069	42035	9.63	2.02
83	80011	80024	12.98	1.40
84	62985	62982	29.95	1.57
85	77437	77419	26.68	1.18
86	14857	14850	34.65	1.57
87	37326	37361	24.98	1.33
88	61813	61735	30.33	1.34
89	45356	45306	23.86	1.11
90	68727	68736	24.83	1.32
91	83607	97913	27.53	1.39
92	40601	40503	27.92	1.24
93	56257	57226	27.32	1.40
94	60537	60506	23.12	1.22
95	40215	47126	25.69	1.05
96	40214	47117	29.21	2.63
97	60007	60004	7.85	1.10
98	33786	33621	27.55	1.39
99	11934	11941	4.95	1.16
100	43607	43606	2.13	1.36

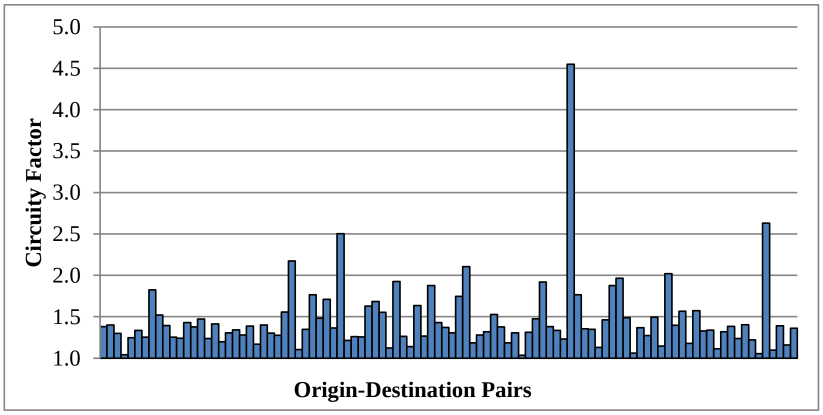

Figure A.2.1: Circuity factors for short trips for pairs of Origin-Destination ZIP codes

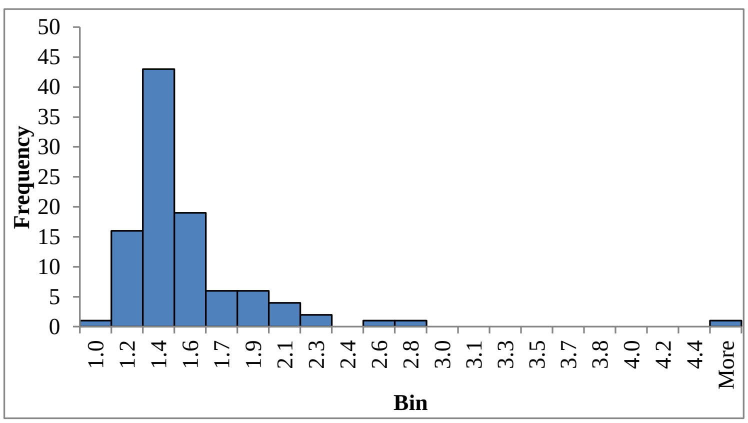

Figure A.2.2: Histogram of circuity factor for short trips

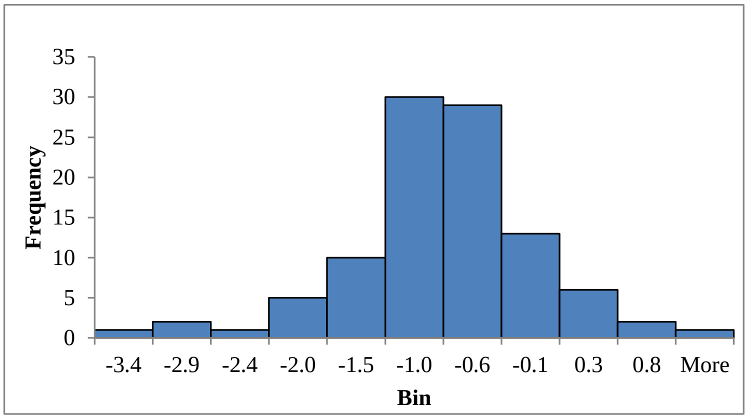

Figure A.2.3: Histogram of normalized circuity factor for short trips
(Circuity factor (CF) was normalized by taking natural logarithm minus one (ln(CF)-1). The normalized values were used in statistical analysis to check for outliers.)

A.3 Optimal Collection Networks

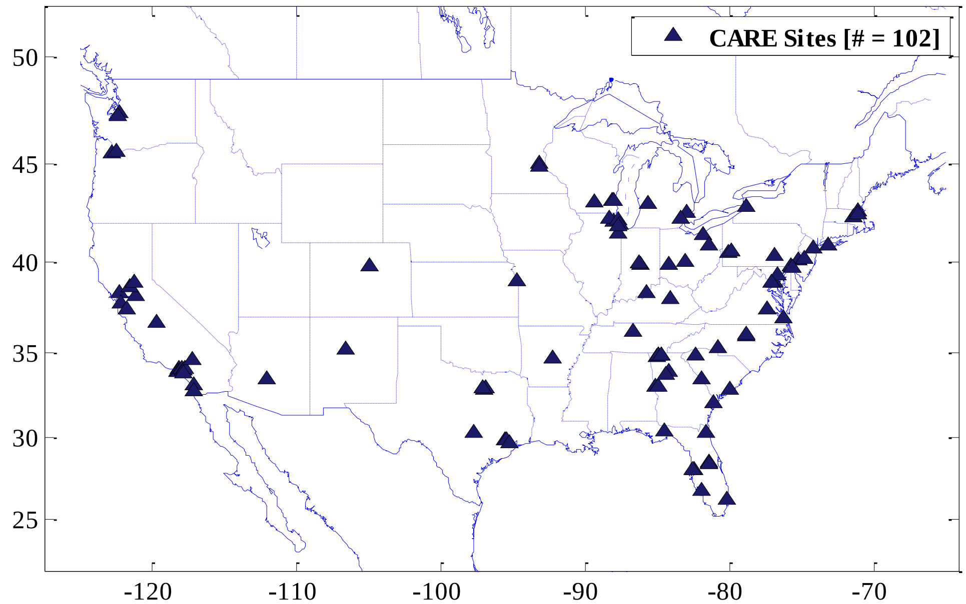

Figure A.3.1: Current CARE collection network

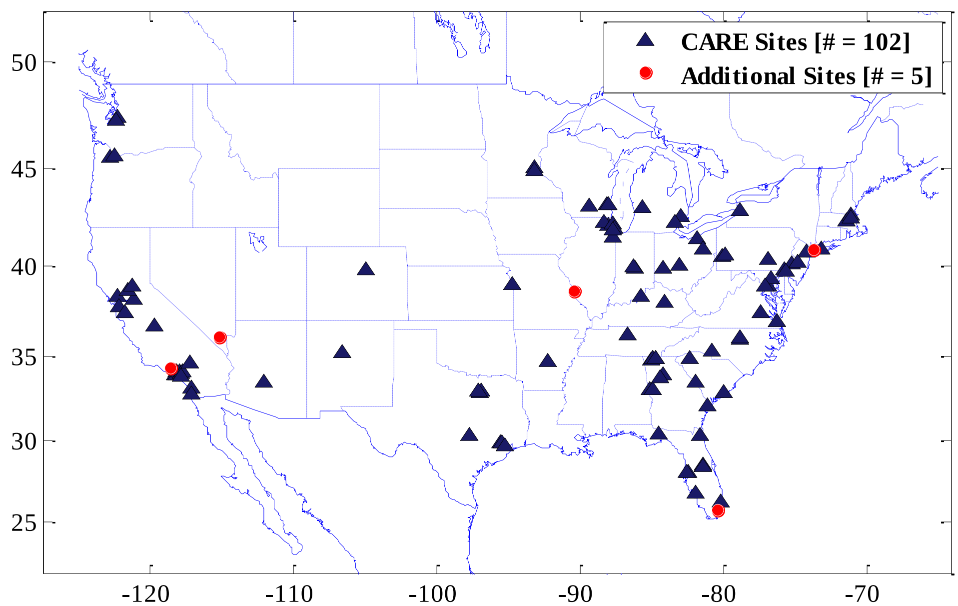

Figure A.3.2: Extension of CARE collection network to 40% target coverage

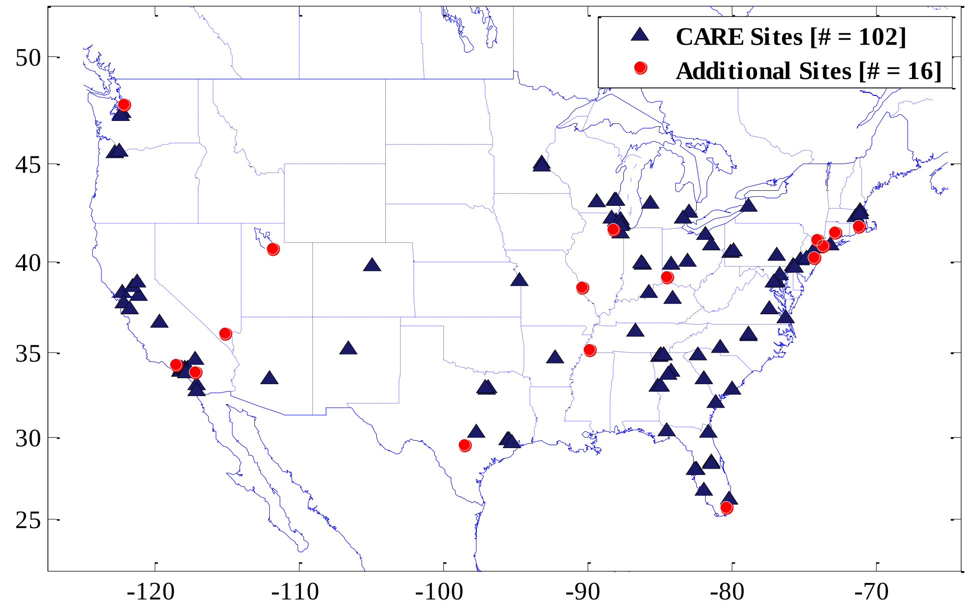

Figure A.3.3: Extension of CARE collection network to 45% target coverage

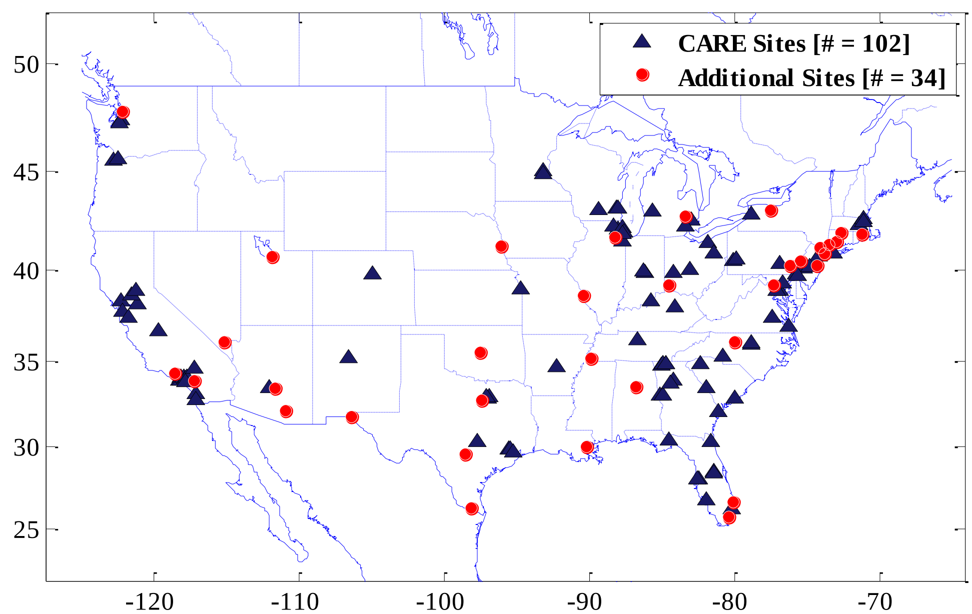

Figure A.3.4: Extension of CARE collection network to 50% target coverage

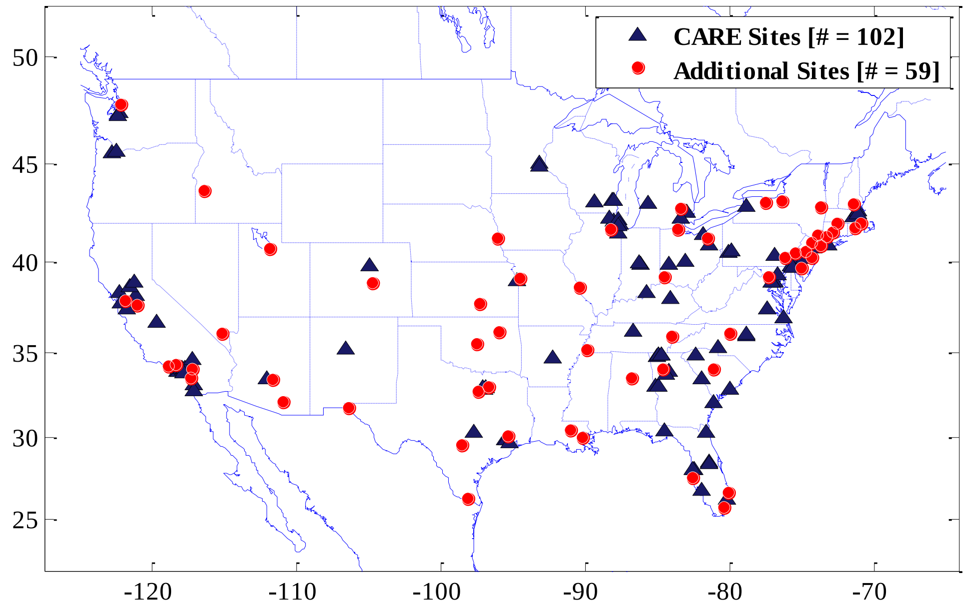

Figure A.3.5: Extension of CARE collection network to 55% target coverage

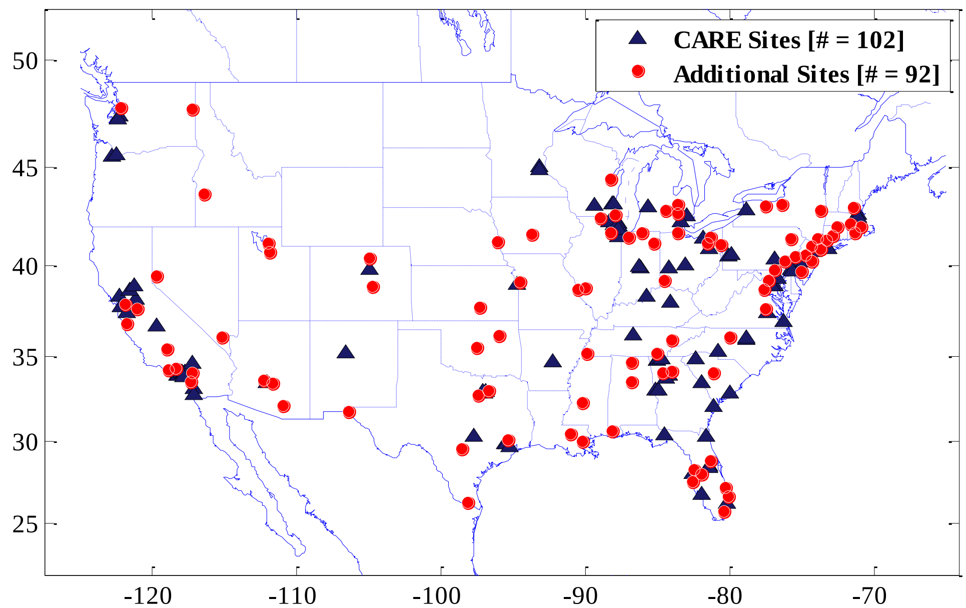

Figure A.3.6: Extension of CARE collection network to 60% target coverage

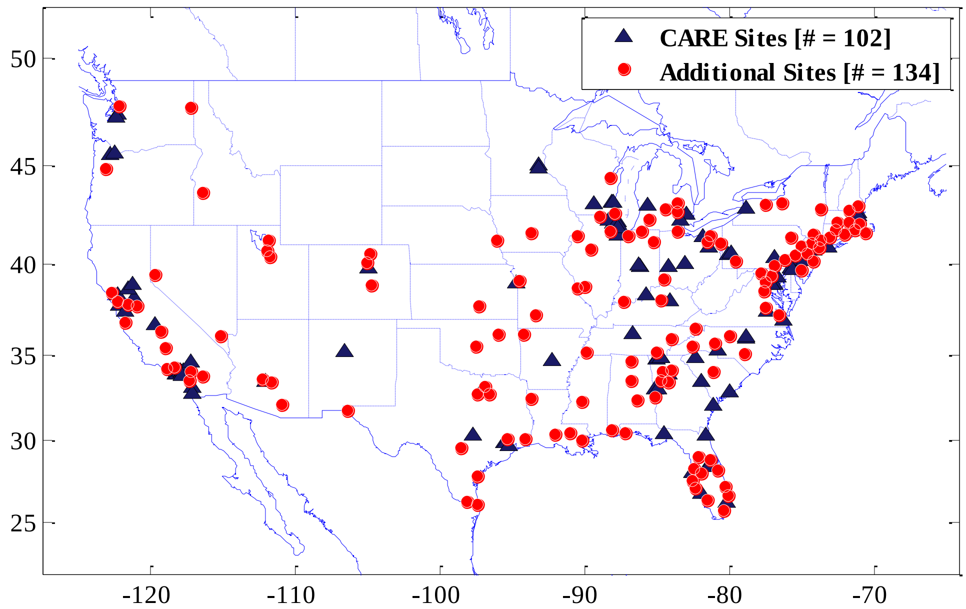

Figure A.3.7: Extension of CARE collection network to 65% target coverage

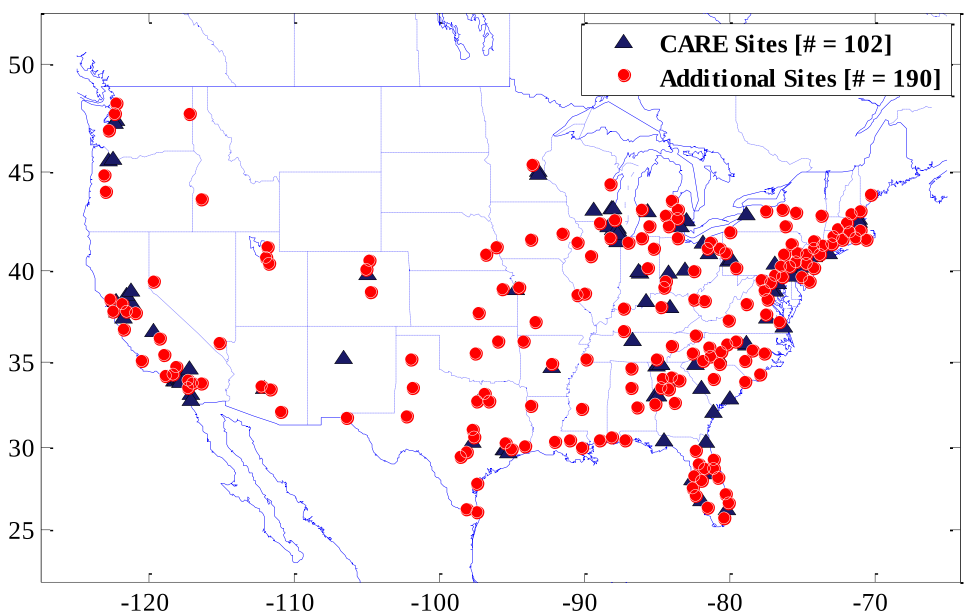

Figure A.3.8: Extension of CARE collection network to 70% target coverage

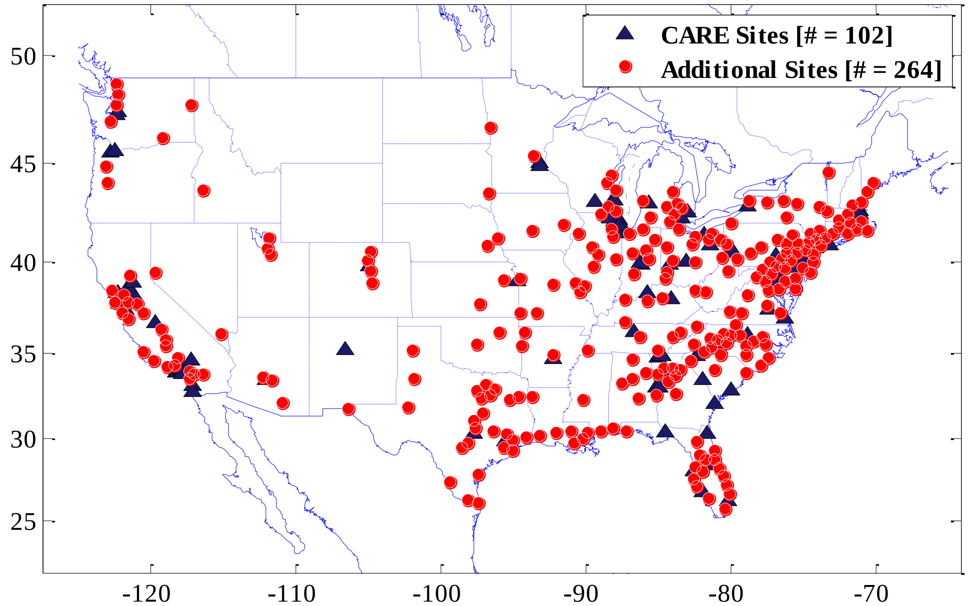

Figure A.3.9: Extension of CARE collection network to 75% target coverage

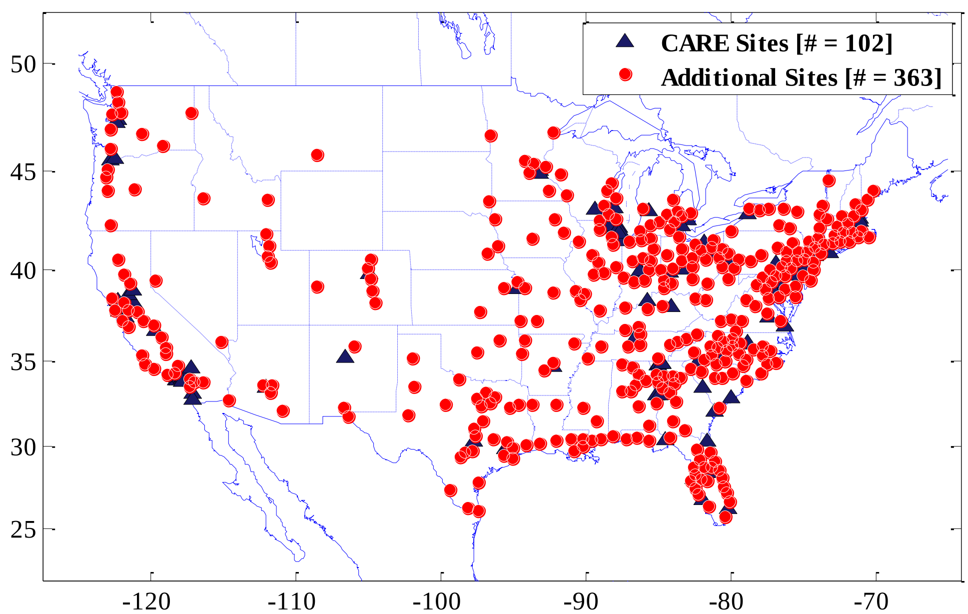

Figure A.3.10: Extension of CARE collection network to 80% target coverage

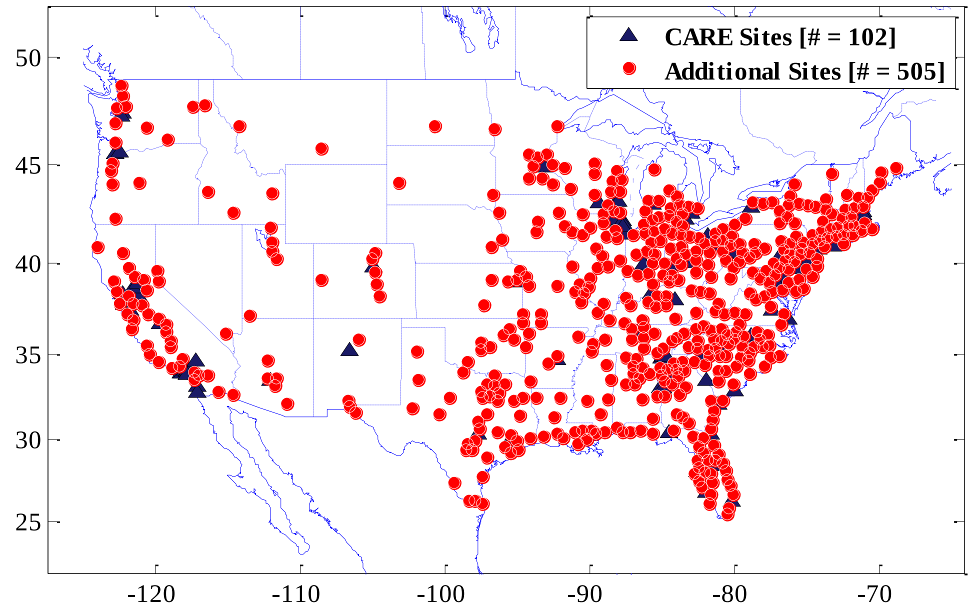

Figure A.3.11: Extension of CARE collection network to 85% target coverage

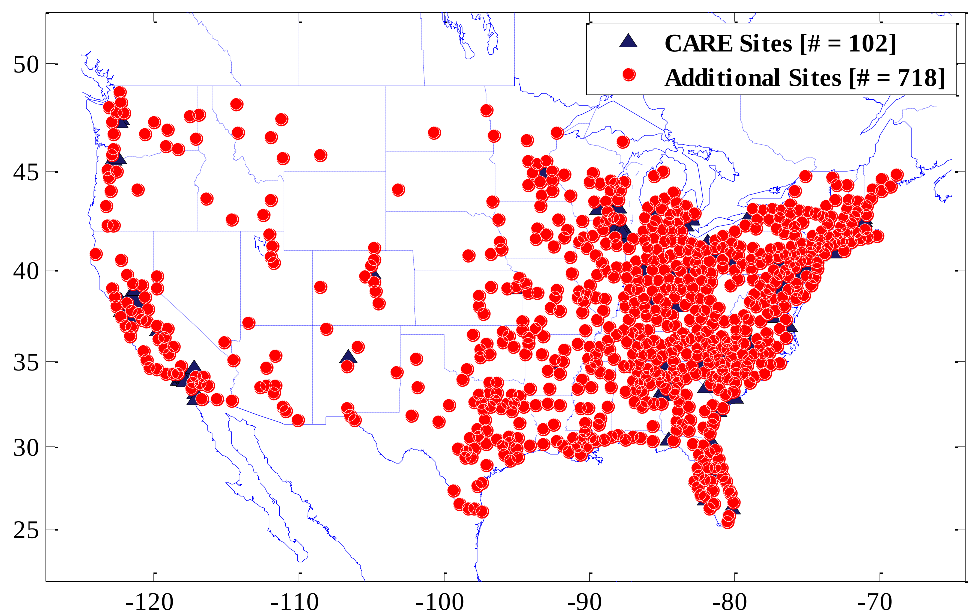

Figure A.3.12: Extension of CARE collection network to 90% target coverage

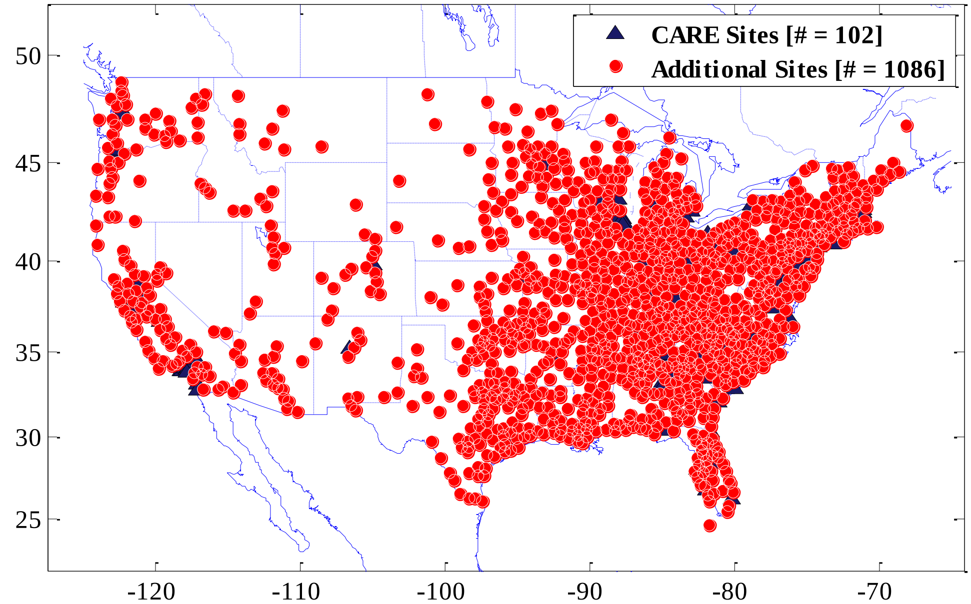

Figure A.3.13: Extension of CARE collection network to 95% target coverage

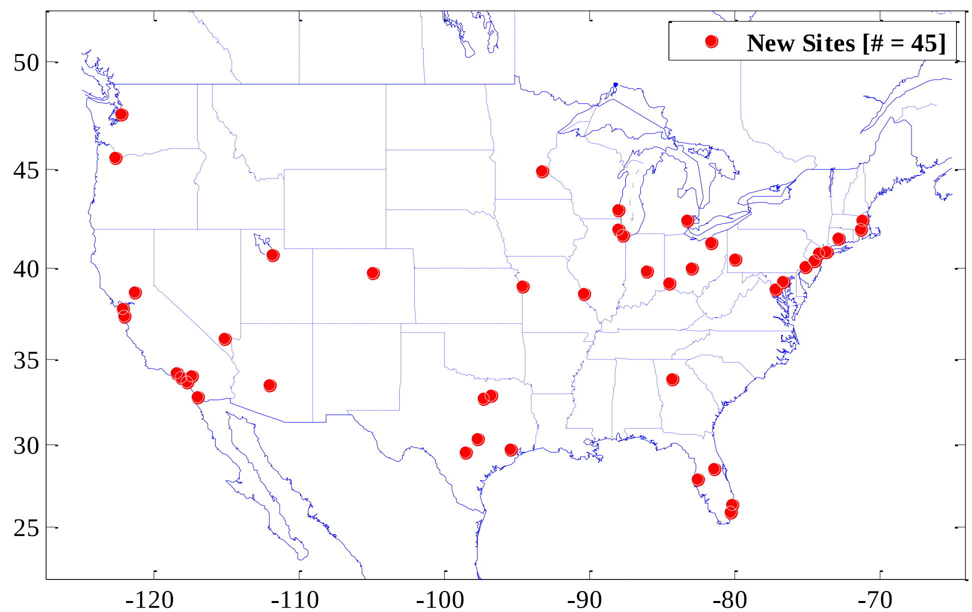

Figure A.3.14: New collection network with 36.39% target coverage

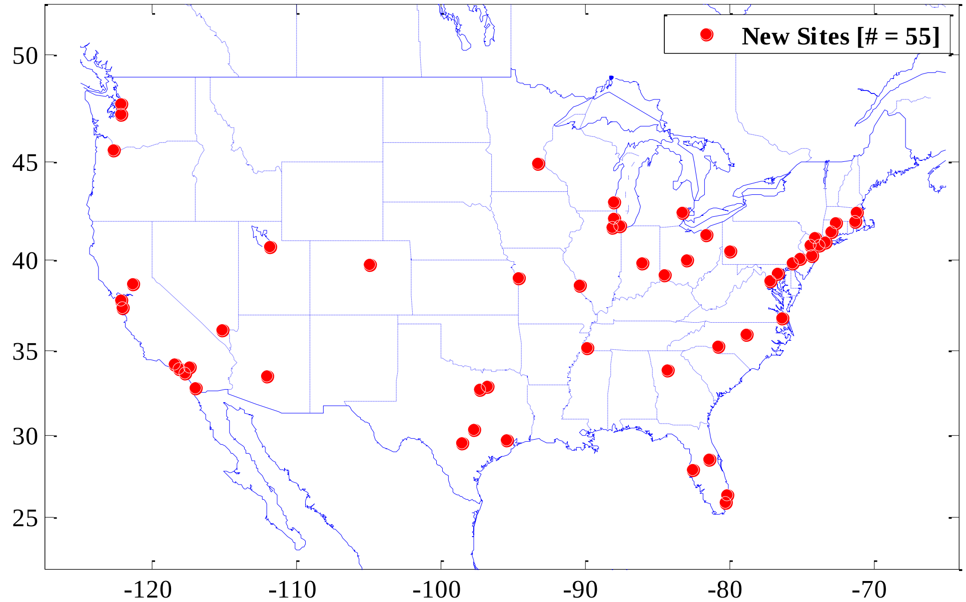

Figure A.3.15: New collection network with 40% target coverage

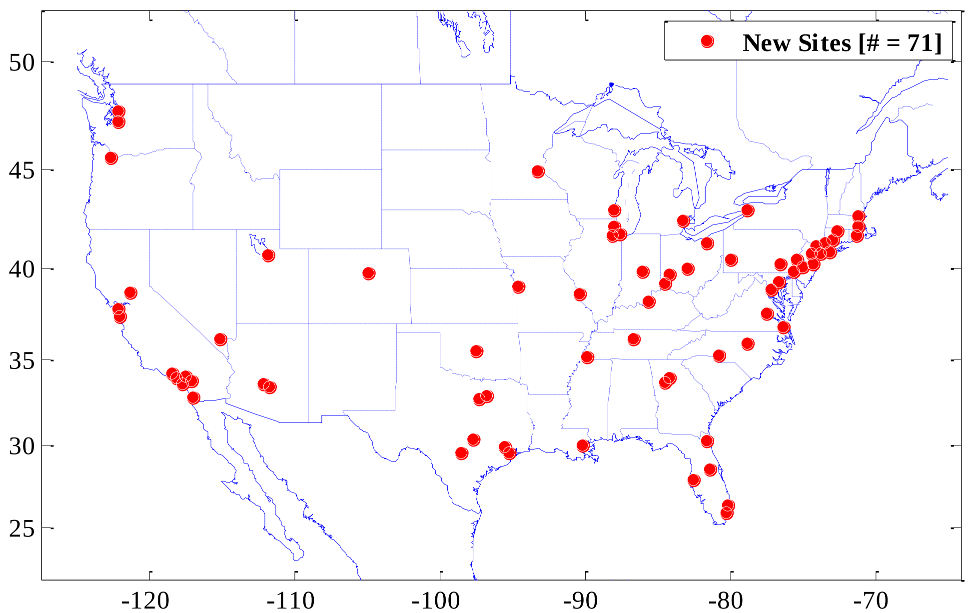

Figure A.3.16: New collection network with 45% target coverage

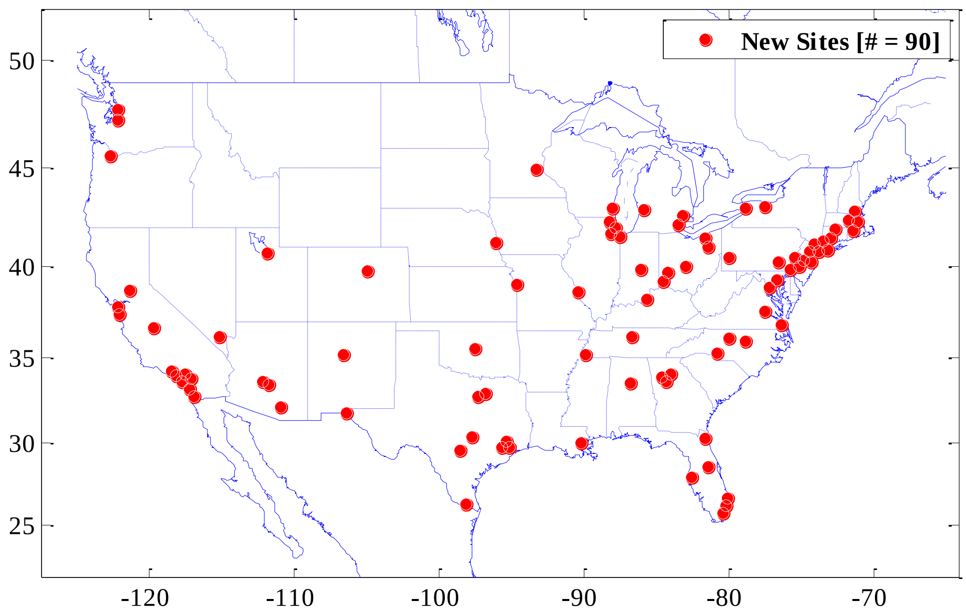

Figure A.3.17: New collection network with 50% target coverage

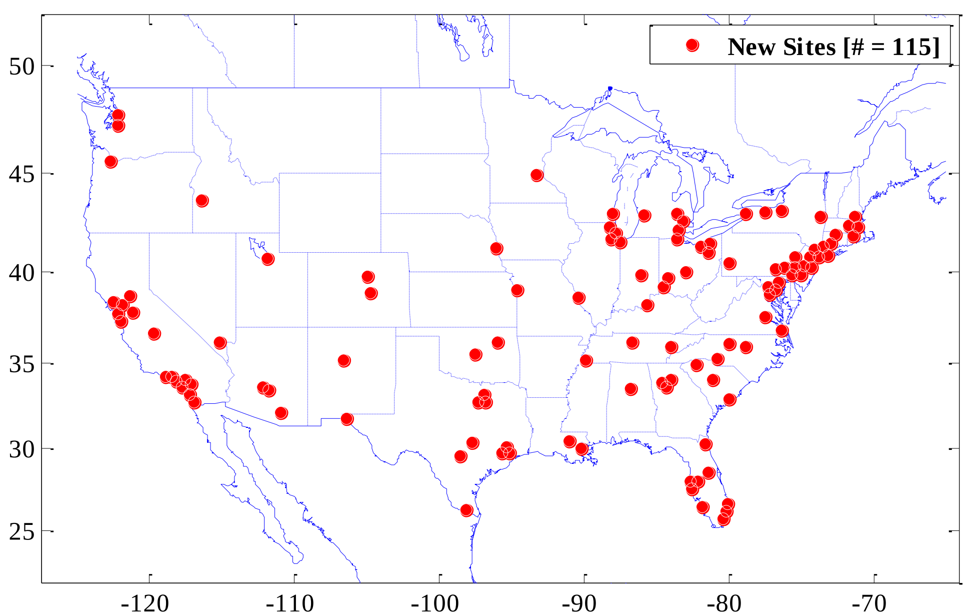

Figure A.3.18: New collection network with 55% target coverage

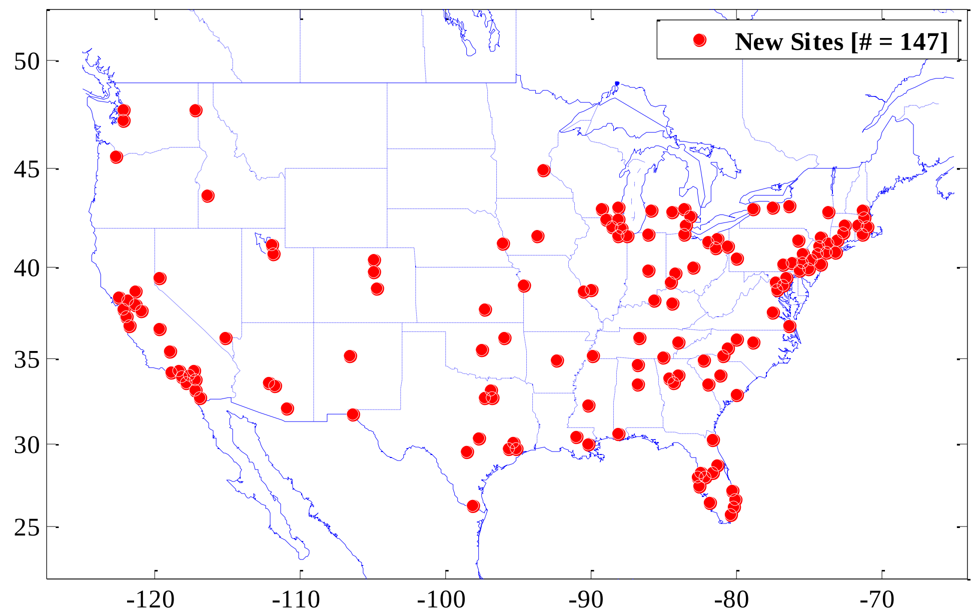

Figure A.3.19: New collection network with 60% target coverage

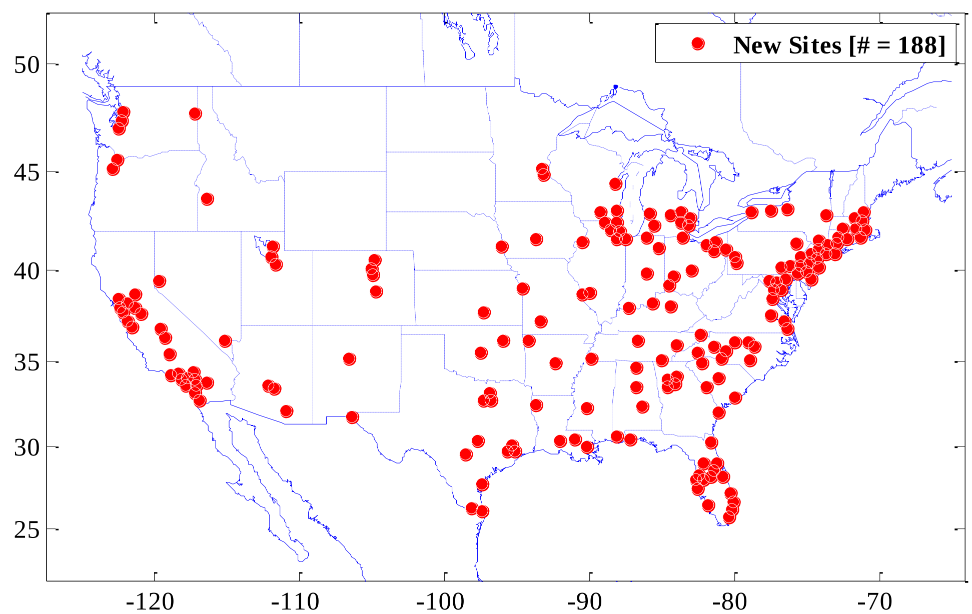

Figure A.3.20: New collection network with 65% target coverage

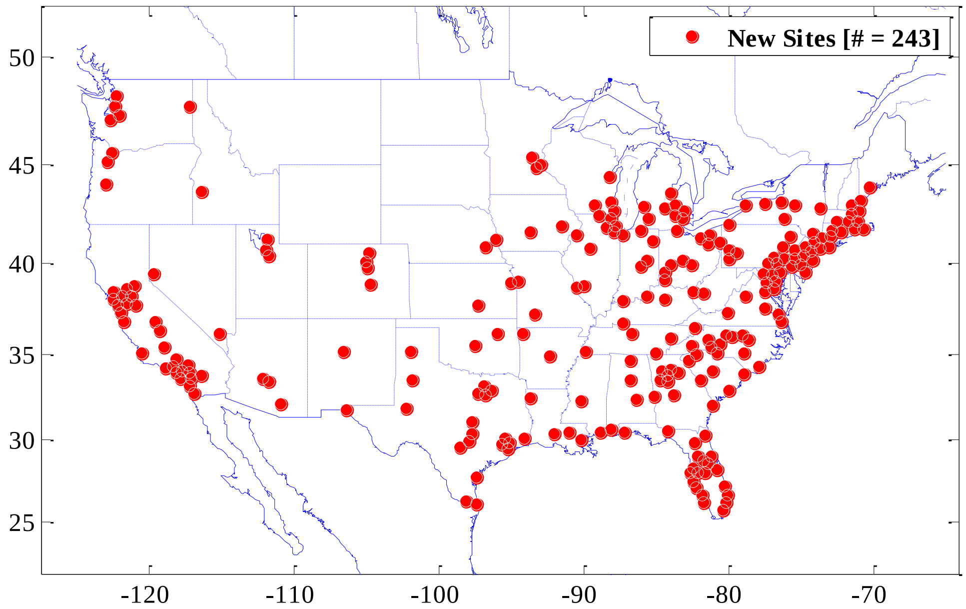

Figure A.3.21: New collection network with 70% target coverage

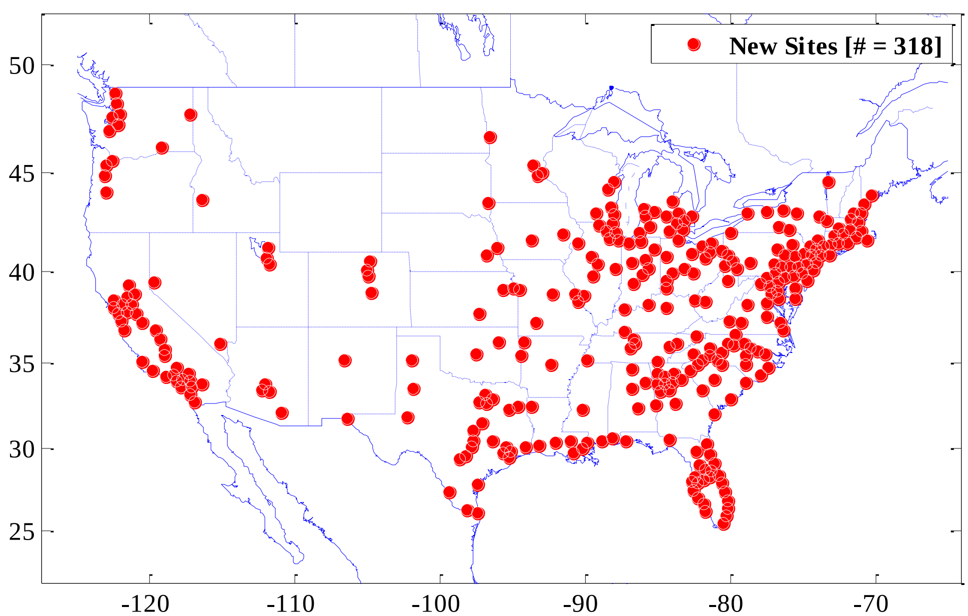

Figure A.3.22: New collection network with 75% target coverage

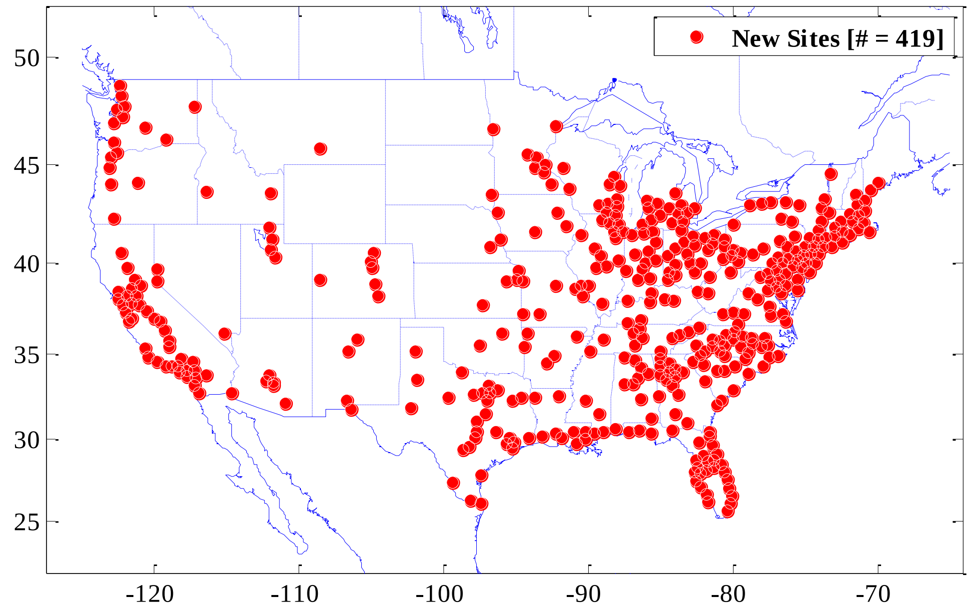

Figure A.3.23: New collection network with 80% target coverage

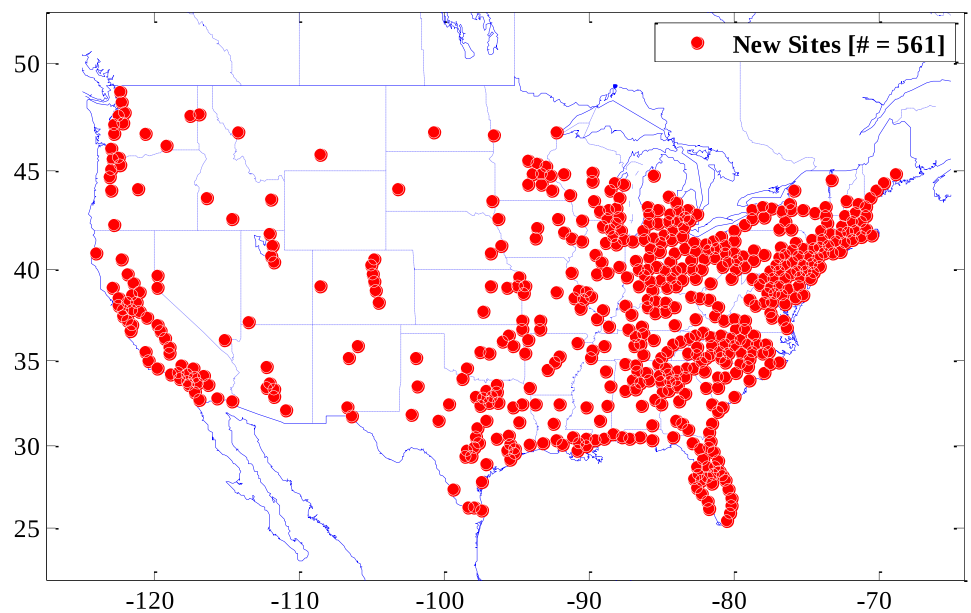

Figure A.3.24: New collection network with 85% target coverage

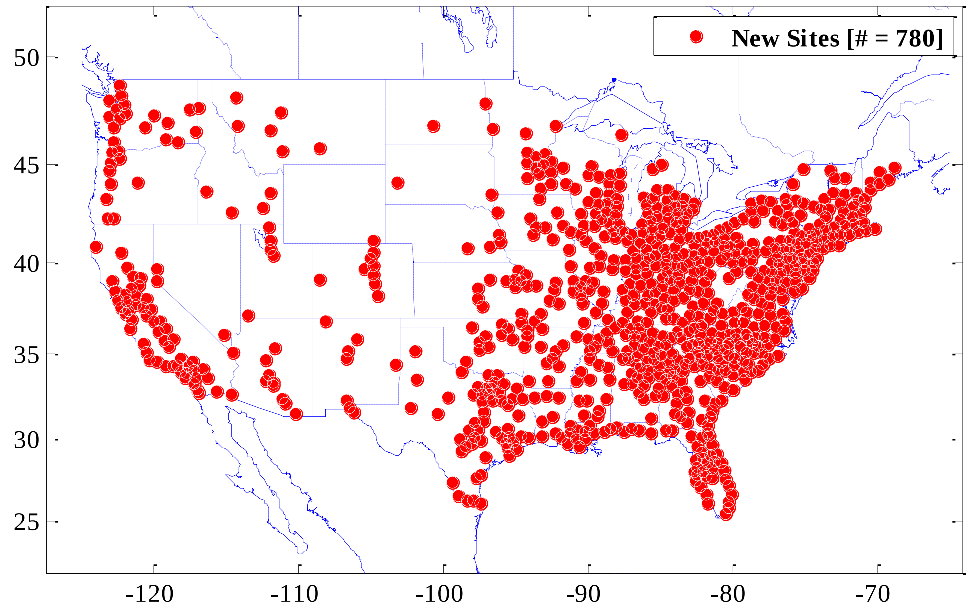

Figure A.3.25: New collection network with 90% target coverage

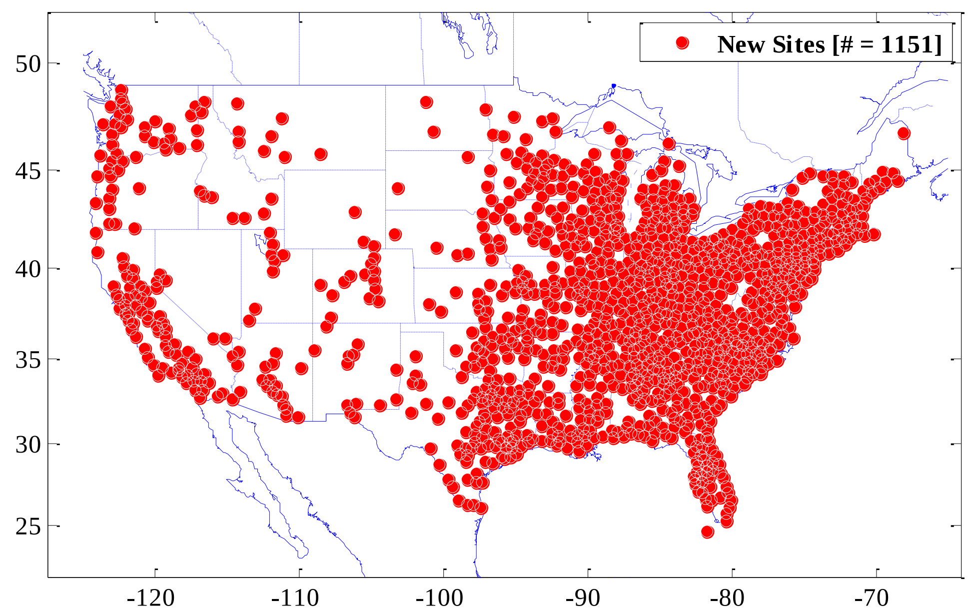

Figure A.3.26: New collection network with 95% target coverage

Appendix B: Supplementary Information for Chapter 4

B.1 Locations of Facilities in Recycling Networks

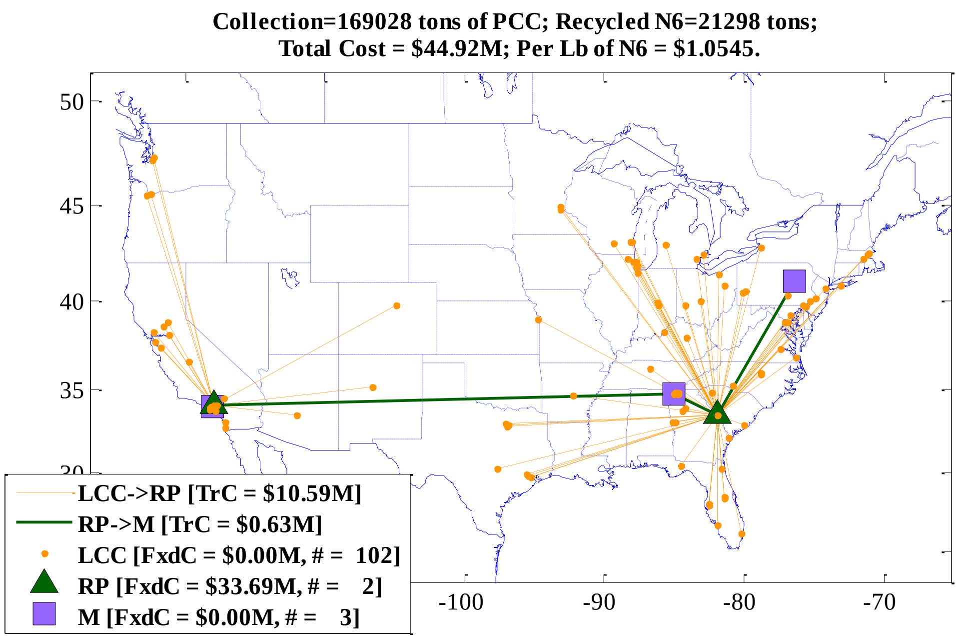

Figure B.1.1: Recycling network (Scenario 1, 36% coverage)

Table B.1.1: Recycling network facilities (Scenario 1, 36% coverage)

Type	Longitude	Latitude	Nearest City	State	ZIP Code	Utilization
RP	-81.9562	33.4372	North Augusta	SC	30901	86%
RP	-117.9854	34.0444	West Puente Valley	CA	91746	36%

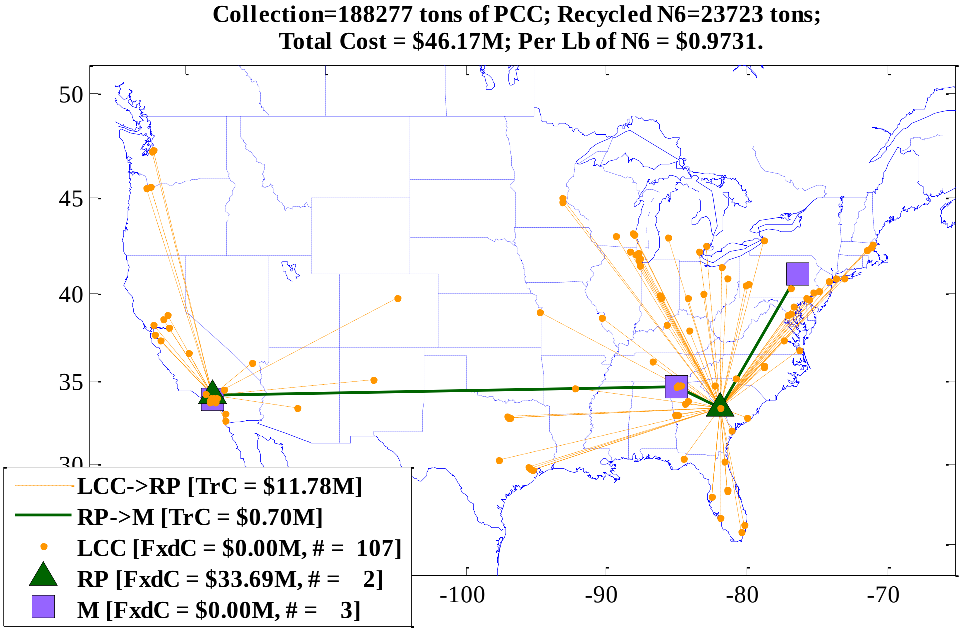

Figure B.1.2: Recycling network (Scenario 1, 40% coverage)

Table B.1.2: Recycling network facilities (Scenario 1, 40% coverage)

Type	Longitude	Latitude	Nearest City	State	ZIP Code	Utilization
RP	-81.9562	33.4372	North Augusta	SC	30901	96%
RP	-118.1073	34.1801	Altadena	CA	91000	40%

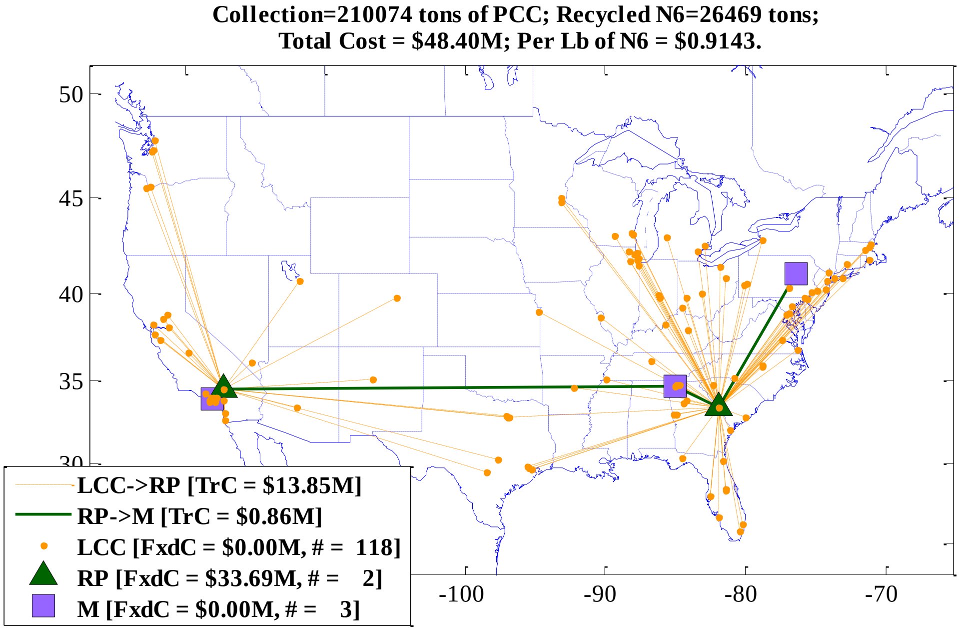

Figure B.1.3: Recycling network (Scenario 1, 45% coverage)

Table B.1.3: Recycling network facilities (Scenario 1, 45% coverage)

Type	Longitude	Latitude	Nearest City	State	ZIP Code	Utilization
RP	-81.9562	33.4372	North Augusta	SC	30901	100%
RP	-117.2916	34.5016	Victorville	CA	92395	51%

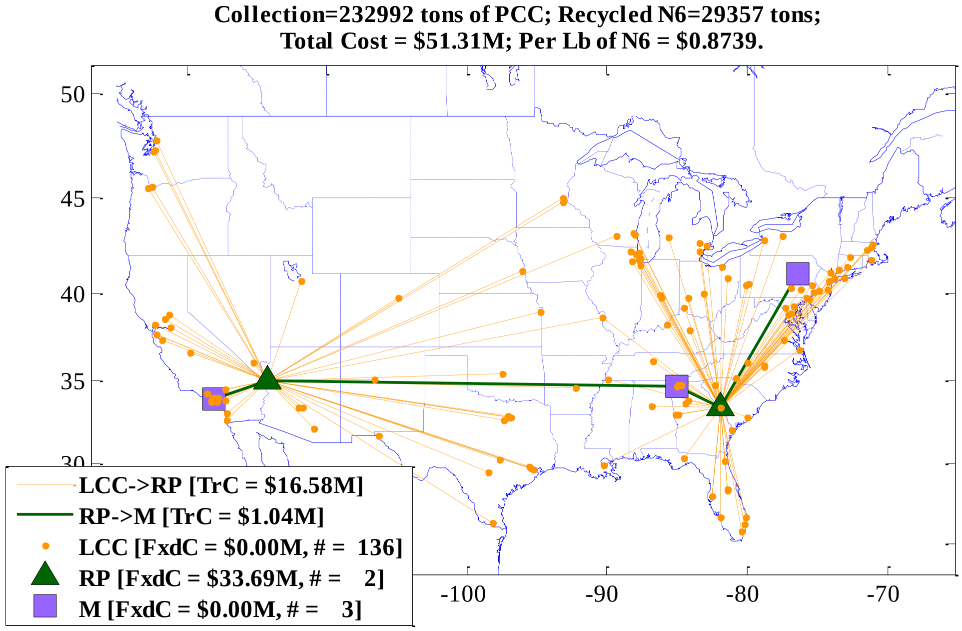

Figure B.1.4: Recycling network (Scenario 1, 50% coverage)

Table B.1.4: Recycling network facilities (Scenario 1, 50% coverage)

Type	Longitude	Latitude	Nearest City	State	ZIP Code	Utilization
RP	-81.9562	33.4372	North Augusta	SC	30901	100%
RP	-114.2215	35.0101	Kingman	AZ	86400	68%

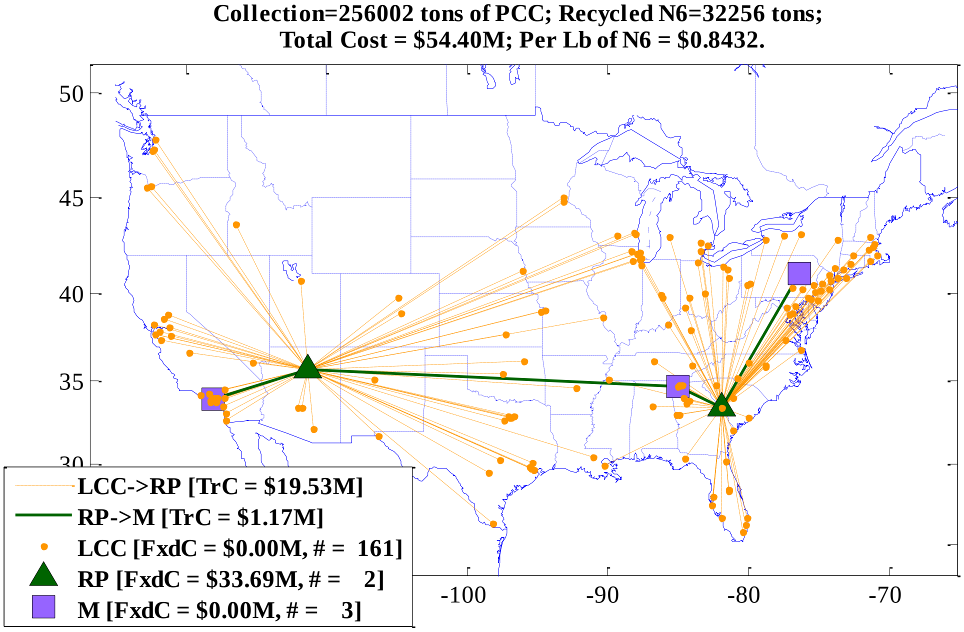

Figure B.1.5: Recycling network (Scenario 1, 55% coverage)

Table B.1.5: Recycling network facilities (Scenario 1, 55% coverage)

Type	Longitude	Latitude	Nearest City	State	ZIP Code	Utilization
RP	-81.9562	33.4372	North Augusta	SC	30901	100%
RP	-111.2960	35.6655	Flagstaff	AZ	86000	84%

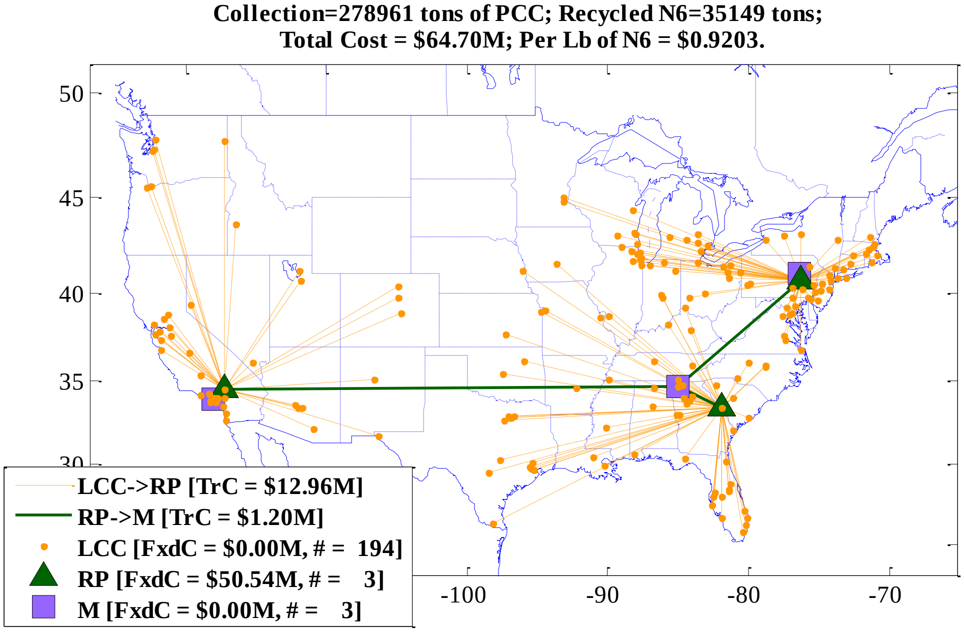

Figure B.1.6: Recycling network (Scenario 1, 60% coverage)

Table B.1.6: Recycling network facilities (Scenario 1, 60% coverage)

Type	Longitude	Latitude	Nearest City	State	ZIP Code	Utilization
RP	-76.2548	40.6903	Pottsville	PA	17900	86%
RP	-81.9562	33.4372	North Augusta	SC	30901	61%
RP	-117.2916	34.5016	Victorville	CA	92395	54%

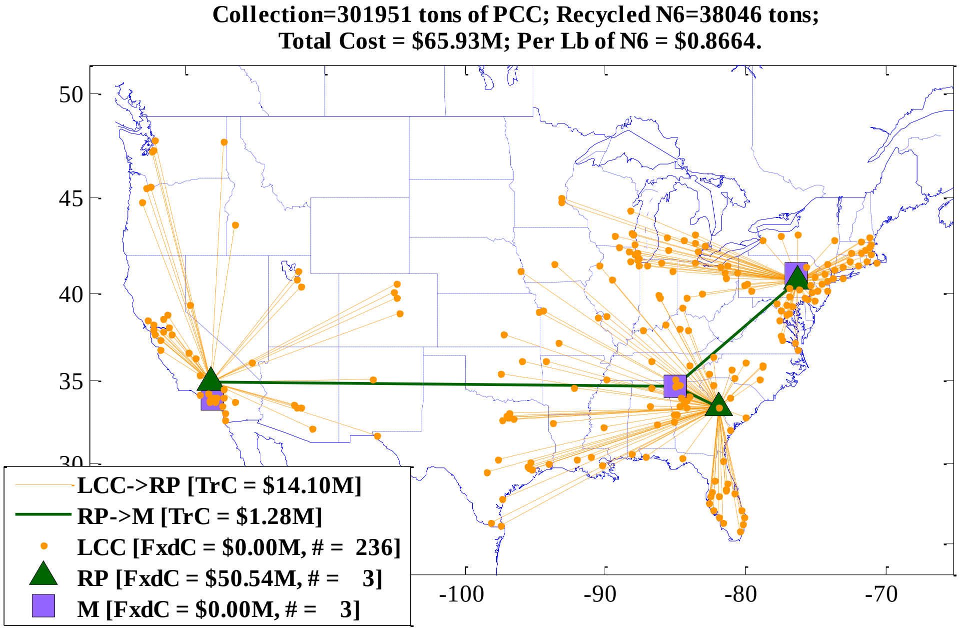

Figure B.1.7: Recycling network (Scenario 1, 65% coverage)

Table B.1.7: Recycling network facilities (Scenario 1, 65% coverage)

Type	Longitude	Latitude	Nearest City	State	ZIP Code	Utilization
RP	-76.2548	40.6903	Pottsville	PA	17900	90%
RP	-81.9562	33.4372	North Augusta	SC	30901	70%
RP	-118.1386	34.9147	Rosamond	CA	93500	57%

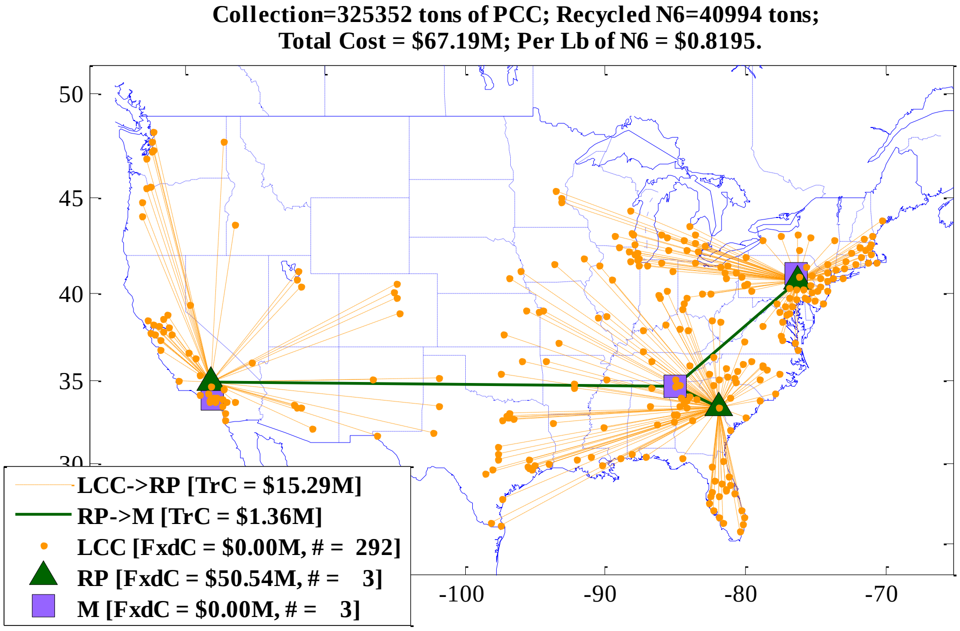

Figure B.1.8: Recycling network (Scenario 1, 70% coverage)

Table B.1.8: Recycling network facilities (Scenario 1, 70% coverage)

Type	Longitude	Latitude	Nearest City	State	ZIP Code	Utilization
RP	-76.2548	40.6903	Pottsville	PA	17900	95%
RP	-81.9562	33.4372	North Augusta	SC	30901	79%
RP	-118.1386	34.9147	Rosamond	CA	93500	60%

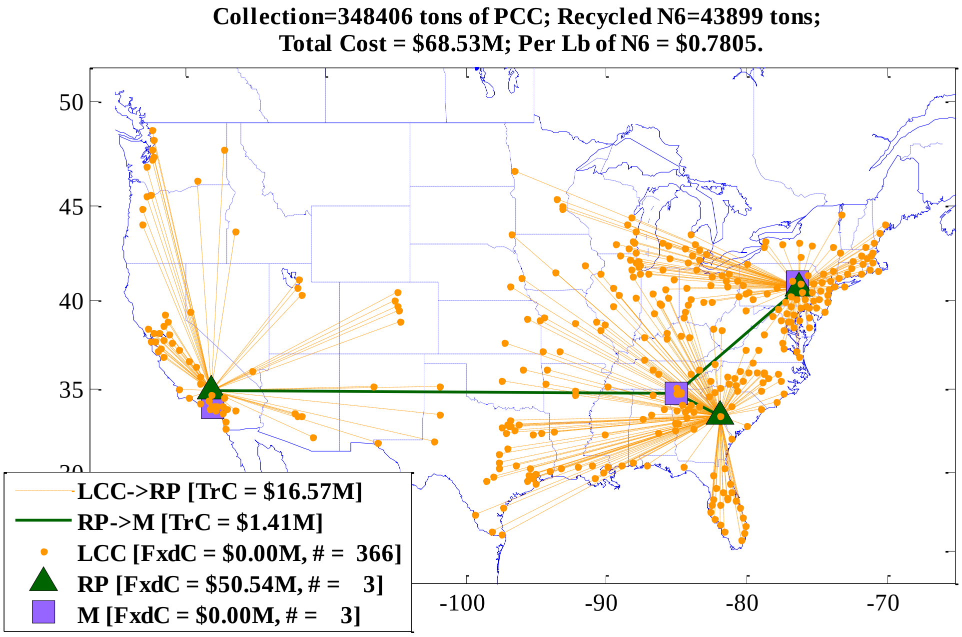

Figure B.1.9: Recycling network (Scenario 1, 75% coverage)

Table B.1.9: Recycling network facilities (Scenario 1, 75% coverage)

Type	Longitude	Latitude	Nearest City	State	ZIP Code	Utilization
RP	-76.2548	40.6903	Pottsville	PA	17900	100%
RP	-81.9562	33.4372	North Augusta	SC	30901	89%
RP	-118.1386	34.9147	Rosamond	CA	93500	62%

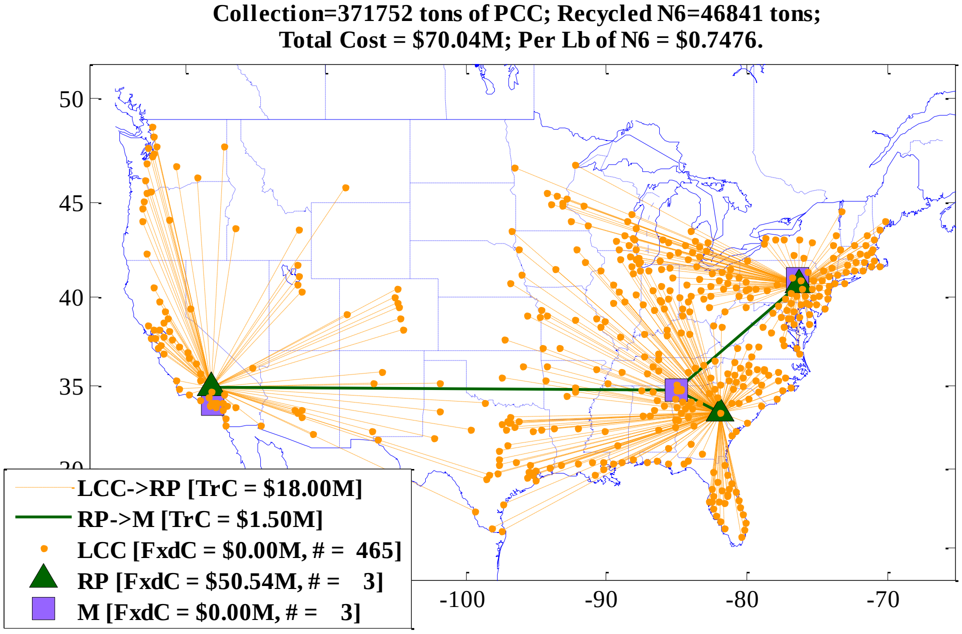

Figure B.1.10: Recycling network (Scenario 1, 80% coverage)

Table B.1.10: Recycling network facilities (Scenario 1, 80% coverage)

Type	Longitude	Latitude	Nearest City	State	ZIP Code	Utilization
RP	-76.2548	40.6903	Pottsville	PA	17900	100%
RP	-81.9562	33.4372	North Augusta	SC	30901	100%
RP	-118.1386	34.9147	Rosamond	CA	93500	68%

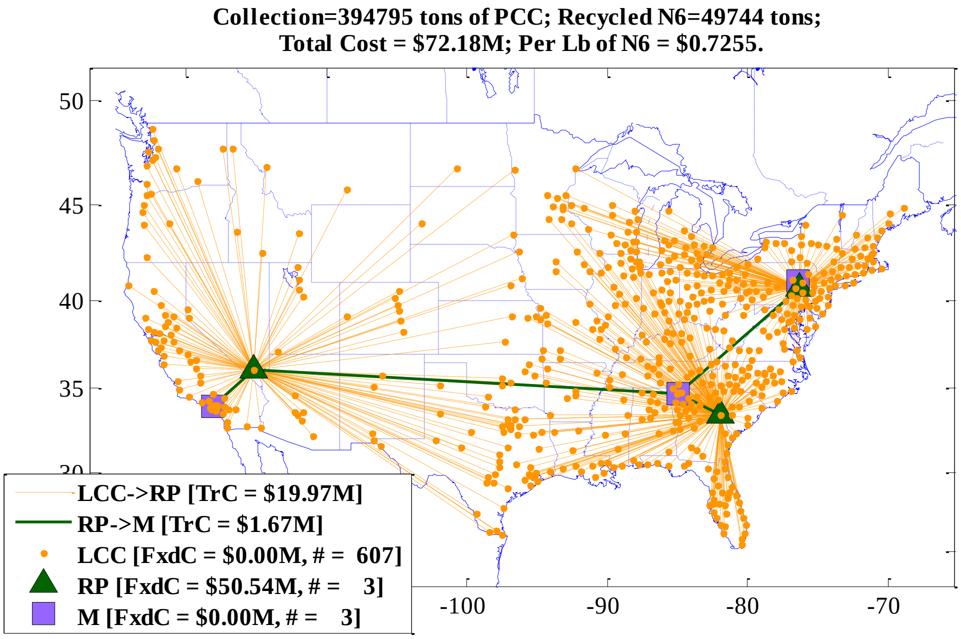

Figure B.1.11: Recycling network (Scenario 1, 85% coverage)

Table B.1.11: Recycling network facilities (Scenario 1, 85% coverage)

Type	Longitude	Latitude	Nearest City	State	ZIP Code	Utilization
RP	-76.2548	40.6903	Pottsville	PA	17900	100%
RP	-81.9562	33.4372	North Augusta	SC	30901	100%
RP	-115.2117	36.1118	Spring Valley	NV	89103	84%

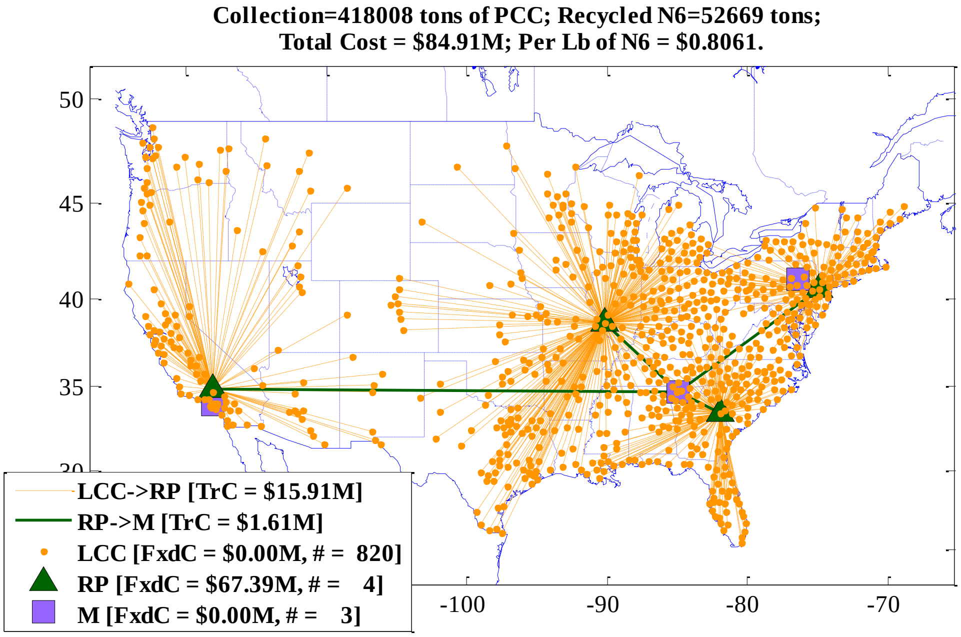

Figure B.1.12: Recycling network (Scenario 1, 90% coverage)

Table B.1.12: Recycling network facilities (Scenario 1, 90% coverage)

Type	Longitude	Latitude	Nearest City	State	ZIP Code	Utilization
RP	-74.8653	40.5251	Bradley Gardens	NJ	08822	81%
RP	-81.9562	33.4372	North Augusta	SC	30901	58%
RP	-90.1650	38.6565	East St. Louis	IL	62059	98%
RP	-118.1386	34.9147	Rosamond	CA	93500	64%

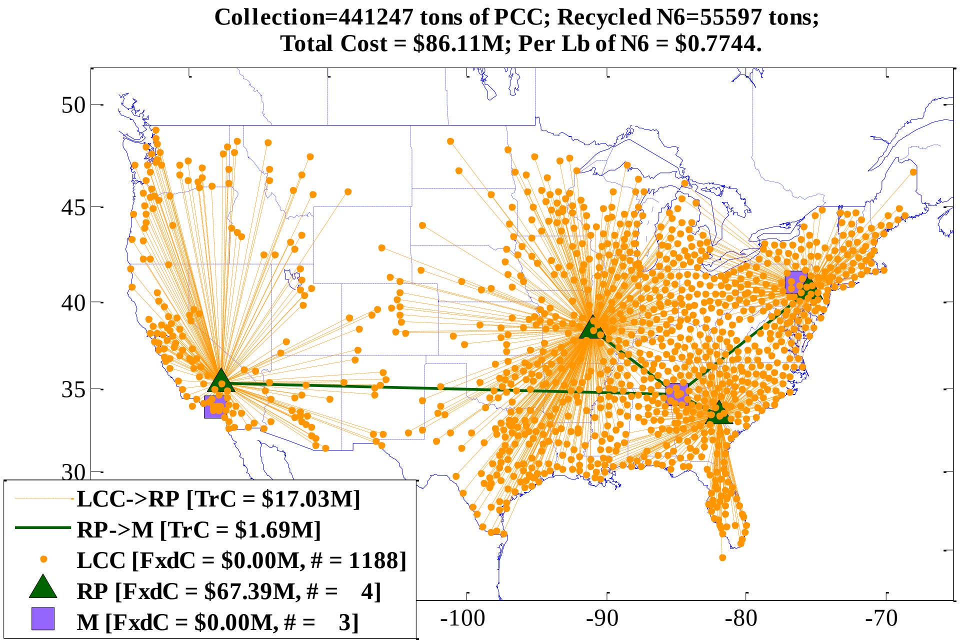

Figure B.1.13: Recycling network (Scenario 1, 95% coverage)

Table B.1.13: Recycling network facilities (Scenario 1, 95% coverage)

Type	Longitude	Latitude	Nearest City	State	ZIP Code	Utilization
RP	-75.4977	40.6000	Allentown	PA	18100	90%
RP	-81.9562	33.4372	North Augusta	SC	30901	60%
RP	-91.0193	38.4219	Union	MO	63084	100%
RP	-117.6433	35.3716	Ridgecrest	CA	93528	67%

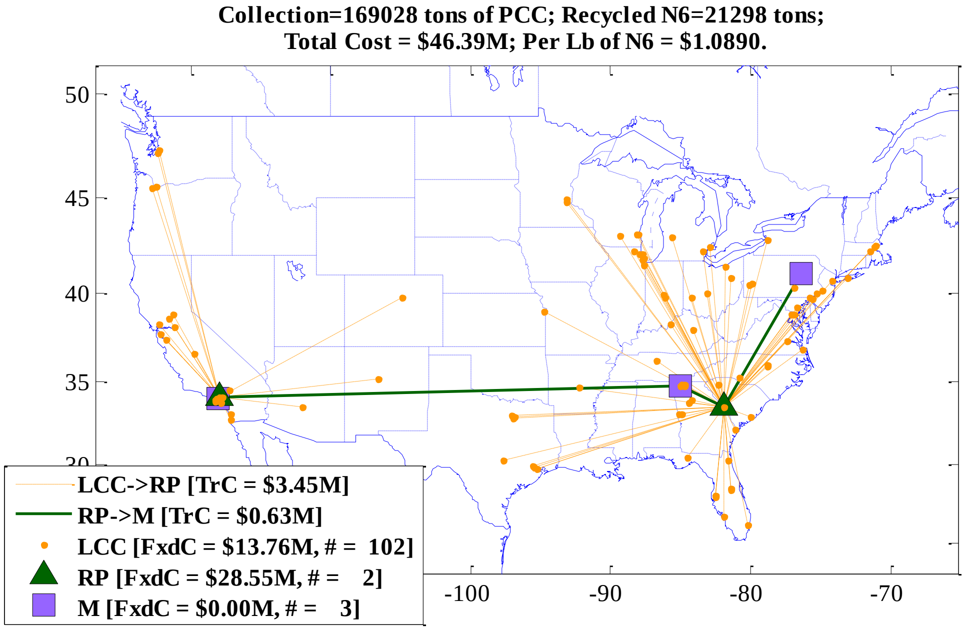

Figure B.1.14: Recycling network (Scenario 2, 36% coverage)

Table B.1.14: Recycling network facilities (Scenario 2, 36% coverage)

Type	Longitude	Latitude	Nearest City	State	ZIP Code	Utilization
RP	-81.9562	33.4372	North Augusta	SC	30901	86%
RP	-117.9854	34.0444	West Puente Valley	CA	91746	36%

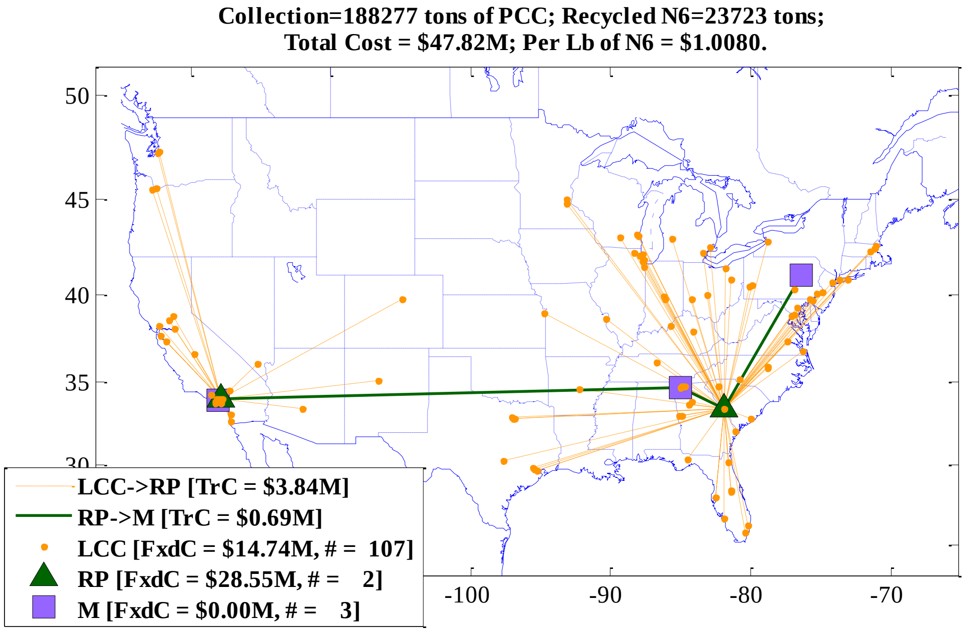

Figure B.1.15: Recycling network (Scenario 2, 40% coverage)

Table B.1.15: Recycling network facilities (Scenario 2, 40% coverage)

Type	Longitude	Latitude	Nearest City	State	ZIP Code	Utilization
RP	-81.9562	33.4372	North Augusta	SC	30901	96%
RP	-117.8286	34.0709	Walnut	CA	91700	40%

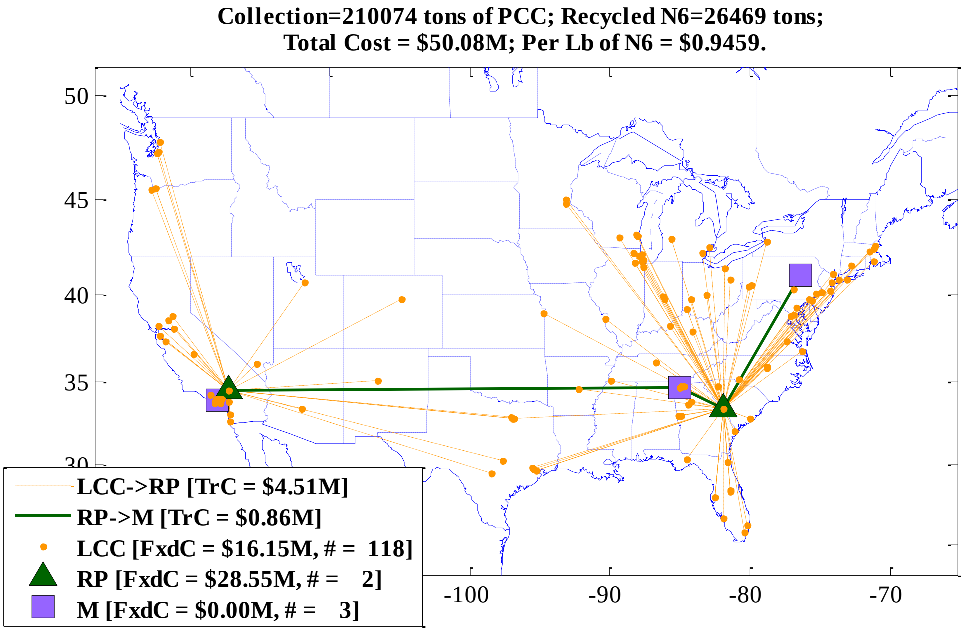

Figure B.1.16: Recycling network (Scenario 2, 45% coverage)

Table B.1.16: Recycling network facilities (Scenario 2, 45% coverage)

Type	Longitude	Latitude	Nearest City	State	ZIP Code	Utilization
RP	-81.9562	33.4372	North Augusta	SC	30901	100%
RP	-117.2916	34.5016	Victorville	CA	92395	51%

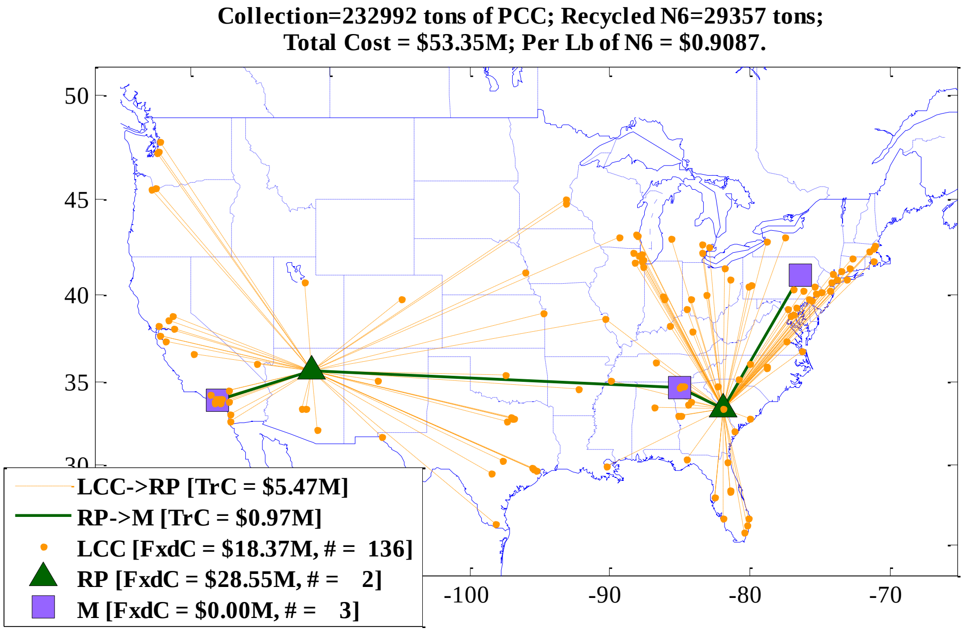

Figure B.1.17: Recycling network (Scenario 2, 50% coverage)

Table B.1.17: Recycling network facilities (Scenario 2, 50% coverage)

Type	Longitude	Latitude	Nearest City	State	ZIP Code	Utilization
RP	-81.9562	33.4372	North Augusta	SC	30901	100%
RP	-111.2960	35.6655	Flagstaff	AZ	86000	68%

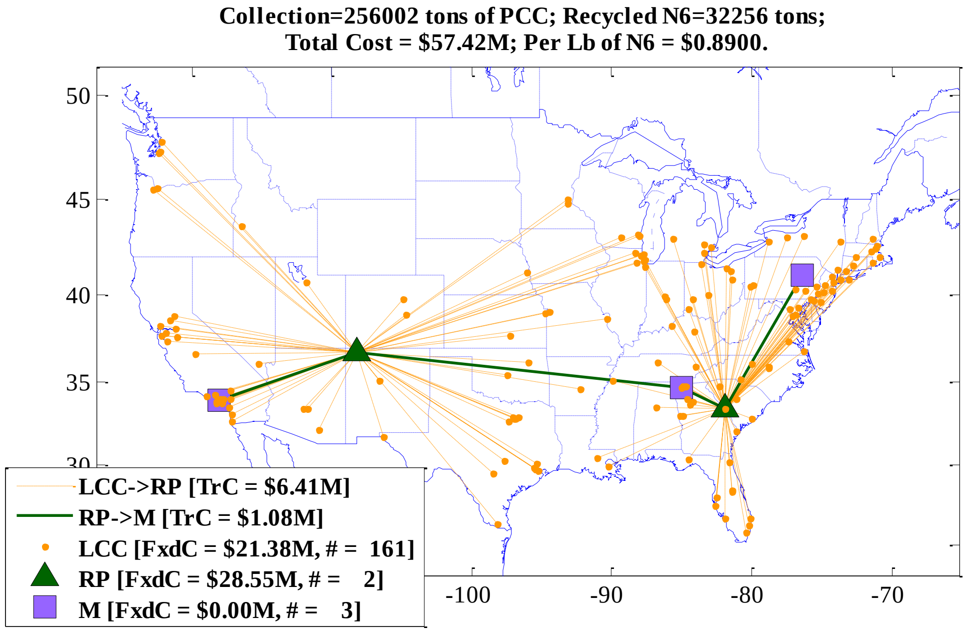

Figure B.1.18: Recycling network (Scenario 2, 55% coverage)

Table B.1.18: Recycling network facilities (Scenario 2, 55% coverage)

Type	Longitude	Latitude	Nearest City	State	ZIP Code	Utilization
RP	-81.9562	33.4372	North Augusta	SC	30901	100%
RP	-108.2061	36.7196	Farmington	NM	87400	84%

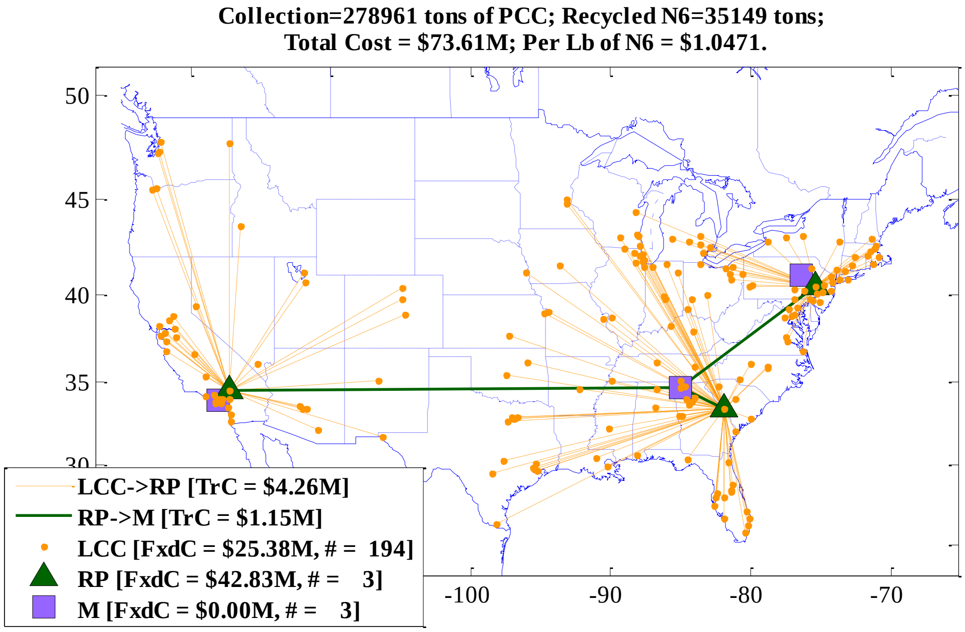

Figure B.1.19: Recycling network (Scenario 2, 60% coverage)

Table B.1.19: Recycling network facilities (Scenario 2, 60% coverage)

Type	Longitude	Latitude	Nearest City	State	ZIP Code	Utilization
RP	-75.4035	40.4370	Emmaus	PA	18935	67%
RP	-81.9562	33.4372	North Augusta	SC	30901	80%
RP	-117.2916	34.5016	Victorville	CA	92395	54%

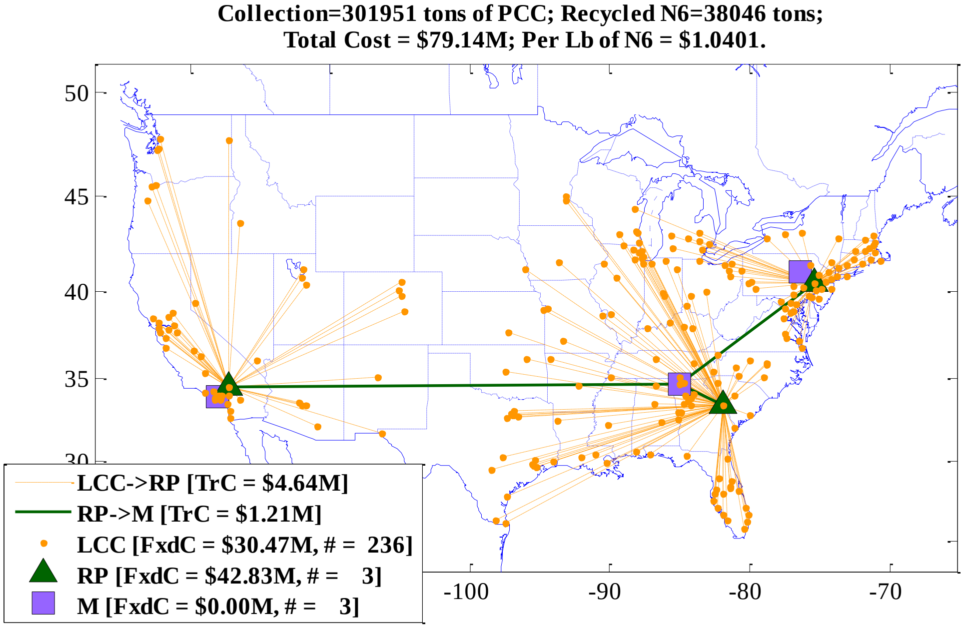

Figure B.1.20: Recycling network (Scenario 2, 65% coverage)

Table B.1.20: Recycling network facilities (Scenario 2, 65% coverage)

Type	Longitude	Latitude	Nearest City	State	ZIP Code	Utilization
RP	-75.4035	40.4370	Emmaus	PA	18935	71%
RP	-81.9562	33.4372	North Augusta	SC	30901	89%
RP	-117.2916	34.5016	Victorville	CA	92395	57%

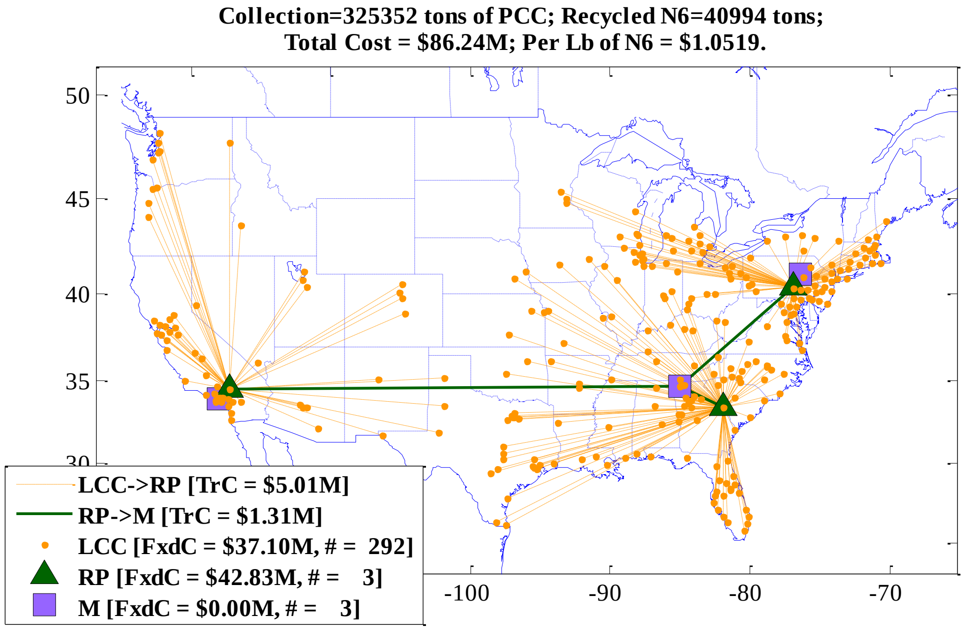

Figure B.1.21: Recycling network (Scenario 2, 70% coverage)

Table B.1.21: Recycling network facilities (Scenario 2, 70% coverage)

Type	Longitude	Latitude	Nearest City	State	ZIP Code	Utilization
RP	-76.9135	40.3196	Harrisburg	PA	17000	95%
RP	-81.9562	33.4372	North Augusta	SC	30901	79%
RP	-117.2916	34.5016	Victorville	CA	92395	60%

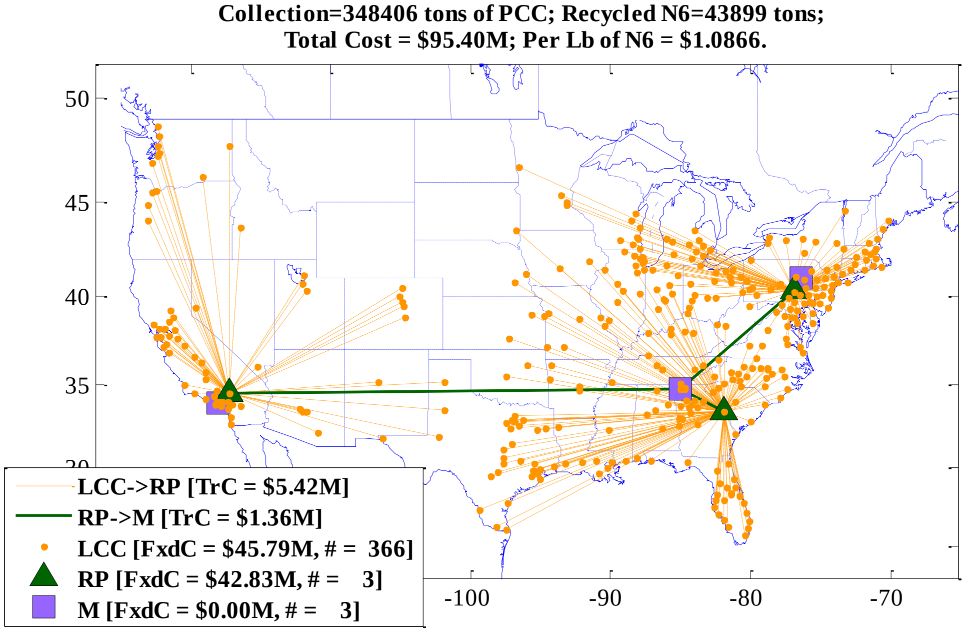

Figure B.1.22: Recycling network (Scenario 2, 75% coverage)

Table B.1.22: Recycling network facilities (Scenario 2, 75% coverage)

Type	Longitude	Latitude	Nearest City	State	ZIP Code	Utilization
RP	-76.9135	40.3196	Harrisburg	PA	17000	100%
RP	-81.9562	33.4372	North Augusta	SC	30901	89%
RP	-117.2916	34.5016	Victorville	CA	92395	62%

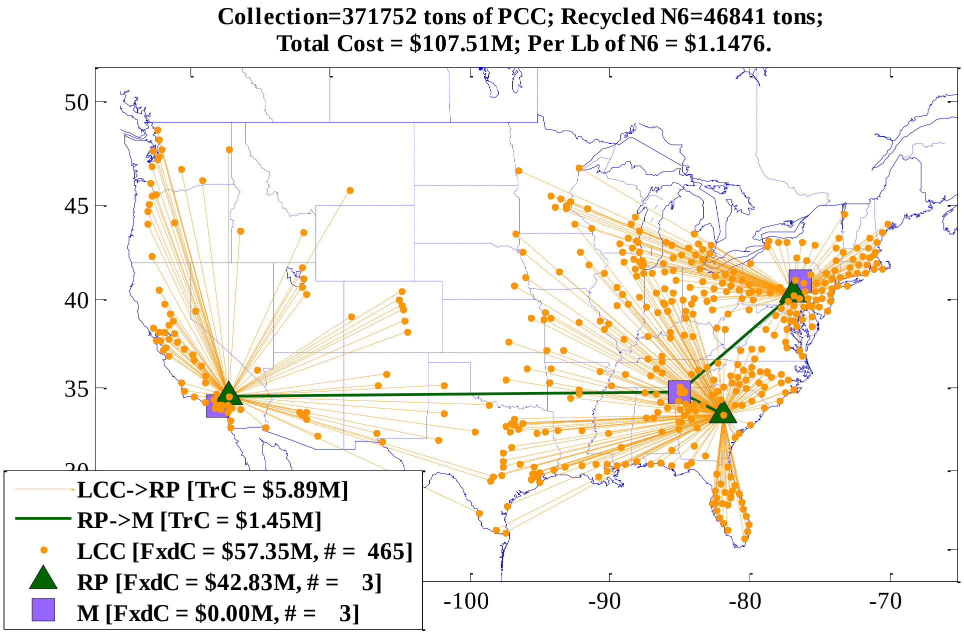

Figure B.1.23: Recycling network (Scenario 2, 80% coverage)

Table B.1.23: Recycling network facilities (Scenario 2, 80% coverage)

Type	Longitude	Latitude	Nearest City	State	ZIP Code	Utilization
RP	-76.9135	40.3196	Harrisburg	PA	17000	100%
RP	-81.9562	33.4372	North Augusta	SC	30901	100%
RP	-117.2916	34.5016	Victorville	CA	92395	68%

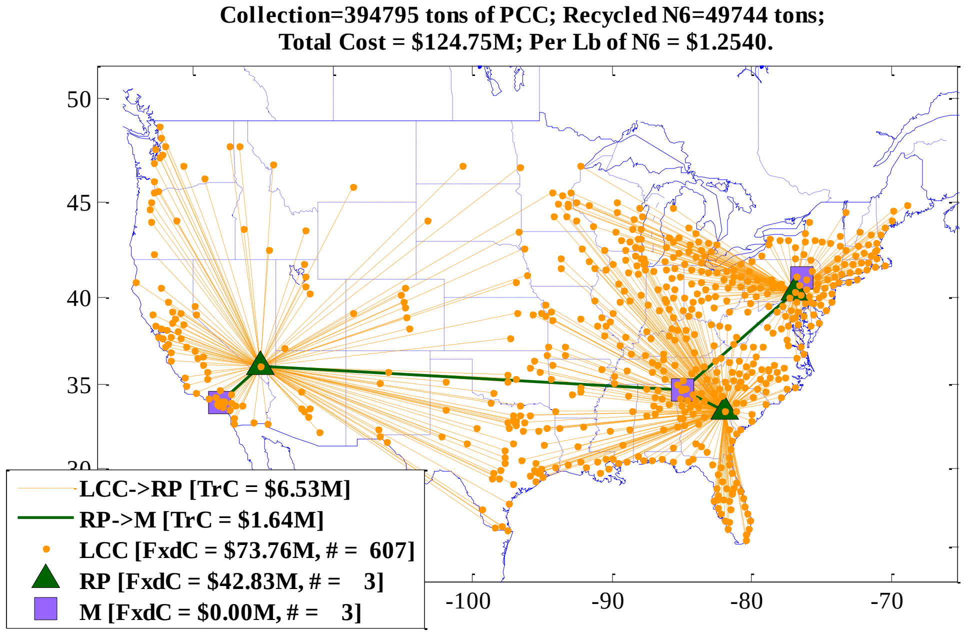

Figure B.1.24: Recycling network (Scenario 2, 85% coverage)

Table B.1.24: Recycling network facilities (Scenario 2, 85% coverage)

Type	Longitude	Latitude	Nearest City	State	ZIP Code	Utilization
RP	-76.9135	40.3196	Harrisburg	PA	17000	100%
RP	-81.9562	33.4372	North Augusta	SC	30901	100%
RP	-115.2117	36.1118	Spring Valley	NV	89103	84%

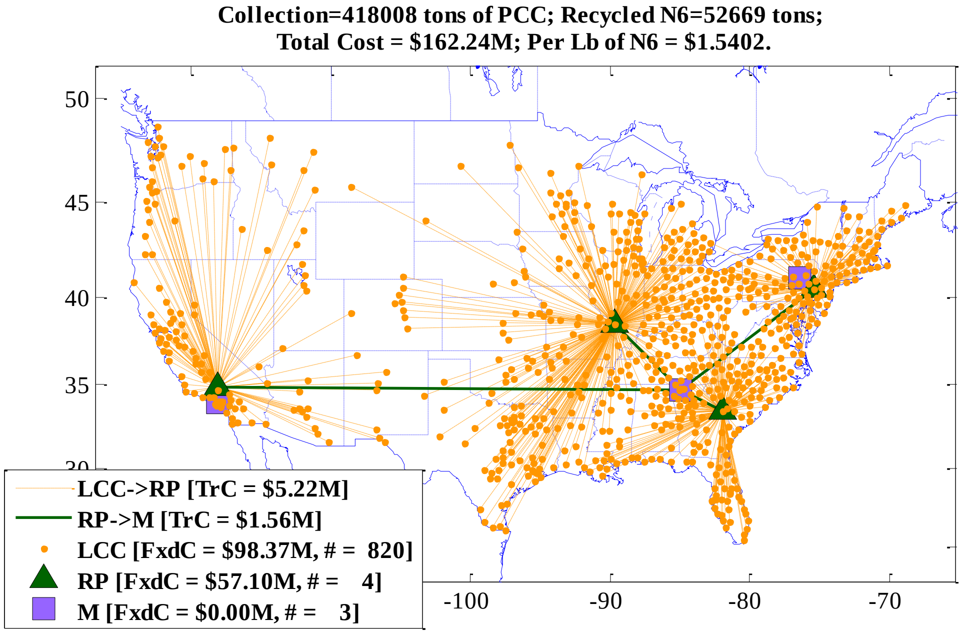

Figure B.1.25: Recycling network (Scenario 2, 90% coverage)

Table B.1.25: Recycling network facilities (Scenario 2, 90% coverage)

Type	Longitude	Latitude	Nearest City	State	ZIP Code	Utilization
RP	-75.4035	40.4370	Emmaus	PA	18935	79%
RP	-81.9562	33.4372	North Augusta	SC	30901	58%
RP	-89.6088	38.5083	Shiloh	IL	62215	100%
RP	-118.1386	34.9147	Rosamond	CA	93500	64%

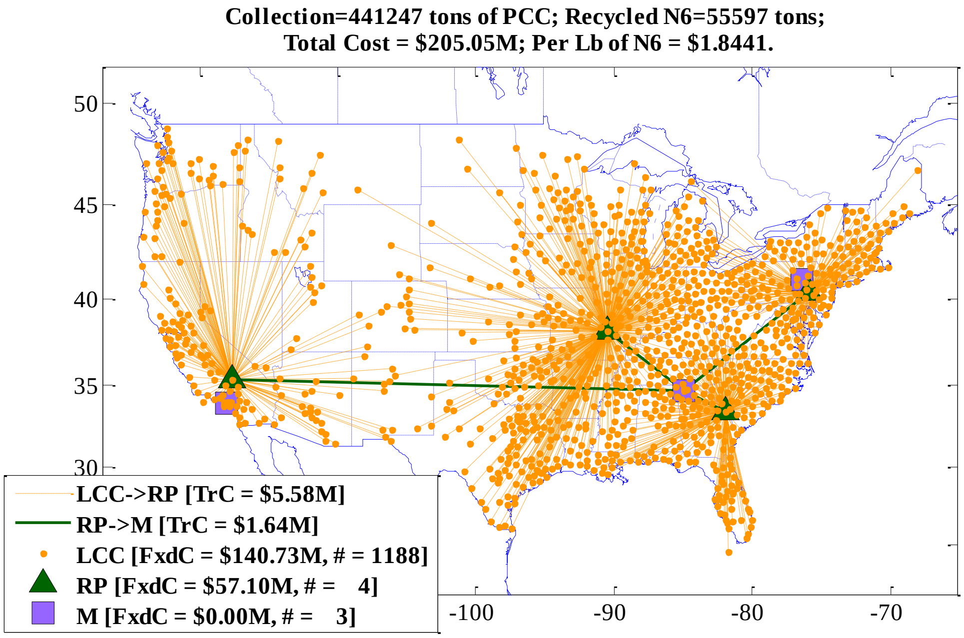

Figure B.1.26: Recycling network (Scenario 2, 95% coverage)

Table B.1.26: Recycling network facilities (Scenario 2, 95% coverage)

Type	Longitude	Latitude	Nearest City	State	ZIP Code	Utilization
RP	-75.8576	40.3853	Reading	PA	19500	89%
RP	-81.9562	33.4372	North Augusta	SC	30901	62%
RP	-90.4874	38.1955	Festus	MO	63047	100%
RP	-117.6433	35.3716	Ridgecrest	CA	93528	67%

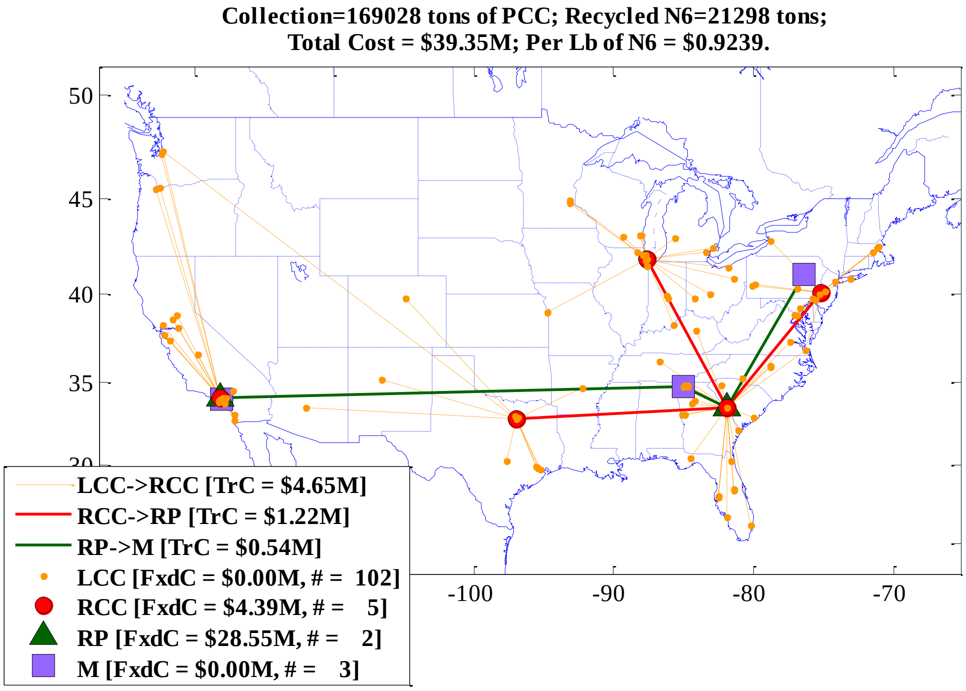

Figure B.1.27: Recycling network (Scenario 3, 36% coverage)

Table B.1.27: Recycling network facilities (Scenario 3, 36% coverage)

Type	Longitude	Latitude	Nearest City	State	ZIP Code	Utilization
RCC	-75.1847	40.0312	Philadelphia	PA	19000	100%
RCC	-81.9562	33.4372	North Augusta	SC	30901	64%
RCC	-87.6291	41.8831	Chicago	IL	60602	85%
RCC	-96.9669	32.8259	Irving	TX	75061	56%
RCC	-118.1343	34.0849	Alhambra	CA	91800	100%
RP	-81.9562	33.4372	North Augusta	SC	30901	92%
RP	-118.1343	34.0849	Alhambra	CA	91800	30%

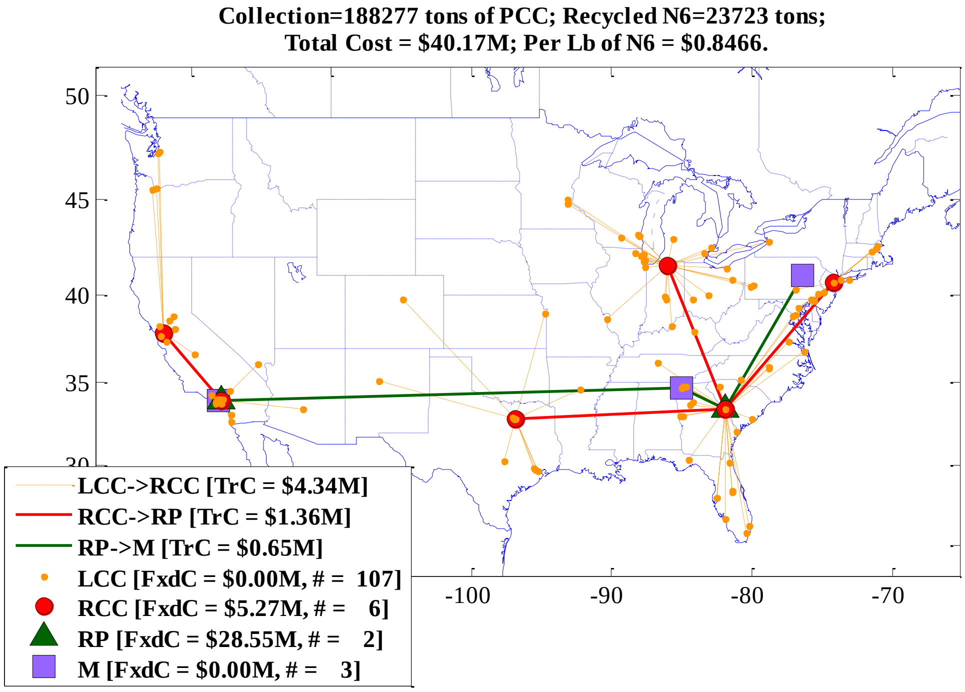

Figure B.1.28: Recycling network (Scenario 3, 40% coverage)

Table B.1.28: Recycling network facilities (Scenario 3, 40% coverage)

Type	Longitude	Latitude	Nearest City	State	ZIP Code	Utilization
RCC	-74.1838	40.6517	Elizabeth	NJ	07206	100%
RCC	-81.9562	33.4372	North Augusta	SC	30901	82%
RCC	-86.0218	41.5471	Goshen	IN	46500	96%
RCC	-96.8761	32.8685	Farmers Branch	TX	75220	51%
RCC	-117.8209	33.9868	Diamond Bar	CA	91765	77%
RCC	-122.0233	37.8669	Alamo	CA	94500	45%
RP	-81.9562	33.4372	North Augusta	SC	30901	99%
RP	-117.8209	33.9868	Diamond Bar	CA	91765	37%

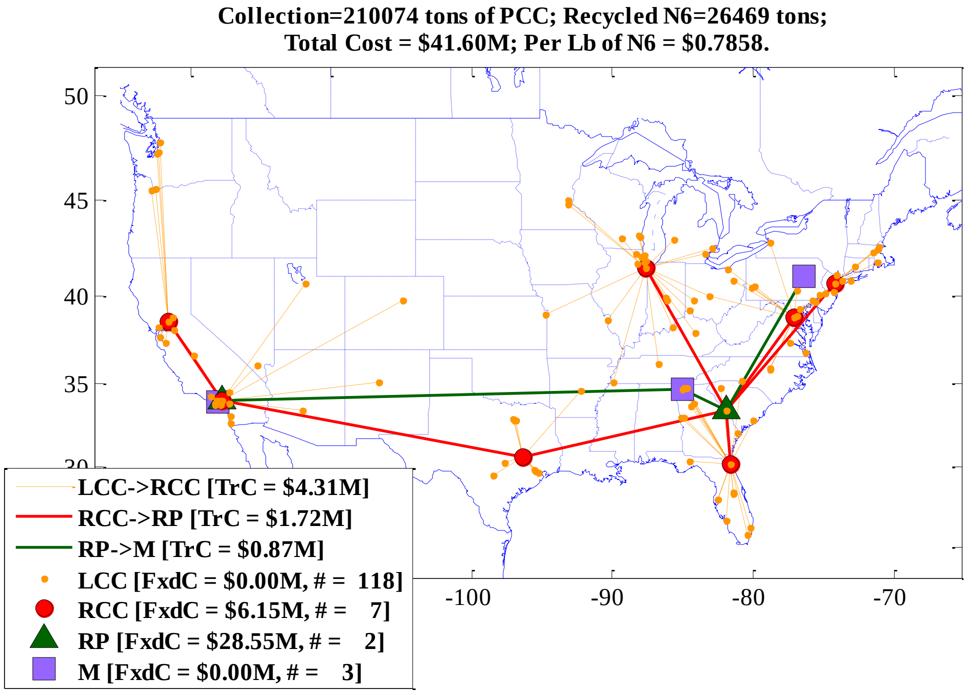

Figure B.1.29: Recycling network (Scenario 3, 45% coverage)

Table B.1.29: Recycling network facilities (Scenario 3, 45% coverage)

Type	Longitude	Latitude	Nearest City	State	ZIP Code	Utilization
RCC	-74.1838	40.6517	Elizabeth	NJ	07206	100%
RCC	-77.1121	38.8131	Alexandria	VA	22304	56%
RCC	-81.6251	30.2380	Jacksonville	FL	32217	58%
RCC	-87.6832	41.4778	Park Forest	IL	60466	100%
RCC	-96.3255	30.5999	College Station	TX	77800	42%
RCC	-117.7561	34.0423	Pomona	CA	91766	100%
RCC	-121.5399	38.5935	West Sacramento	CA	95605	48%
RP	-81.9562	33.4372	North Augusta	SC	30901	100%
RP	-117.7561	34.0423	Pomona	CA	91766	51%

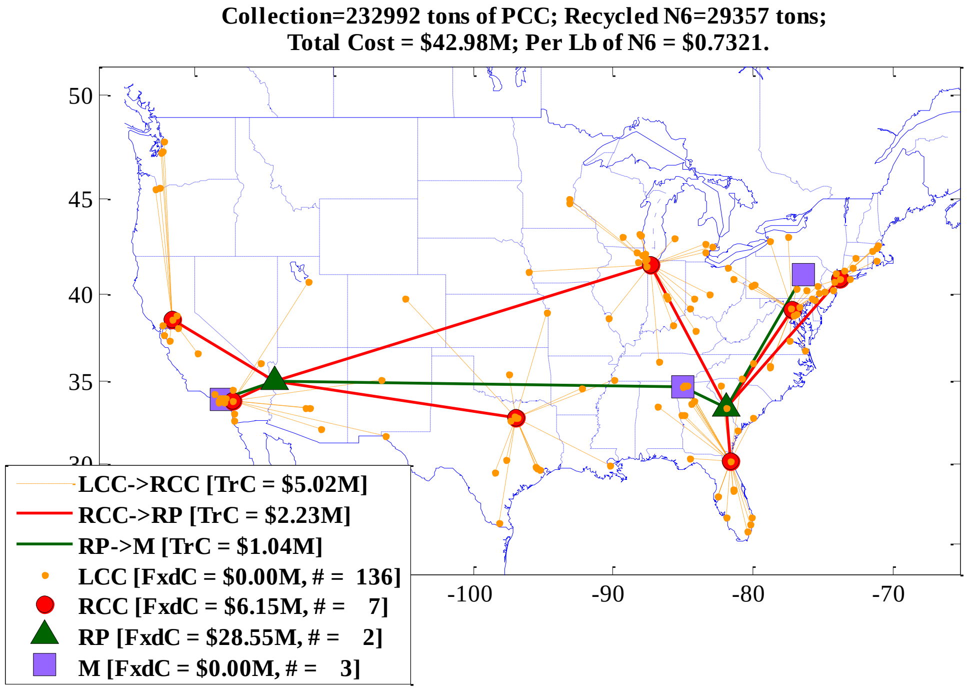

Figure B.1.30: Recycling network (Scenario 3, 50% coverage)

Table B.1.30: Recycling network facilities (Scenario 3, 50% coverage)

Type	Longitude	Latitude	Nearest City	State	ZIP Code	Utilization
RCC	-73.7337	40.7987	Port Washington	NY	11023	100%
RCC	-77.1759	39.1039	Rockville	MD	20800	76%
RCC	-81.6251	30.2380	Jacksonville	FL	32217	64%
RCC	-87.3345	41.5505	Gary	IN	46400	100%
RCC	-96.9669	32.8259	Irving	TX	75061	71%
RCC	-117.2784	33.8891	Mead Valley	CA	92518	98%
RCC	-121.5399	38.5935	West Sacramento	CA	95605	50%
RP	-81.9562	33.4372	North Augusta	SC	30901	100%
RP	-114.2215	35.0101	Kingman	AZ	86400	68%

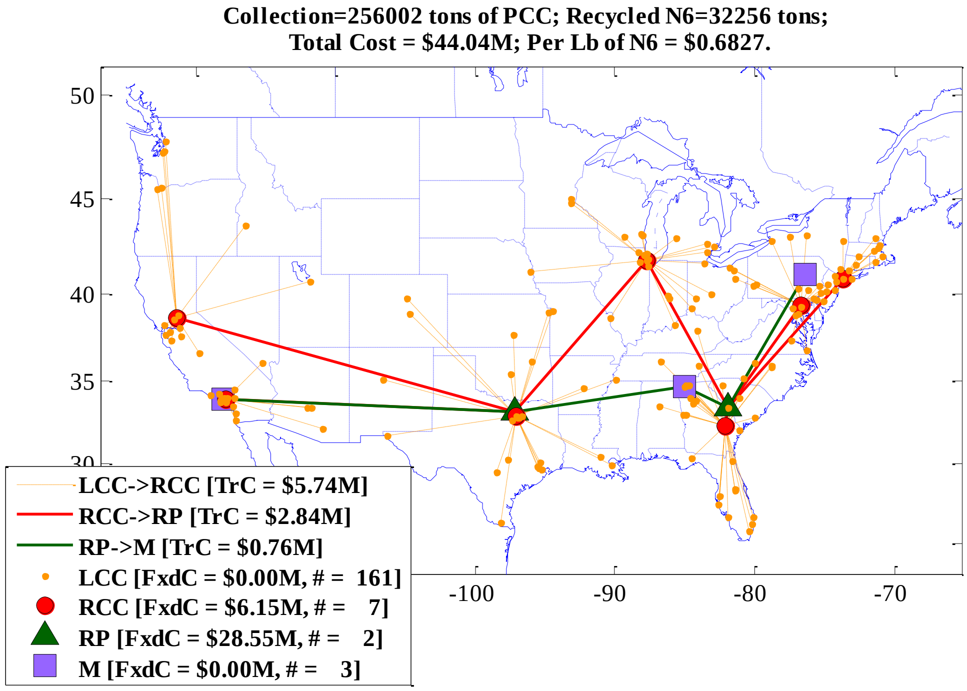

Figure B.1.31: Recycling network (Scenario 3, 55% coverage)

Table B.1.31: Recycling network facilities (Scenario 3, 55% coverage)

Type	Longitude	Latitude	Nearest City	State	ZIP Code	Utilization
RCC	-73.6931	40.8399	Port Washington	NY	11050	100%
RCC	-76.7062	39.3215	Lochearn	MD	21100	87%
RCC	-82.0689	32.3919	Statesboro	GA	30400	85%
RCC	-87.7133	41.8102	Chicago	IL	60632	98%
RCC	-97.0715	32.9258	Grapevine	TX	76051	91%
RCC	-117.8209	33.9868	Diamond Bar	CA	91765	93%
RCC	-121.3546	38.6270	Carmichael	CA	95600	61%
RP	-81.9562	33.4372	North Augusta	SC	30901	100%
RP	-97.2131	33.2133	Denton	TX	76200	84%

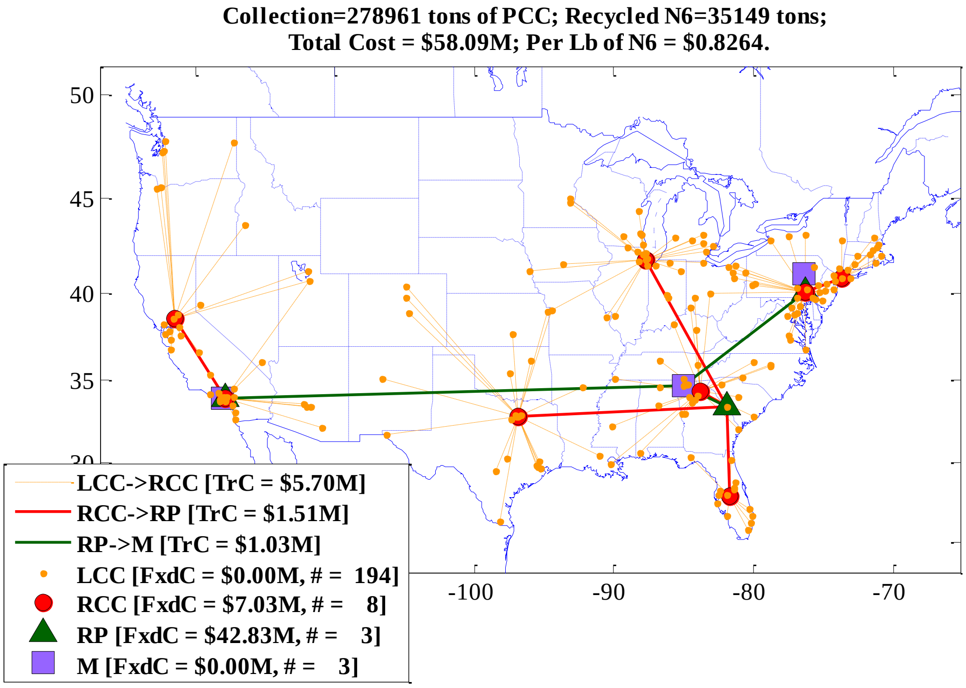

Figure B.1.32: Recycling network (Scenario 3, 60% coverage)

Table B.1.32: Recycling network facilities (Scenario 3, 60% coverage)

Type	Longitude	Latitude	Nearest City	State	ZIP Code	Utilization
RCC	-73.6931	40.8399	Port Washington	NY	11050	100%
RCC	-76.2989	40.0390	Lancaster	PA	17600	100%
RCC	-83.8160	34.4006	Gainesville	GA	30500	75%
RCC	-81.7579	27.9265	Bartow	FL	33800	47%
RCC	-87.7133	41.8102	Chicago	IL	60632	100%
RCC	-96.8761	32.8685	Farmers Branch	TX	75220	83%
RCC	-117.8209	33.9868	Diamond Bar	CA	91765	100%
RCC	-121.4847	38.5665	Sacramento	CA	94200	64%
RP	-76.2989	40.0390	Lancaster	PA	17600	60%
RP	-81.9562	33.4372	North Augusta	SC	30901	92%
RP	-117.8209	33.9868	Diamond Bar	CA	91765	49%

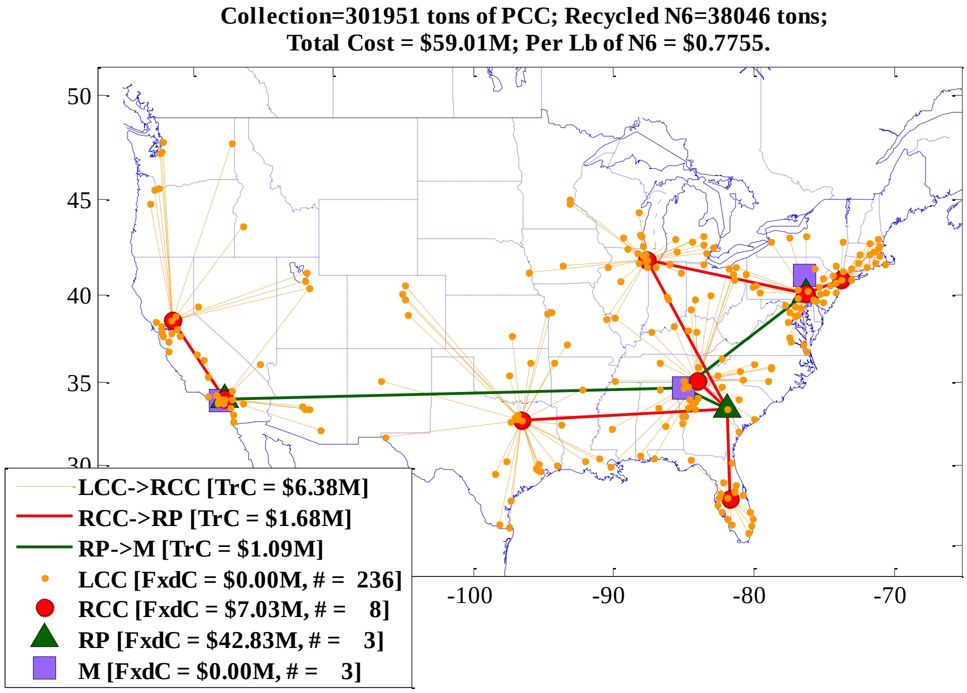

Figure B.1.33: Recycling network (Scenario 3, 65% coverage)

Table B.1.33: Recycling network facilities (Scenario 3, 65% coverage)

Type	Longitude	Latitude	Nearest City	State	ZIP Code	Utilization
RCC	-73.7337	40.7987	Port Washington	NY	11023	100%
RCC	-76.2989	40.0390	Lancaster	PA	17600	100%
RCC	-83.9717	35.1066	Athens	TN	28900	100%
RCC	-81.7579	27.9265	Bartow	FL	33800	53%
RCC	-87.6291	41.8831	Chicago	IL	60602	100%
RCC	-96.5900	32.7600	Mesquite	TX	75185	100%
RCC	-117.7561	34.0423	Pomona	CA	91766	100%
RCC	-121.4344	38.5706	Sacramento	CA	95800	72%
RP	-76.2989	40.0390	Lancaster	PA	17600	66%
RP	-81.9562	33.4372	North Augusta	SC	30901	100%
RP	-117.7561	34.0423	Pomona	CA	91766	52%

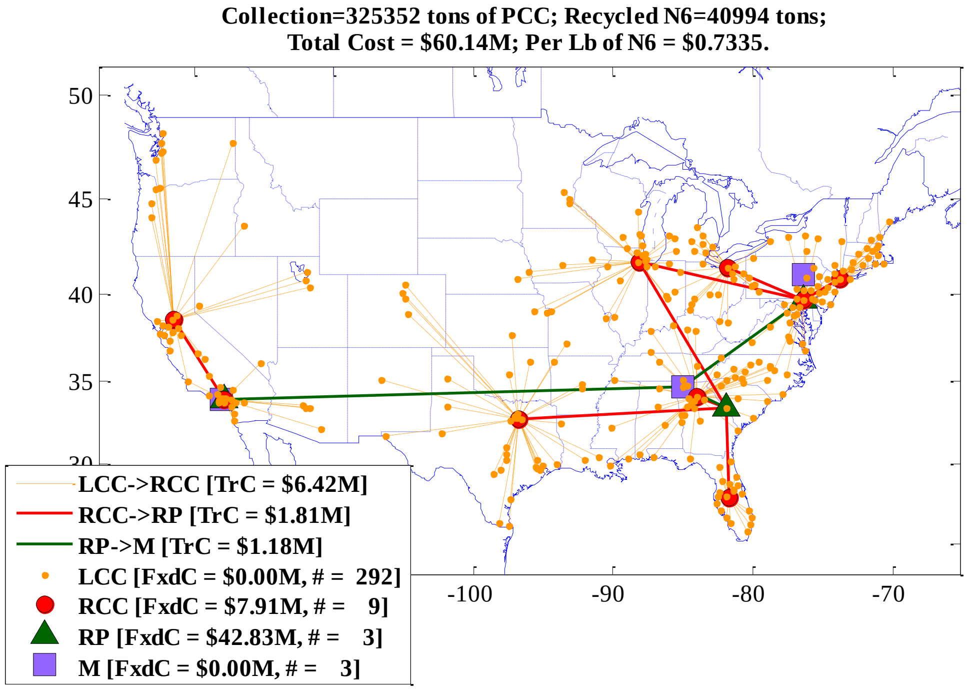

Figure B.1.34: Recycling network (Scenario 3, 70% coverage)

Table B.1.34: Recycling network facilities (Scenario 3, 70% coverage)

Type	Longitude	Latitude	Nearest City	State	ZIP Code	Utilization
RCC	-73.7337	40.7987	Port Washington	NY	11023	100%
RCC	-76.3605	39.6574	Bel Air North	MD	21154	100%
RCC	-83.9900	34.1100	Buford	GA	30515	89%
RCC	-81.7579	27.9265	Bartow	FL	33800	55%
RCC	-81.8343	41.3997	Brook Park	OH	44142	68%
RCC	-88.1784	41.7431	Naperville	IL	60500	90%
RCC	-96.7733	32.7943	Dallas	TX	75300	99%
RCC	-117.8209	33.9868	Diamond Bar	CA	91765	100%
RCC	-121.4344	38.5706	Sacramento	CA	95800	79%
RP	-76.3605	39.6574	Bel Air North	MD	21154	80%
RP	-81.9562	33.4372	North Augusta	SC	30901	100%
RP	-117.8209	33.9868	Diamond Bar	CA	91765	54%

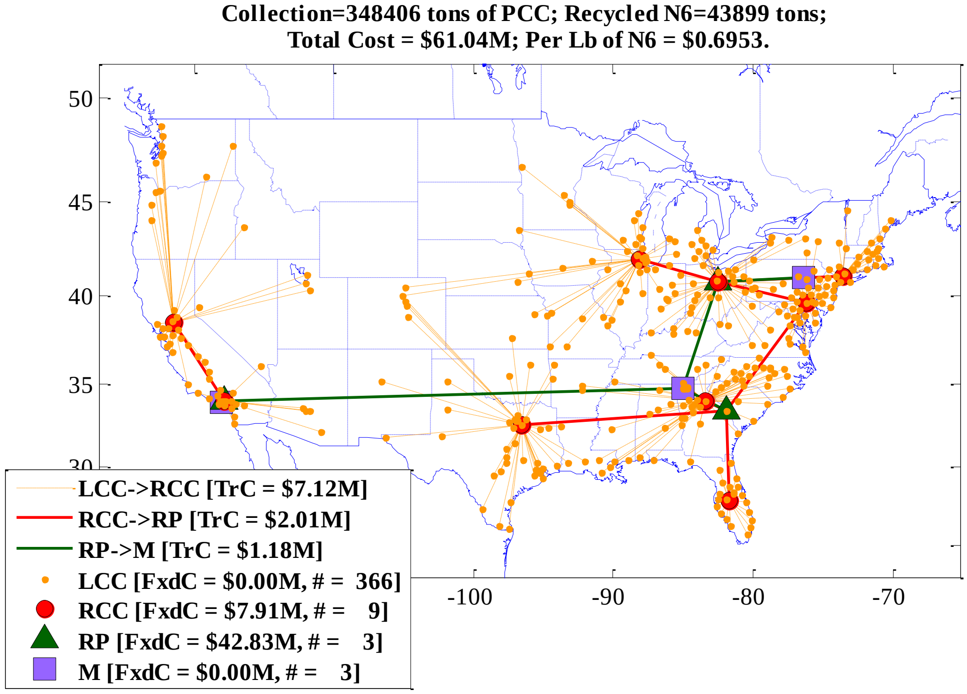

Figure B.1.35: Recycling network (Scenario 3, 75% coverage)

Table B.1.35: Recycling network facilities (Scenario 3, 75% coverage)

Type	Longitude	Latitude	Nearest City	State	ZIP Code	Utilization
RCC	-73.5435	41.0767	Stamford	CT	06900	100%
RCC	-76.2230	39.6407	Havre de Grace	MD	21034	100%
RCC	-83.4476	34.0173	Athens-Clarke	GA	30607	99%
RCC	-81.7579	27.9265	Bartow	FL	33800	56%
RCC	-82.5367	40.7500	Mansfield	OH	44900	98%
RCC	-88.1742	41.9698	Bartlett	IL	60100	99%
RCC	-96.6217	32.5367	Seagoville	TX	75125	100%
RCC	-117.8209	33.9868	Diamond Bar	CA	91765	100%
RCC	-121.4344	38.5706	Sacramento	CA	95800	85%
RP	-81.9562	33.4372	North Augusta	SC	30901	95%
RP	-82.5367	40.7500	Mansfield	OH	44900	100%
RP	-117.8209	33.9868	Diamond Bar	CA	91765	55%

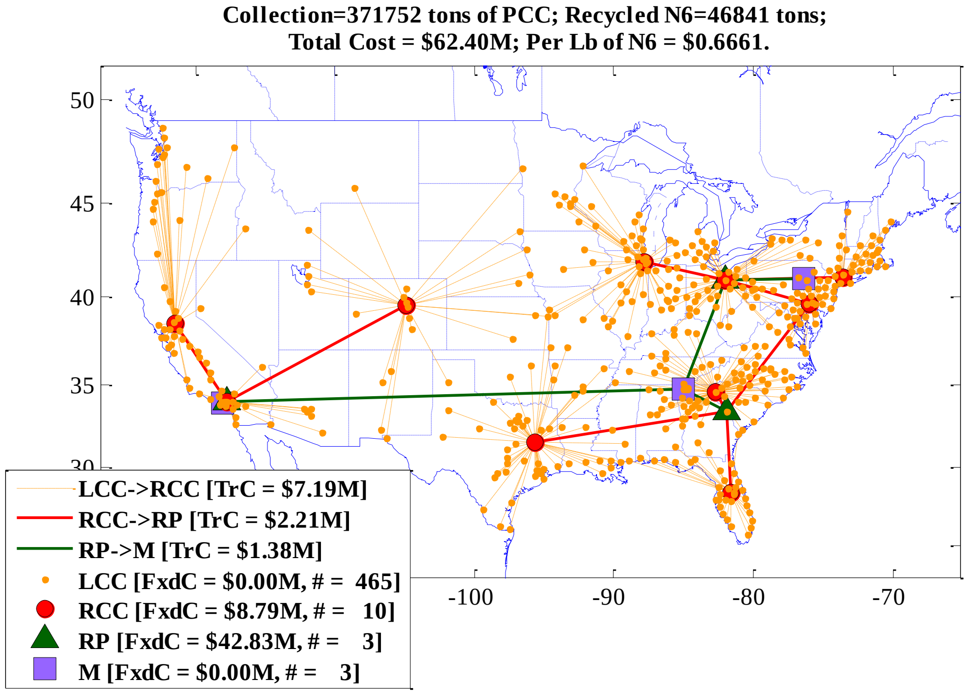

Figure B.1.36: Recycling network (Scenario 3, 80% coverage)

Table B.1.36: Recycling network facilities (Scenario 3, 80% coverage)

Type	Longitude	Latitude	Nearest City	State	ZIP Code	Utilization
RCC	-73.5435	41.0767	Stamford	CT	06900	100%
RCC	-75.9432	39.6119	Elkton	MD	21900	100%
RCC	-82.7635	34.5590	Anderson	SC	29625	100%
RCC	-81.5637	28.4344	Lake Butler	FL	34700	68%
RCC	-81.9998	40.9519	Wooster	OH	44214	100%
RCC	-87.7952	41.8883	Oak Park	IL	60300	100%
RCC	-95.6822	31.5393	Palestine	TX	75800	98%
RCC	-104.9105	39.5172	Lone Tree	CO	80100	41%
RCC	-117.7561	34.0423	Pomona	CA	91766	100%
RCC	-121.4847	38.5665	Sacramento	CA	94200	84%
RP	-81.9562	33.4372	North Augusta	SC	30901	100%
RP	-81.9998	40.9519	Wooster	OH	44214	100%
RP	-117.7561	34.0423	Pomona	CA	91766	68%

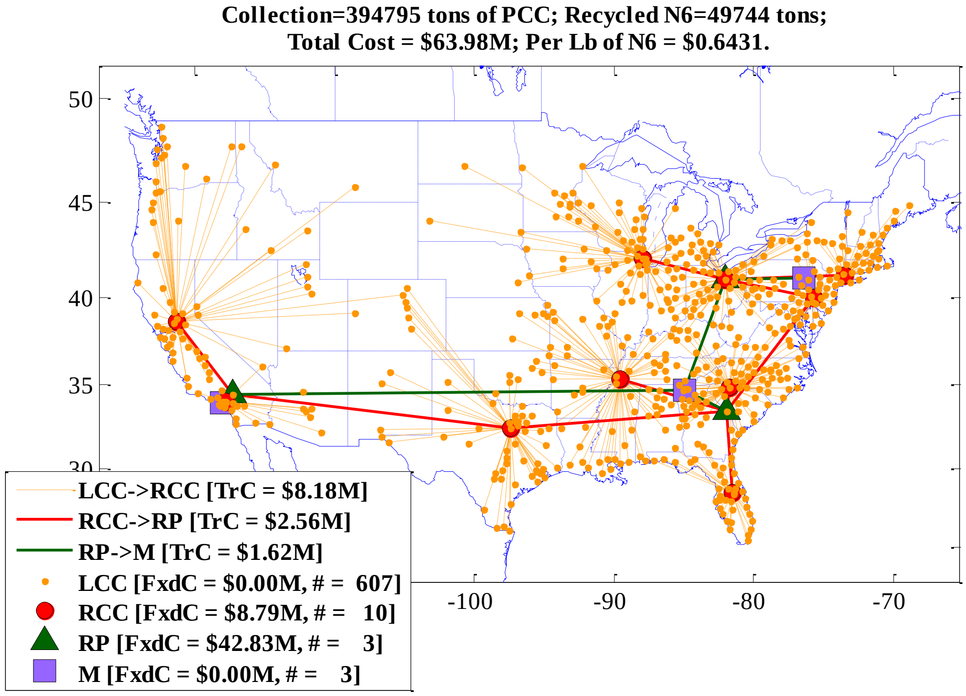

Figure B.1.37: Recycling network (Scenario 3, 85% coverage)

Table B.1.37: Recycling network facilities (Scenario 3, 85% coverage)

Type	Longitude	Latitude	Nearest City	State	ZIP Code	Utilization
RCC	-73.4398	41.2168	Westport	CT	06800	100%
RCC	-75.7011	39.9483	West Chester	PA	19300	100%
RCC	-81.7113	34.9017	Gaffney	SC	29372	100%
RCC	-81.5637	28.4344	Lake Butler	FL	34700	67%
RCC	-89.5891	35.4073	Arlington	TN	38000	80%
RCC	-81.9998	40.9519	Wooster	OH	44214	100%
RCC	-87.9855	42.0645	Rolling Meadows	IL	60005	100%
RCC	-97.4220	32.4741	Burleson	TX	76058	100%
RCC	-117.7561	34.0423	Pomona	CA	91766	100%
RCC	-121.2876	38.6508	Fair Oaks	CA	95700	100%
RP	-81.9562	33.4372	North Augusta	SC	30901	100%
RP	-81.9998	40.9519	Wooster	OH	44214	100%
RP	-117.2916	34.5016	Victorville	CA	92395	84%

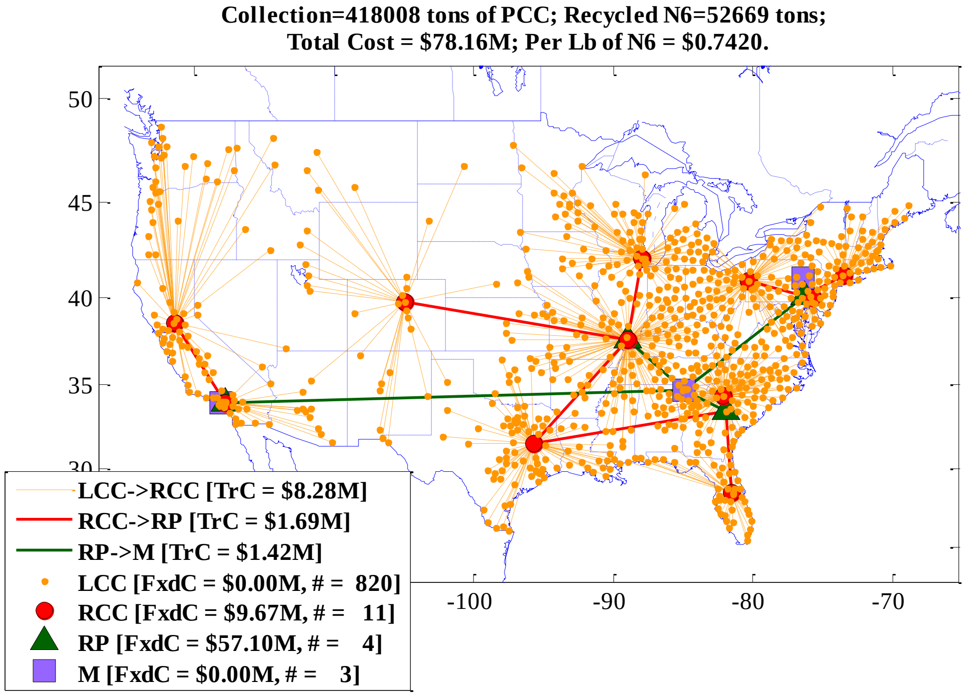

Figure B.1.38: Recycling network (Scenario 3, 90% coverage)

Table B.1.38: Recycling network facilities (Scenario 3, 90% coverage)

Type	Longitude	Latitude	Nearest City	State	ZIP Code	Utilization
RCC	-73.4398	41.2168	Westport	CT	06800	100%
RCC	-80.3334	40.8882	New Castle	PA	16157	100%
RCC	-75.7011	39.9483	West Chester	PA	19300	100%
RCC	-82.0901	34.3434	Greenwood	SC	29384	100%
RCC	-81.5637	28.4344	Lake Butler	FL	34700	71%
RCC	-87.9855	42.0645	Rolling Meadows	IL	60005	100%
RCC	-88.9826	37.6348	Marion	IL	62900	100%
RCC	-95.6822	31.5393	Palestine	TX	75800	100%
RCC	-104.9166	39.7338	Denver	CO	80220	36%
RCC	-117.8209	33.9868	Diamond Bar	CA	91765	100%
RCC	-121.4344	38.5706	Sacramento	CA	95800	96%
RP	-76.2604	40.0864	Lancaster	PA	17500	90%
RP	-81.9562	33.4372	North Augusta	SC	30901	52%
RP	-88.9826	37.6348	Marion	IL	62900	100%
RP	-117.8209	33.9868	Diamond Bar	CA	91765	59%

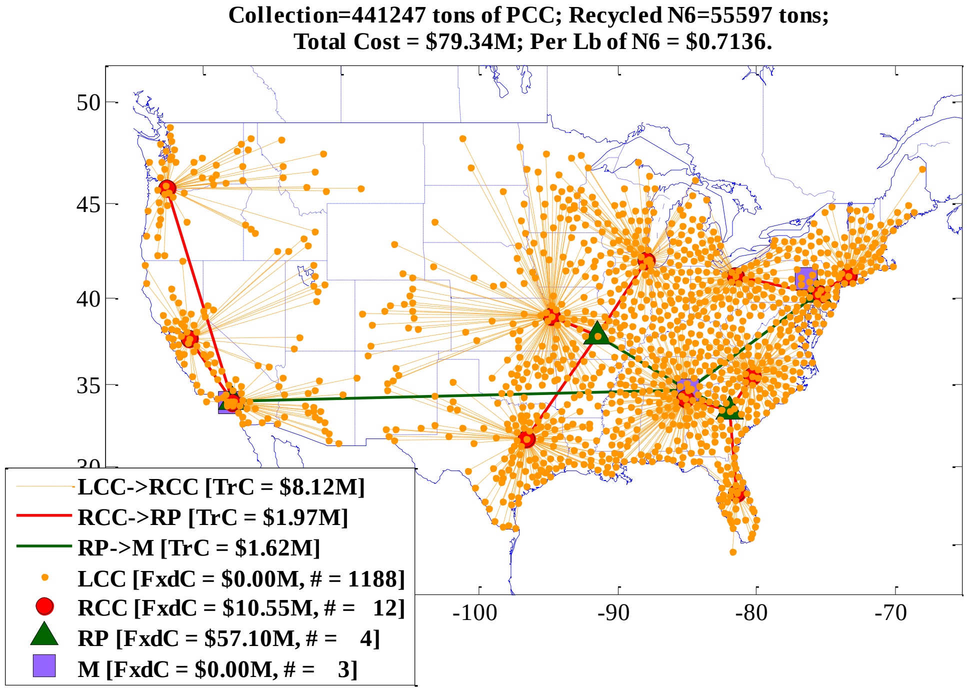

Figure B.1.39: Recycling network (Scenario 3, 95% coverage)

Table B.1.39: Recycling network facilities (Scenario 3, 95% coverage)

Type	Longitude	Latitude	Nearest City	State	ZIP Code	Utilization
RCC	-73.3668	41.2281	Westport	CT	06883	100%
RCC	-75.4162	40.1824	Norristown	PA	19400	100%
RCC	-80.3163	35.5176	Albemarle	NC	28071	86%
RCC	-85.1716	34.2417	Rome	GA	30161	100%
RCC	-81.4291	28.3794	Hunters Creek	FL	32837	66%
RCC	-81.5400	41.2296	Cuyahoga Falls	OH	44264	100%
RCC	-87.9855	42.0645	Rolling Meadows	IL	60005	100%
RCC	-94.7762	38.9524	Lenexa	KS	66219	92%
RCC	-96.6614	31.7163	Corsicana	TX	76635	100%
RCC	-117.8209	33.9868	Diamond Bar	CA	91765	100%
RCC	-120.9466	37.6729	Modesto	CA	95355	74%
RCC	-122.5861	45.7994	Battle Ground	WA	98600	41%
RP	-75.5901	40.2064	Pottstown	PA	19457	90%
RP	-81.9562	33.4372	North Augusta	SC	30901	76%
RP	-91.4947	37.8520	Rolla	MO	65449	88%
RP	-117.8286	34.0709	Walnut	CA	91700	65%