Planning the e-Scrap Reverse Production System Under Uncertainty in the State of Georgia: A Case Study

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***Abstract*—Due to legislative requirements, environmental concerns, and market image, the disposition of end-of-life e-scrap is attracting tremendous attention in many parts of the world today. Effective management of returned used product flows can have a great impact on the profitability and resulting financial viability of associated e-scrap reverse production systems. However, designing efficient e-scrap reverse production systems is complicated by the high degree of uncertainty surrounding several key factors. Very few examples of this complex design problem are documented in the academic literature. This paper contributes as analysis of a new, large-scale application that designs an infrastructure to process used televisions, monitors, and computer central processing units (CPUs) in the state of Georgia in the U.S. The case study employs a scenario-based robust optimization model for supporting strategic e-scrap reverse production infrastructure design decisions under uncertainty. A mixed integer linear programming (MILP) model is used to maximize the system net profit for specified deterministic parameter values in each scenario, and then a min–max robust optimization methodology finds a robust solution for all of the scenarios.**

***Index Terms*—Electronics recycling, reverse production systems, robust optimization.**

I. Introduction

ELECTRONICS are ubiquitous in current society. Their variety and volumes today make it inevitable that we inherit significant reuse/recycling/disposal challenges, including collection, transportation and processing costs along with serious hazardous waste concerns (lead, cadmium, mercury, etc.). However, with challenge comes opportunity. In this case, the opportunity is to view the scrap electronics (e-scrap) as resource, and to capture value from the returned stream of used electronics.

This paper presents a case study for the design of a large-scale system for collecting, transporting, and processing used electronics in the state of Georgia in the U.S. Data used in our case study are collected from a variety of sources and through interaction with industry. Our objective is to maximize the financial viability of the infrastructure and minimize the deviation of performance from the optimal investment when faced with key uncertainties. Due to their predominance in the waste stream, our primary focus at this time is a subset of the used electronics stream: televisions (TVs), CPUs, and monitors.

The problem is definitely large scale. For example, we predict that more than 5 570 000 lb of used televisions, 3 300 000 lb of used computer monitors, and 1 800 000 lb of used CPUs could be collected and processed in the state of Georgia each year if 30% of Georgia residents with something to recycle participate in the system. With interviews with the state government agency, consortia, and industry firms, we consider the configuration of a regional electronics recycling system with local municipal collection sites and a host of processors ranging from large and small commercial firms to nonprofit organizations [1]–[3]. An illustration of the physical flows of the reverse production system (RPS) for Georgia's used electronics is shown in Fig. 1. Municipal collection sites and nonprofit recycling sites are assumed to collect e-scrap, including TVs, CPUs, and monitors, supplied by residential and small business sectors. Commercial processing sites collect after-sorted e-scrap from several local municipal or nonprofit recycling sites for further processing. In addition, recyclers for large commercial sources focus on collection and processing of e-scrap of CPUs and monitors from business sources. Different sites may involve different functions and different contact parties. For example, recyclers for large commercial sources may only contract with business sources for e-scrap collection and processing, while other commercial processing sites may handle after-sorted e-scrap from both municipal and nonprofit collection sites.

The remainder of the paper is organized as follows. In Section II, we overview the underlying technical background and previous literature. The mathematical programming approach we utilize is presented in Section III. Section IV details the regional case study for the state of Georgia. Discussion of the case study and conclusions are presented in Section V.

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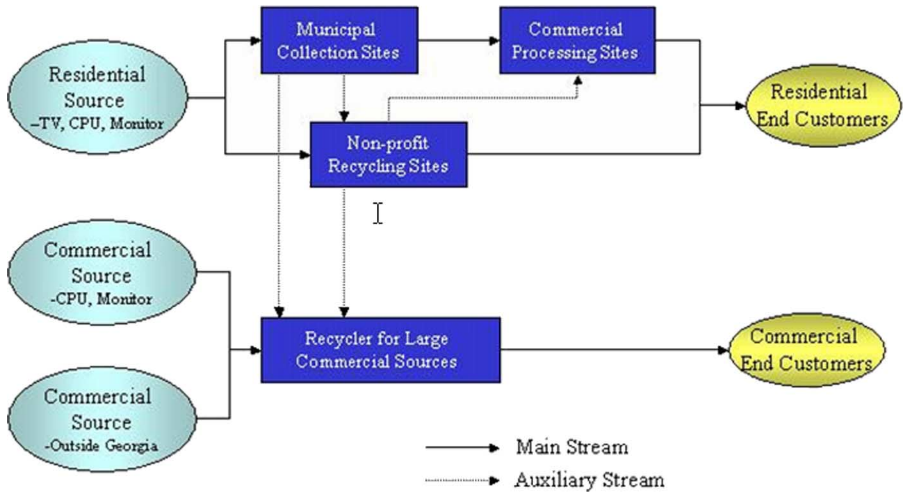

Fig. 1. Physical flow of used electronics.

II. Background and Literature Reveiw

The design and analysis of reverse production systems have developed as topics of recent interest. Alternative views and models for the general problem can be found in sources such as Ammons *et al.* [4] and Guide *et al.* [5]. Flapper [6], [7], Dowlatshahi [8], and Fleishmann *et al.* [9] give systematic overviews of the logistic aspects of reuse and recycling system. Fleischmann *et al.* [10] also present a characterization of logistic networks for product recovery. Carter and Ellram [11] and Kang and Schoenung [12] give reviews of the literature on reverse logistics and U.S. infrastructure and technology options in electronic waste recycling. Spengler *et al.* [13] and Gungor and Gupta [14] present product recovery integrated with environmental issues and a comprehensive bibliography in this area. Spengler *et al.* [15] later present a MILP model for integrated planning of acquisition, disassembly, and bulk recycling in e-scrap recovery. The safety stock planning in a general supply chain with the integration of external and internal product return and reuse is discussed in [16]. Hirsch *et al.* [17] propose a simulation tool to analyze the behavior of a given logistic infrastructure on the basis of predefined parameters. Guide *et al.* [18] also use simulation to evaluate the performance of alternative workflow control rules in a remanufacturing environment. Research on reverse supply chain design for specific materials such as refrigerators, copiers, and electronics includes Krikke *et al.* [19], Krikke *et al.* [20], and Sodhi and Reimer [21]. Nagurney and Toyasaki [22] take another perspective viewing several independent agents in electronics recycling systems, and analyze the individual behavior of acquisition and flow decisions.

The approach used in this paper is termed robust, or "worst case," optimization. Kouvelis an Yu [23] propose the definition of robust optimization including absolute, relative, and minimax robustness criteria. This case study employs the measure of minimax robust deviation, in which the robust solution is one that minimizes the maximum deviation from the optimal value for all possible realizations of the parameters in the model.

The uncertainties may have critical impact on the design of reverse production systems. A simple, but limited, approach for understanding the impact of uncertainty is traditional scenario/parametric analysis [24]. Alternatively, Listes and Dekker [25] demonstrate the application of conventional stochastic programming to the sand recycling case study reported earlier by Barros *et al.* [26]. However, assumptions on the distributions of parameters are required for such an approach and the objective is the maximization of the expected value. It is not clear that an expected value function is the appropriate objective for actual strategic decisions in cases like these. Other examples of applying stochastic programming for planning and product distribution/recovery problems include Clay and Grossmann [27] and Inderfurth *et al.* [28]. Yu and Li [29] present the use of robust optimization model for a stochastic logistics problem.

Mulvey *et al.* [30] make a strong case for the application of robust optimization using a minimax objective function as superior to stochastic optimization when dealing with single or infrequent decisions involving great uncertainty. This observation is the basis for our previous results for uncertain reverse production system infrastructure determination where robust optimization is applied using scenarios to represent uncertainty [24]. Other work applying robust optimization to the forward/reverse logistic problem includes Genaro *et al.* [31]. Mausser and Laguna [32] describe a formulation for a robust mixed integer programming (MIP) problem for certain types of parameter ranges. This formulation uses the fact that the parameters found only in the objective function can be set to their extreme values; however, this approach only allows for uncertainty in objective function and can not deal with uncertainty in other parameters in the mathematical model.

In contrast, the case study presented here applies robust optimization to reverse production system design while explicitly considering the impact of uncertainty on parameters in the constraint matrix and the right-hand side. Probability distributions are not required or used in this approach, so there is no need to estimate (or speculate upon) them. Compared to previous work, the case study is also distinguished by its solution of a very large scale robust optimization problem. As Section IV documents, the approach addresses more than a million continuous variables, thousands of discrete variables, and more than a million constraints.

Maximize: ***Net Profit*** (Revenues – Operating and Fixed Costs)

Subject to: ***Flow balances between sites***
based on material consumed and produced by the tasks at sites.

Upper and lower bounds
on storage, transportation and processing of material at sites.

Logical constraints on sites
such as the need to open a site before allowing tasks to be located there.

Fig. 2. General form of mixed integer linear programming model.

III. Methodology

A deterministic mixed integer programming (MILP) model is used to design the reverse production system and determine the flows in the resulting network, where the objective is to maximize the profit of the system, subject to a set of constraints that enforce material balances and other prescriptions that ensure network feasibility. The continuous decisions, denoted by the set X, are the material flows in the resulting network and processed amounts for the particular tasks.

The discrete decisions, denoted by the set Y, include site opening decisions, task location decisions, and transportation selection among locations. It is assumed that a superset of potential locations for various tasks is already known to the decision maker, and that the network of possible production routes from product to recycled materials is defined. Site opening decision variables refer to location selections in the infrastructure design. The second class of discrete variables, task location decisions, indicates that the tasks can be restricted to be located at certain subsets of locations (and then only if the location itself is open). If no integer variable for a task takes a nonzero value then the task is not selected. The third class of discrete variables refers to the transportation selection among locations. The material flows are forced through the subset of locations that are open.

In this way, we can represent a superstructure of recycling tasks (such as various levels of processing and disassembly). Through material balances we force a feasible combination of tasks to be selected so that no material is left in a state in which it cannot be sold or disposed of and where several tasks may be left out completely. The superstructure of tasks are tailored by specific processing alternatives for different product types. As we have previously reported in [33], the MILP model takes the general form shown in Fig. 2. This generic representation separating the task structure and site connectivity has been of significant value in chemical engineering scheduling and planning formulations and empirically has provided reasonable computational behavior (see [34] and [35]).

Mixed Integer Linear Programming Approach for the Scenario-Based Robust RPS Design: The fundamental goal of strategic design models for RPS is to allow "good" long-term infrastructure decisions, strategically committing significant resources, development effort, and future operational viability to a particular configuration design. As we have pointed out, uncertainty plays a significant role in strategic decisions in RPS design, and the above model does not incorporate this uncertainty. The model has been extended to consider limited forms of uncertainty in the parameters such as collected volume

Minimize: δ

Subject to:

$$\delta \geq \{ O_\omega^* - R_\omega \} \qquad \forall\, \omega \in \Omega$$

Flow balances between sites for each scenario ω (based on material consumed and produced by the tasks at those sites for each scenario).

Upper and lower bounds for each scenario ω on storage, transportation and processing of material at sites (constant over all scenarios except for upper bound on the volumes of materials collected).

Logical constraints on sites across all scenarios such as the need to open a site before allowing tasks to be located there (constant across all scenarios).

Fig. 3. General statement of robust scenario model.

and prices, and we have focused on using a scenario-based approach coupled with a robust objective function [24]. The scenarios are defined by deterministic values of parameters that are thought to represent likely situations predicted by an expert. The expert is not required to assign any probability to the scenarios. The expert should require that the solution be "*robust*" if the parameter combination in the scenario should be the one that actually occurs in the future. We have used the measure of robust deviation defined by Kouvelis and Yu [23], such that for each scenario we will subtract the objective function value of a specified robust solution from the objective function value (net profit) of the RPS model optimal solution. For the given robust solution, the largest, or maximum deviation is determined across all scenarios. The "optimal" robust solution will be the one with the *minimum maximum deviation*. This captures a notion of "risk"—the decision maker wants to protect her/himself from doing very poorly in a given scenario when she/he could have done much better by making a different set of choices.

To execute the robust approach, we first solve the MILP model to optimality for each specified scenario. This fixes the set of Y variables that are optimal for the scenario. In other words, define Ω as the set of all specified scenarios, and solve the MILP model for each scenario $\omega \in \Omega$. The optimal objective function value (net profit) of the RPS model for scenario $\omega \in \Omega$ is denoted by O_ω^*. We define a *configuration* to be the set of Y variables that have the value of 1 in the solution. We use Y_Ω to denote a configuration that is to be evaluated against scenarios in the set Ω. The evaluation takes the form of finding the optimal value of the configuration when the parameters are set to the values in scenario ω, and we denote this as R_ω. A robust configuration is a configuration that minimizes the maximum deviation of R_ω and O_ω^* across all the scenarios in the set Ω. The degrees of freedom that the robust configuration is allowed to manipulate are the continuous operational variables X. The robust model is stated in Fig. 3. With the following notation:

- O_ω^* optimal solution net profit for scenario ω;
- R_ω net profit of robust solution Y_Ω for scenario ω.

Application of the deterministic model and the robust scenario model are both demonstrated in a case study of developing recycling infrastructure for electronics for the state of Georgia in the U.S.

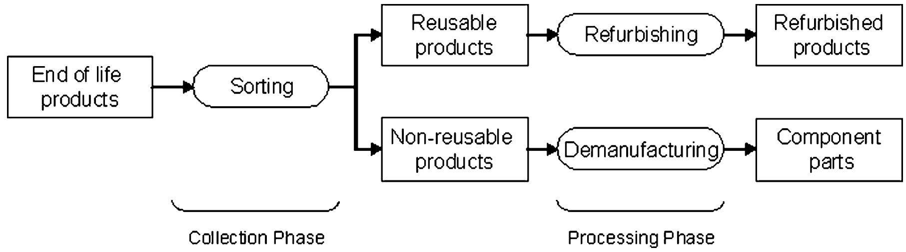

Fig. 4. General process flows in the case study.

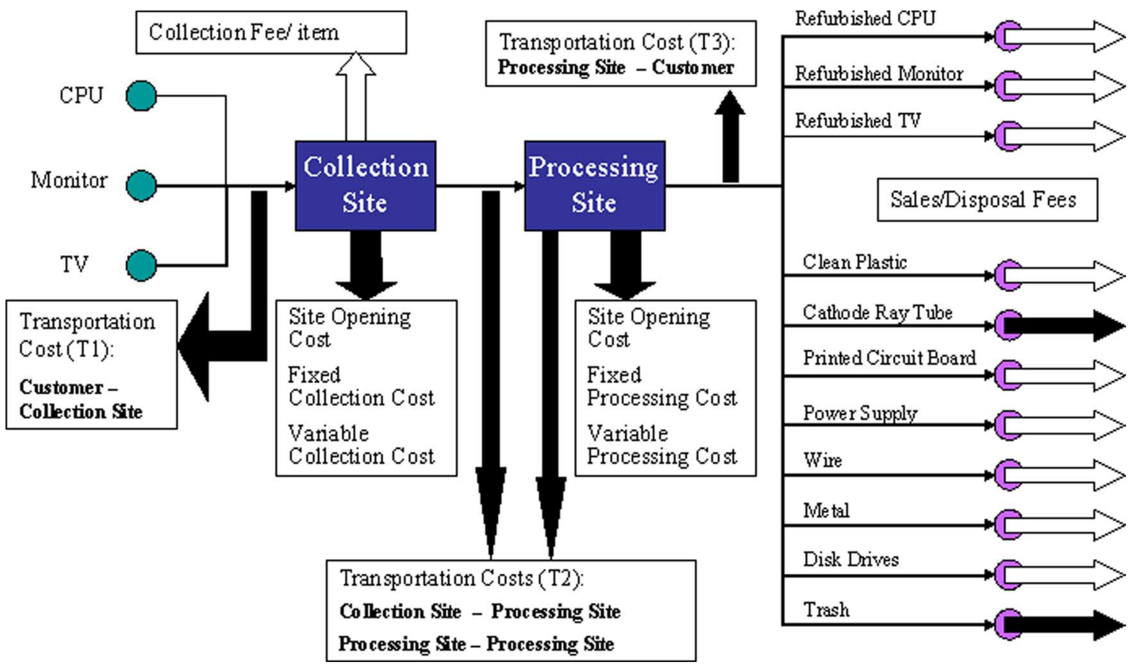

Fig. 5. Cash flow diagram with costs in black arrows and profits in white arrows.

IV. Case Study

We want to plan a regional e-scrap processing infrastructure to handle the used electronics that are accumulating within the state of Georgia, an area covering approximately 57 906 square miles (149 911 square km) with an estimated population of 8.4 million people. In the following sections, we develop our data required for problem definition, including e-scrap supply information, collection site characteristics, processing site descriptions, transportation alternatives, and transportation and processing costs. Then we define the scenarios to be studied based on key uncertainties in participation rate, capacity utilization in collection facilities, and reusability percentages of collected equipment. Optimal solutions are obtained for each of the scenarios, and then a corresponding robust infrastructure solution is found.

A. Case Study Overview and Input Data

This case study is concerned with designing the infrastructure for the product recovery processes for electronic equipment collected from the residential and business sectors in Georgia. At this initial stage, we consider the predominant physical inputs to the system to be used televisions, computer monitors, and CPUs. We assume that no material may go deliberately uncollected; in other words the variables that represent the inflow of the material to the system must equal to the amount available for collection. We consider three general major processes: sorting, refurbishing, and demanufacturing processes conducted in each associated site. The general process flows are detailed in Fig. 4. In general, any sites involving the collection phase perform the sorting process to initially separate end-of-life products into reusable or nonreusable items, and sites in the processing phase may take refurbishing or/and demanufacturing processes for product recovery. We note that one physical site may involve one or more processes of sorting, refurbishing, and demanufacturing processes. The outputs after refurbishing or demanufacturing process are several categories of refurbished units, component parts, and materials listed in Fig. 5. The financial flows, depicting profits and costs in white and black shades, are also indicated in Fig. 5.

To accomplish this RPS design with maximum profit or with minimum budget, an effective infrastructure of collection sites, processing sites and transportation network is required. For this case study, we divide the State of Georgia into 12 different regions based on service delivery regions defined by Georgia's Department of Community Affairs (DCA) as shown in Fig. 6 [1]. Each region represents a source of electronic waste streams, a geographically centered collection site and also a demand point for the units after a refurbishing process. The approximate

TABLE I
GEORGIA E-SCRAP SUPPLY ESTIMATES

Region	Supply for TVs (lbs)*	Supply for Monitors (lbs)*	Supply for CPUs (lbs)*
1	474,518	275,757	113,817
2	309,815	162,284	74,312
3	2,333,349	1,385,431	734,875
4	274,843	143,966	65,924
5	298,219	156,210	135,771
6	299,458	156,859	71,828
7	295,979	155,037	70,993
8	240,368	125,907	57,654
9	185,677	97,259	44,536
10	240,100	125,766	57,590
11	248,295	130,059	59,556
12	369,441	193,517	88,614
13	0	90,000	90,000
14	0	90,000	90,000

* Amount of supply = participation % (30%) × 4 lbs/person × population × product proportion in weight

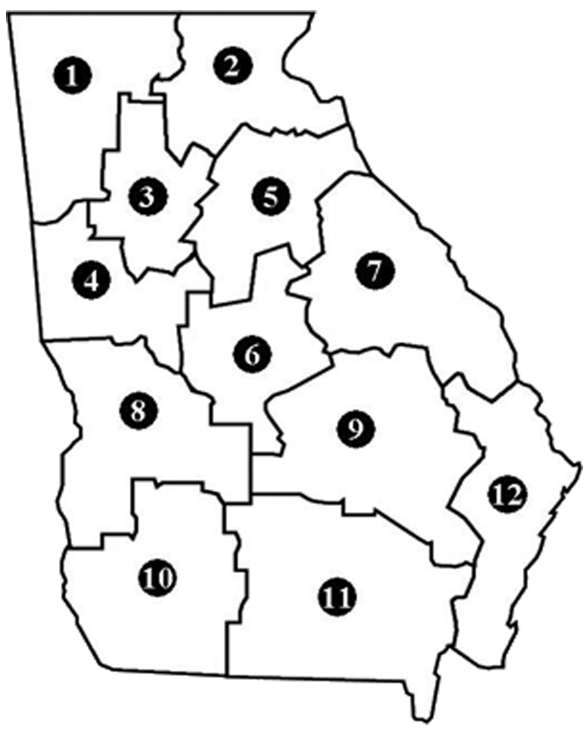

Fig. 6. State of Georgia divided into 12 DCA regions.

amount of used electronic equipment available for each region is estimated from its population. The parameters and information used in the model are detailed in the following subsections that describe e-scrap supply, collection sites, processing sites, demand, and transportation information.

Supply Information: Based upon recycling percentages determined from recent studies in Florida [36], we estimate the supply of e-scrap by assuming that on average each resident produces 4 lb of electronic items per year ready for recycling, and studies have shown that between 10%–30% of those residents with something to recycle participate in the collection program. We study how this range affects the design of the network as part of the robust solution approach. We assume that the relative proportions of the collection amounts (in units) for televisions, computer monitors, and CPUs for material collected in Georgia is 35.8:38.5:25.7 and the average weights for televisions, computer monitors, and CPUs are 61.6, 30.0, and 20.6 lb, respectively. The proportion amounts and the average weights are from the statistical data of the nearby state, Florida, which is available at http://www.dep.state.fl.us/waste/default.htm.

In addition to the residential and business sources within the state, some Georgia e-scrap processors import business e-scrap from other neighboring states. We represent imported e-scrap as two sources providing obsolescence of computer monitors and CPUs denoted as regions 13 and 14 [2]. Table I shows the estimated supply information for each type of electronic equipment from each region under the assumption that 30% of the people who have e-scrap (4 lb of e-scrap per resident) participate in the collection program.

Collection Sites: For the e-scrap originating within the state, we have considered 12 potential state of Georgia government-collection centers located in the center county of each DCA region. For the imported e-scrap, we have designated external regions 13 and 14. Each collection center is assumed to collect televisions, monitors, and CPUs supplied by the small business and resident sources located within a 100 mile transport circle centered at the collection center. We assume that it may be possible for the designated collection sites also to be able to perform sorting and processing functions. Additionally, this case study includes six nonprofit collection centers throughout the state and one large commercial collection center located in Marietta, Georgia. The large scale collection center is assumed to collect monitors and CPUs supplied by large business sources both inside and outside of Georgia.

The incurred collection cost is separated as fixed, variable, and opening cost. The fixed cost includes the staffing, overhead costs, and the opening cost corresponding to the space rental and utility fees. The variable cost accounts for the rest of the hidden cost and is proportional to the collection amount. The specific numbers used in the study for the collection site information are given in Table II.

Processing Sites: We consider 15 potential commercial processing sites (nine sites in Georgia, two sites in Tennessee, two sites in North Carolina, and two sites in South Carolina),

TABLE II
COLLECTION SITE DATA USED IN THE CASE STUDY

Description	Value
Fixed collection cost of municipal sites	$46,800 per year per site*
Fixed collection cost of non-profit sites	$93,600 per year per site**
Variable Collection cost	$0.01 per pound♦ [37]
Opening cost for municipal collection sites	$5,000 per year*** [38]
Opening cost for non-profit collection sites	$28,800 per year [3]
Opening cost for the large commercial-collecting center	$134,500 per year [2]
The collection fee charged for small business and residential sources	$5.00 per item for CPUs and monitors [39] $0.3 per pound for TVs♦♦
The collection fee charged by the large commercial center	$0.6 per item [2]

* It is assumed that 1 person per municipal collection site with pay rate of $10 per hour working for 8 hours per day for 250 days per year. 1.8 of overhead and 1.3 of fringe scaling factors are applied.
** 2 persons are dedicated per non-profit collection site.
*** Assuming subsidies reduce the final cost.
♦ Several significant costs are already included in the fixed collection cost and opening cost.
♦♦ The data are from http://www.scrapcomputers.com.

TABLE III
GENERAL INFORMATION FOR ALL 23 POTENTIAL PROCESSING SITES [2], [3]

Processing Site Designation	State	County/City	ZIP Code	Type
1A	Georgia	Catoosa	30742	Commercial processing sites
2A	Georgia	Carroll	30116	
3A	Georgia	Cobb	30126	
4A	Georgia	Fulton	30318	
5A	Georgia	DeKalb	30341	
6A	Georgia	Gwinnett	30071	
7A	Georgia	Washington	31082	
8A	Georgia	Baldwin	31061	
9A	Georgia	Richmond	30815	
10A	Tennessee	Davidson	37201	
11A	Tennessee	Anderson	37830	
12A	North Carolina	Buncombe	28801	
13A	North Carolina	Mechlenburg	28202	
14A	South Carolina	Charleston	29449	
15A	South Carolina	Lexington	29072	
1NP	Georgia	Marietta	30008	Nonprofit processing sites
2NP	Georgia	Atlanta	30318	
3NP	Georgia	Atlanta	30318	
4NP	Georgia	Tucker	30084	
5NP	Georgia	Sandersville	31082	
6NP	Georgia	East Point	30344	
1PR	Florida	Malone	32455	Prison processing site
1AA	Georgia	Marietta	30062	Large commercial processing site

six nonprofit processing sites, one large commercial processing site, and one prison processing site in this case study. Each facility represents an actual refurbishing and/or demanufacturing facility located in Georgia or nearby states. Refurbishing process includes fixing and replacing operations for the broken parts. Demanufacturing process refers to the combination of disassembly, mechanical fragmentation and separation of materials. Table III contains general information for all 23 potential processing sites considered in this case study.

For each processing site, we consider six main potential processes: television refurbishment, monitor refurbishment, CPU refurbishment, television demanufacturing, monitor demanufacturing, and CPU demanufacturing, but not all processing sites necessarily perform all six processes. The cost information for each of the six processes is presented in Tables IV and V.

Demand and Prices for Demanufactured/Refurbished Equipment, Parts, and Recycled Materials: The processing sites provide an output of demanufactured equipment, parts, and recycled material to a set of demand locations. We consider four types of demand sources and estimate the quantities using the assumption that the demand for refurbished products is greater than or equal to the supply of old used products provided by that region. The first type of demand comes from people within Georgia who are interested in buying refurbished electronic equipment. For this type of demand, we use the same 12 DCA regions to designate the demand location. The second type of

TABLE IV
VARIABLE COSTS FOR REFURBISHING AND DEMANUFACTURING PROCESSES

Description	Value
Variable processing cost for refurbishing TVs	$0.23 per pound *
Variable processing cost for refurbishing monitors	$0.44 per pound *
Variable processing cost for refurbishing CPUs	$0.51 per pound *
Variable processing cost for demanufacturing TVs	$0.05 per pound **
Variable processing cost for demanufacturing monitors	$0.09 per pound **
Variable processing cost for demanufacturing CPUs	$0.08 per pound **
Variable processing cost for the demanufacturing process at a prison site	$0.00425 pound ***

* This cost includes testing cost, refurbishing cost, and the cost associated with the replacing of broken parts with new spare parts. It is estimated by assuming the processing labor cost is $10 per hour and refurbishing costs are $8, $8, and $10 for TVs, monitors, and CPUs respectively. The testing process will take on average of 10 minutes and the refurbishing process will take on average of 20 minutes [40].
** This information is the average of the information from Waters [41], Pepi [42], and Minnesota Office of Environmental Assistance [43].
***It is assumed that prison labor cost is approximately 10% of the normal wage rate.

TABLE V
FIXED PROCESSING COSTS FOR PROCESSING SITES

Sites	Description	Annualized Value
Commercial processing sites	Fixed processing cost for refurbishing all products	$8,820 per process [40]
	Fixed processing cost for demanufacturing all products	$8,000 per process [2]
Non-profit processing sites	Fixed processing cost	$26,667 per process [3]
Large commercial processing site	Fixed processing cost for the refurbishing process	$6,250 per process [2]
	Fixed processing cost for the demanufacturing process	$32,000 per process [2]
Prison processing site	Fixed processing cost for the demanufacturing process	$500 per process *

* Estimated utility fee per year for the process in the prison

demand source is the group of recycling facilities interested in buying metal, plastic, cathode ray tubes (CRTs), and other demanufactured materials. We consider a total of five recyclers located in several states: Georgia (metal recycler), Florida (CRT products and electronics recycler), Texas (plastics recycler), and Pennsylvania (CRT glass recycler). The third type of demand comes from both resident and commercial sources who are interested in buying refurbished commercial electronic equipment in large batches provided by the large commercial processing site. The demand locations for the third type of demand are assumed to be the same places as those used for the 12 DCA regions. The last type of demand describes landfills to which we can dispose the nonhazardous trash that results from demanufacturing. We consider eight landfills located in Georgia and group them into five demand points located based on the DCA regions. (Landfill location information can be found at http://www.wastebyrail.com/network.html.)

The selling price for each of the refurbished product types and the demanufactured material types is shown in Table VI. Some selling price data are taken from the year 2000, and may not reflect current prices (2005), but all of the other costs and prices are more current.

Transportation Information: We include three types of *transportation costs*. The first type represents the transportation cost of the people who drive to the collection center and drop off their used electronic equipment. This type of transportation cost is approximated by the gasoline cost ($0.15 per mile) and we assume that on average one car carries 50 lb of electronic equipment per trip. With this approximation, the transportation cost per pound per mile is $0.003. This type of transportation cost may be considered as free since it is paid by people who bring e-scrap to the collection center. However, the transportation cost from the e-scrap source to the collection center is still included for a "macro system" perspective.

The second type represents the transportation costs for moving material between collection centers and processing centers, the transportation costs for moving material between processing sites and recycler demand points, and the transportation costs for moving material between processing sites and landfill demand points. We perform this type of transportation with a large truck costing $2 per ton per mile or $0.0009 per pound per mile.

The last type represents the transportation cost for shipping refurbished products from processing sites to customers, which is assumed to be shipped by the private transportation service provider. As a reasonable estimate of the cost of this shipping, we use $0.26 per mile per item—the amount charged by the United Parcel Service (UPS) (cost information is given at http://www.ups.com).

B. Experimental Design for the Case Study

The data for the state of Georgia case study specifies a large-scale electronics recycling infrastructure design problem. The objective of the problem is to maximize net profit for the system while determining which collection and processing sites to utilize and then what quantities of each item type to process into what materials at each site. We apply our mathematical

TABLE VI
PRICE INFORMATION FOR REFURBISHED PRODUCTS AND DEMANUFACTURED MATERIALS

Parameter	Value
Selling price for plastic ($ per lb)	0.21♦
Selling price for printed circuit board ($ per lb)	0.9 *
Selling price for disc drive ($ per lb)	0.839♦
Selling price for CRT ($ per lb)	-0.184♦
Selling price for metal ($ per lb)	0.0175 *
Selling price for wire ($ per lb)	0.45♦
Selling price for power supply ($ per lb)	0.06 *
Selling price for trash ($ per lb) (land fill tipping fee)	-0.028 *
Selling price for used TV ($ per unit)	45.16 ***
Selling price for used monitor ($ per unit)	33.00 ***
Selling price for used CPU ($ per unit)	36.00 ***
Selling price for broken CPU ($/lbs)	0.02 **
Selling price for usable CPU ($/lbs)	0.108 **
Selling price for broken monitor ($/lbs)	-0.233 **
Selling price for usable monitor ($/lbs)	0.0444 **
Selling price for broken television ($/lbs)	-0.3 **
Selling price for usable television ($/lbs)	-0.3 **

* EPA-901-R-00-002, September 2000 [44]
** The data are from http://www.scrapcomputers.com.
***The data are taking average on http://www.boxq.net and http://www.ebay.com.
♦ The data are from http://pacific.recycle.net.

TABLE VII
KEY UNCERTAINTY VALUE SETTINGS FOR 16 SCENARIOS

Reusable %: TV: 10% CPU: 30% Monitor: 25%		Collection Utilization	
		45%	75%
Percent Participation	*10%*	***Sc 1***	***Sc 2***
	30%	***Sc 3***	***Sc 4***

Reusable %: TV: 5% CPU: 30% Monitor: 25%		Collection Utilization	
		45%	75%
Percent Participation	*10%*	***Sc 5***	***Sc 6***
	30%	***Sc 7***	***Sc 8***

Reusable %: TV: 10% CPU: 10% Monitor: 10%		Collection Utilization	
		45%	75%
Percent Participation	*10%*	***Sc 9***	***Sc 10***
	30%	***Sc 11***	***Sc 12***

Reusable %: TV: 5% CPU: 10% Monitor: 10%		Collection Utilization	
		45%	75%
Percent Participation	*10%*	***Sc 13***	***Sc 14***
	30%	***Sc 15***	***Sc 16***

programming approach described in Section III to solve the problem.

The results provide a robust configuration for a large scale e-scrap RPS, and the associated net profit (or loss) is predicted. The key uncertain parameters (see [44] and [45]) that we examined are described as follows.

1) *Participation rate.* For one half of the scenarios, we examined the situation where 10% of the population who have e-scrap (4 lb per resident) contributed at least one used electronic item for collection. For the other half of the scenarios, we used a participation rate of 30%. In other words, 0.4 lb per resident of e-scrap is collected in the case of 10% participation rate and 1.2 lb per resident is collected in the case of 30% participation rate.

2) *Utilization of collection infrastructure.* Collection points are more spread out compared to processing points. Thus, the collection capacity is dependent on the geographical segment. In order not to overestimate or underestimate the capacity in the collection facility, we set the low and high level of capacity utilization in the collection infrastructure. For one half of scenarios, we solved problems where collection infrastructure only utilizes 45% of collection capacity. The other half of the scenarios, we solved adopt the level of 75% of collection capacity.

3) *CPU and monitor reusability percentages.* A key uncertainty is the condition of the CPUs and monitors that are collected. We ran one half of our problems assuming reusability rates of (CPU 30%, monitor 25%) and the

TABLE VIII
OPTIMAL AND ROBUST SOLUTIONS FOR GEORGIA E-SCRAP RPS INFRASTRUCTURE

Scenario			1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	Robust
Participation			L	L	H	H	L	L	H	H	L	L	H	H	L	L	H	H	
TV reusability			H	H	H	H	L	L	L	L	H	H	H	H	L	L	L	L	
CPU & monitor reusability			H	H	H	H	H	H	H	H	L	L	L	L	L	L	L	L	
Collection facility utilization			L	H	L	H	L	H	L	H	L	H	L	H	L	H	L	H	
	Site	Location																	
Collection Sites	1	Gordon Co., GA			●	●			●	●			●	●			●	●	●
	2	White Co., GA			●	●			●	●			●	●			●	●	●
	3	DeKalb Co., GA		●	●			●	●			●	●			●	●		●
	4	Meriwether Co., GA	●		●	●	●		●	●	●		●	●	●		●	●	●
	5	Oconee Co., GA	●		●		●		●		●		●		●		●		●
	6	Bibb Co., GA	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●
	7	Richmond Co., GA				●				●				●				●	
	8	Chattahoochee Co., GA			●				●				●				●		●
	9	Toombs Co., GA	●	●	●	●	●	●	●		●	●	●		●	●	●		●
	10	Dougherty Co., GA			●	●			●	●			●	●			●	●	●
	11	Ware Co., GA			●				●	●			●	●			●	●	●
	12	Chatham Co., GA			●	●			●	●			●	●			●	●	●
Non-profit Sites	1NP	Marietta, GA, GA			●				●				●				●		●
	2NP	Atlanta, GA	●		●	●	●	●	●	●	●		●	●	●		●	●	●
	3NP	Atlanta, GA	●	●	●	●	●		●	●	●	●	●	●	●	●	●	●	●
	4NP	Tucker, GA			●				●				●				●		●
	5NP	Sandersville, GA			●				●				●				●		●
	6NP	East Point, GA			●	●			●	●			●	●			●	●	●
Commercial Processing Sites	1A	Catoosa Co., GA			●	●			●	●			●	●			●	●	
	2A	Carroll Co., GA			●	●			●	●			●	●			●	●	●
	3A	Cobb Co., GA	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●
	4A	Fulton Co., GA			●				●	●			●				●	●	
	5A	DeKalb Co., GA																	
	6A	Gwinnett Co., GA	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●
	7A	Washington Co., GA			●				●			●	●		●	●	●		●
	8A	Baldwin Co., GA		●		●	●	●						●					
	9A	Richmond Co., GA				●				●				●				●	
	10A	Davidson Co., TN																	
	11A	Anderson Co., TN																	
	12A	Buncombe Co., NC																	
	13A	Mechlenburg Co., NC																	
	14A	Charleston, SC																	
	15A	Lexington Co., SC																	
*	1PR	Jackson Co., FL			●	●			●	●	●		●	●			●	●	●
**	1AA	Marietta, GA	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●

* The prison processing site
** The large commercial processing site
● The site opened

other half with (CPU 10%, monitor 10%). The parameter settings here are based upon several estimates in [44], [46], and [47].

4) *Television reusability percentage*. Used televisions that cannot be refurbished and resold are an expensive cost. However, many households hold on to their televisions until they no longer work. We assume that the television reusability percentage is lower than the reusability of CPUs and monitors. In this study, we solve one half of the scenarios that only 5% of the collected televisions are in a reusable condition. The other half of the scenarios specify that 10% of the televisions are reusable.

The four types of uncertainty factors, with two levels specified for each factor, result in 2^4 or 16 scenarios to be studied. In other words, each scenario describes a unique electronics recycling infrastructure design problem to be solved. The 16 problems or scenarios are defined in Table VII.

C. Overall Results

Our case study problems is solved on a Windows 2000-based personal computer with Pentium 1.80 GHz with 1-GB RAM using C++ program and CPLEX 9.0 [48] for the optimization software. MS-Access and the Visual Basic programming language are used as the case study database and user interface programs. This case study involves in a MILP model with 3500 binary variables, 1.2 million continuous variables, and 1.4 million constraints. When applying a direct solution approach for the robust problem, the optimal solution can not be found. The

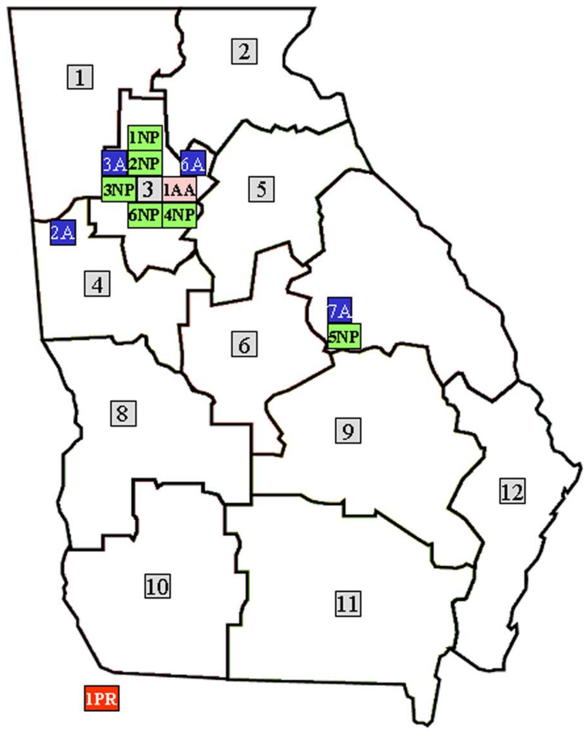

Fig. 7. e-Scrap RPS robust infrastructure solution for the state of Georgia.

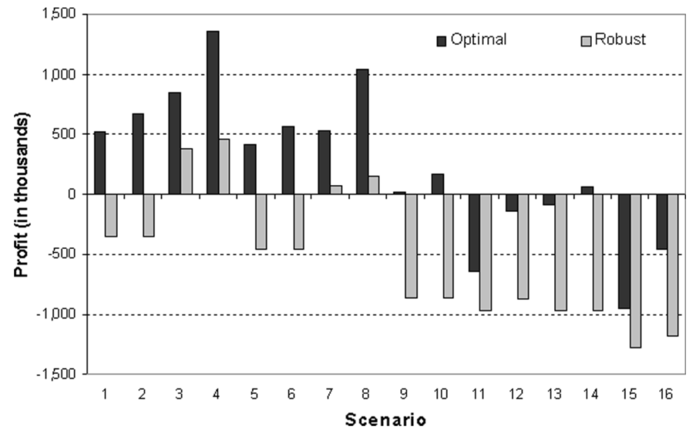

Fig. 8. Comparison of net profit of the optimal solution to the net profit of the robust solution for each scenario.

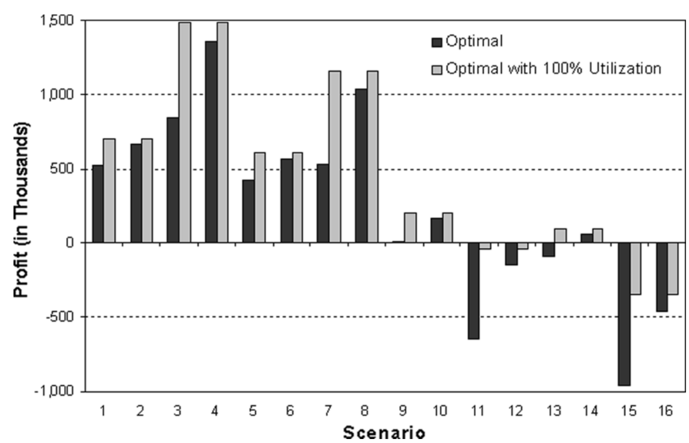

Fig. 9. Comparison of net profit of the optimal solution to the net profit with fully utilized collection facilities for each scenario.

computer requires more than 192 h of computational time without returning any feasible solution. A heuristic method [49] is used to solve the case study to optimality for the robust model, and it requires not more than 50 h of computational time.

Using the optimal solutions for the individual scenarios, we solve the robust optimization problem to obtain the robust infrastructure solution. The optimal infrastructure solutions and the robust infrastructure are given in Table VIII. The geographically robust infrastructure solution is also illustrated in Fig. 7. Based upon the robust infrastructure, the corresponding values of continuous variables are obtained for each of the 16 scenarios.

The robust solutions for the individual scenarios can be examined to understand the relative performance of the robust infrastructure solution in each scenario. Fig. 8 provides a comparison of the net profit associated with the optimal solution for each scenario to the net profit associated with the robust solution for each scenario. As expected, the value of the optimal solution serves as an upper bound on the value of the robust solution for each scenario.

There are several conclusions that can be drawn from Fig. 8. First, for the input data values detailed in Section IV, it appears that economically viable solutions (i.e., solutions that yield a positive net profit) can be found for several problem scenarios. However, several scenarios are with the estimated negative profits due to the poor setting of data input (i.e., low utilization in collection facilities, and low reusability for items collected). Second, it is clear that two factors of the high utilization in collection facilities and the high reusability rate in e-scrap are preferable directions toward a higher profit. However, the solution indicates that a high participation rate leads to a better profit in high reusability scenarios, but a high participation rate results in the poor profit in low reusability scenarios. It implies the impact of participation rates on the profit performance is not always in the same direction, but depends on the case of the reusability level in this case study. Fig. 9 provides a comparison of the net profit for each scenario to the net profit when collection facilities are fully 100% utilized in the collection capacity. The dark bars in Fig. 9 are the optimal net profits for all scenarios, the same as optimal values shown in Fig. 8, and the gray bars are the profits when collection facilities are fully 100% utilized in associated scenarios. As expected, the net profit value with 100% utilization is also an upper bound for each scenario.

It is also interesting to analyze how the cost burdens compare between highly favorable economic conditions (like Scenario 4, with a high number of reusable televisions, CPUs, and monitors collected, and a high collection capacity utilization) and unfavorable ones (like Scenario 15, with many more unusable televisions, CPUs, and monitors, and a low collection capacity utilization). Fig. 10 illustrates this comparison. The transportation costs both in Scenarios 4 and 15 are more than half of the total system costs for electronics recycling (logistics).

Similarly, the relative sources of revenues can be compared when economic conditions are highly favorable (Scenario 4) or when they are not as good (Scenario 15). Fig. 11 illustrates this

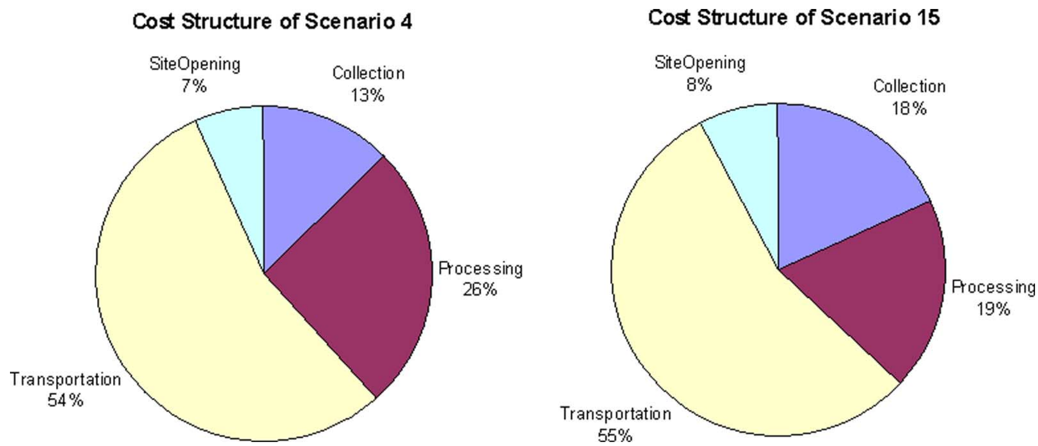

Fig. 10. Comparisons of relative costs for highly favorable conditions (Scenario 4) and unfavorable ones (Scenario 15).

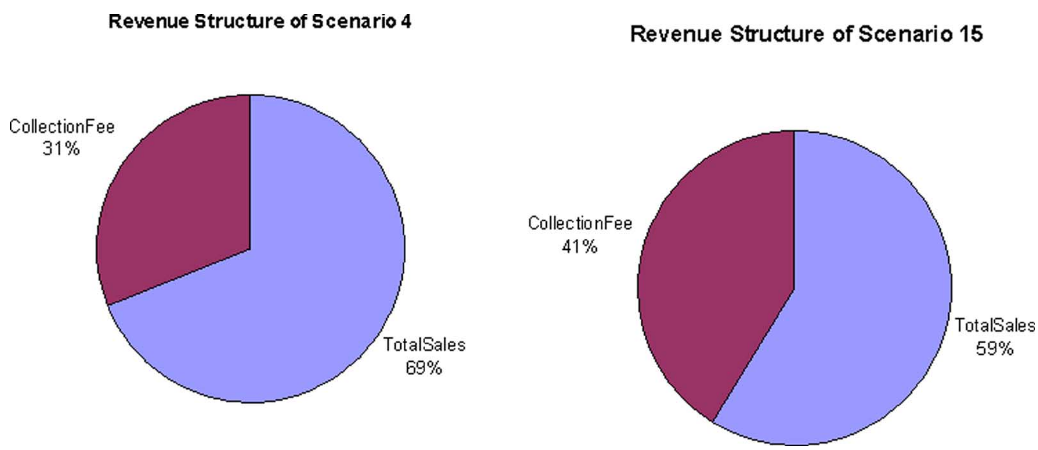

Fig. 11. Comparisons of revenue sources for highly favorable conditions (Scenario 4) and unfavorable ones (Scenario 15).

comparison. As expected, under less favorable economic conditions the revenue stream is more highly dependent on collection fees as a source of revenue.

V. Conclusion and Extensions

In this paper, our method successfully creates a design for used electronics RPS infrastructure in the state of Georgia. It is distinguished from previous approaches to this problem by the way that it captures uncertainty and produces robust solutions. The case study is a large scale, with millions of variables and constraints. The problem provides a challenging large scale benchmark data set for other robust optimization solution approaches.

Data based on a variety of sources has been used to approximate the regional electronics recycling infrastructure design problem for Georgia. Because very little publically available data exist for this relatively new problem in the U.S., these data may be helpful to other designers of e-scrap collection and processing systems.

Sixteen alternative problem scenarios have been analyzed to understand how the infrastructure design solutions are affected by key uncertainties in the resident participation rates, the percentage of used-collected electronics that are reusable, and the capacity utilization in collection facilities. From these solutions, we have learned that the resulting net profits and corresponding material flows vary greatly depending on the predicted conditions. The resulting solutions suggest that an economically viable electronics recycling infrastructure is possible for the state of Georgia in several problem scenarios. In fact, this result disproves our informal initial hypotheses that the e-scrap collection and processing system is doomed to lose money in many of the scenarios. In other words, the e-scrap collected in the state of Georgia may be seen as a positive financial resource in the case of the high reusability of e-scrap collected, and the corresponding collection and processing infrastructure as a source of economic development and job creation.

A key extension of this work is to incorporate additional types of e-scrap including printers, cell phones, telephones, laptop computers, personal digital assistant products (PDAs), etc. in case study analysis, especially with the increasing popularity of mobile products. Also, inclusion of additional collection sites and processing alternatives would extend the study to more comprehensive systems. Several other sources of uncertainty should be investigated, including the uncertainties associated with demand quantities, demand prices, and transportation costs, and their two- and three-way interactions, since these can be critical drivers of revenues and costs. Data security and privacy are other issues that should be examined in more detail in future work since cleaning or erasing the data may cause extra costs in processing e-scrap products. Finally, investigations on effects of preloading the free software systems or removing the operating systems in refurbished computers are also interesting future directions.

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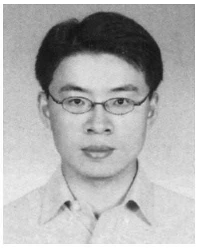

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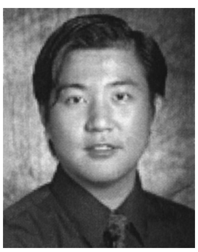

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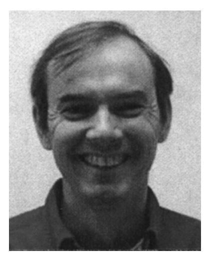

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