Selecting an E-Scrap Reverse Production System Design Considering Multicriteria and Uncertainty

Wen-Chih Chen and I-Hsuan Hong

Abstract—**A reverse logistics and production network that deals with recycled material flows has become essential due to the growing concern about the environmental impact of disposed waste and the economic value of recovered materials. Reverse logistics infrastructure design is typically based on tradeoffs between different criteria and faces challenges posed by uncertain system parameters such as the reusability percentage and total supply of end-of-life products. This paper presents a novel method for selecting alternative infrastructure designs to effectively and systematically handle multicriteria cases without subjective weight determination for different criteria. The proposed method, in practice, helps decision makers evaluate and select a design from a pool of alternatives proposed by contractors who place bids for public tenders where the bids include infrastructure design information and associated performance estimates under different uncertain system parameters.**

Index Terms—**Alternative selection, multicriteria, reverse logistics, robust, scrap electronics.**

I. Introduction

A REVERSE production system (RPS) includes collection, sorting, demanufacturing, and refurbishing processes for end-of-life products. A scrap electronics (e-scrap) RPS infrastructure design prescribes the facility location of collection and processing sites. This paper presents a novel method for e-scrap RPS infrastructure design selection that involves a decision process for evaluating and selecting alternatives under multicriteria evaluation and uncertainty regarding the external environment.

The increased urgency to maximize the efficiency of recycled material flows is due to concerns associated with the environmental impact of disposed waste and the economic value of recovered materials. An estimated 133 000 electronic devices are discarded daily in the U.S., amounting to 3 million tons of e-scrap (Hong *et al.* [10]). Another estimate of worldwide reverse logistics cost was in the neighborhood of US$137.2 billion in 1996 (Hong *et al.* [10]). Governmental regulations also play an important role in recycled e-scrap flows (e.g., Waste Electrical and Electronic Equipment (WEEE) and Reduction of Hazardous Substances Directive (RoHS) of the European Union) (see Europa, [6]). The WEEE directive seeks to minimize the environmental impact of e-scrap by making producers responsible for financing its collection, processing and recovery. An RPS infrastructure design has two key concerns—tradeoffs between different criteria and uncertain external environments; these concerns have been addressed in several studies (e.g., Oral *et al.* [15], Realff *et al.* [16]).

In the last decade, the number of studies investigating the design, planning and modeling of "closed-loop" supply chain systems has increased (e.g., Fleishmann *et al.* [7], Guide and Harrison [9], Hong *et al.* [11], Realff *et al.* [16], Shih, [19], Wang and Yang [20]). Most of these studies focus on searching an optimal solution (infrastructure design) in a well-expressed but simplified solution space. However, such work requires explicit expressions of considered constraints or parameters, which may not be available in the real world. Instead, this study presents a method for *evaluating* and *selecting* an e-scrap infrastructure design from a pool of alternatives with associated performance estimates under different uncertain system parameters. The primary uncertain factors include estimates of the amount and quality of end-of-life products as well as acquisition prices of refurbished products and recovered materials. Decisions based on inaccurate data due to uncertainty may lead to significant loss. Decision makers thus prefer measuring the benefits and losses associated with each potential decision in each circumstance. Solution robustness is an index for measuring how a design performs in an uncertain context.

In addition to uncertainty in alternative selection problems, another concern is the multicriteria for decision making. Evaluating and selecting alternatives with multicriteria is a common problem in numerous applications such as flexible manufacturing systems (Khouja [12]), supplier selection (De Boer *et al.* [5], Weber *et al.* [21]), and research and development (R&D) project selection (e.g., Cook and Seiford [3], Cook and Roll [4], Oral *et al.* [15]). Generally, the key function is to determine the tradeoffs among different criteria and thereby aggregate all criteria into one overall index. These studies, however, do not consider issues associated with both multicriteria and uncertainty simultaneously.

This work is motivated by the need of system decision makers (e.g., the government) to evaluate and select a proposal for RPS infrastructure design. A potential contractor may place a bid, a proposed alternative, including information on infrastructure design and associated performance estimates under different uncertainties regarding system parameters. This study presents an alternative selection method for e-scrap infrastructure design that handles two key challenges—multicriteria and uncertainty.

In addition to a need for RPS infrastructure design, the proposed method can be adopted for the contexts of solution gener-

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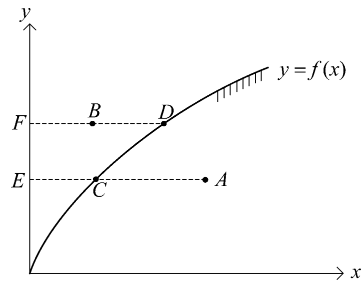

Fig. 1. Two-criteria example.

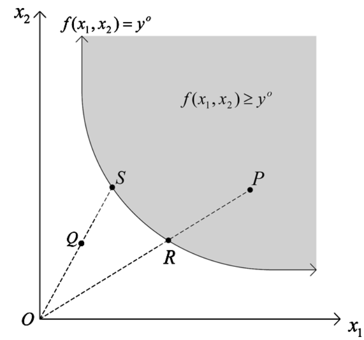

Fig. 2. Three-criteria example ($y = y^o$).

ation and selection framework. Conventional optimization techniques find the optimal solution in a well-defined solution space, i.e., clear expressions of constraints that are very likely unavailable in reality. In complex practical cases, one can generate a bunch of alternatives (possible solutions) and the corresponding performance values based on different means such as simulation, and then evaluate and select the "best" solution among alternatives. The proposed method contributes to this research stream.

The remainder of this paper is organized as follows. Section II addresses multicriteria evaluation and the worst-case approach for alternative selection under possible scenarios. Section III demonstrates the effectiveness of the proposed method for an e-scrap case study. Conclusions are given in Section IV.

II. Methodology

This section presents the method for alternative evaluation and selection that accommodates multicriteria performance and several key uncertain parameters. The proposed method adopts a viewpoint different from that in conventional multicriteria alternative selection studies, which typically focus on how to aggregate criteria. In particular, this work focuses on a feasible performance region and ideal performance, which is close to other engineering disciplines.

A. Performance Limit

This work first discusses performance limits. Fig. 1 is a simple example with two criteria. The x-axis is the value for a minimizing oriented criterion, x, i.e., the smaller the better; the y-axis represents the value for a maximizing oriented criterion, y, i.e., the larger the better. Suppose the performance limit, the ideal relationship between x and y, is $f(x) = y$, where $f(x)$ is the ideal value of criterion y given a value of criterion x. The performance bundle (x', y') in the area below $f(x')$, $f(x') \geq y'$, is feasible. This is because (x', y') can be better off, namely, not beyond the limit, relative to ideal performance $(x', f(x'))$. In fact, the form of $f(x)$ is commonly seen in engineering disciplines. For example power $= f(\text{fuel})$ reveals that power generated by fuel consumed is ideal; power generated and fuel consumed can be interpreted as two performance criteria.

Suppose point A is claimed as a performance bundle (Fig. 1). Point A is underperformed since point C on limit function $f(x)$ consists of a lower level of the minimizing-oriented criterion x while C keeps the same y value as A. The difference between A and ideal performance C can be measured as CE/AE. This measure suggests that the x value can be improved from AE to CE when the y value remains the same; clearly, $CE/AE < 1$. Another point B is not within the feasible region, and its x value needs to increase from BF to DF to be feasible. The difference between B and ideal performance can be measured as $DF/BF > 1$. Obviously, points C and D are associated with the performance limit, and the difference measure relative to the ideal performance is unity. For notation simplicity, let f^{-1} denote the inverse function of f. The difference between a performance bundle (x, y) and performance limit $f(x)$, as illustrated in Fig. 1, can be formalized and defined as

$$D(x, y) = \frac{f^{-1}(y)}{x} = \min\{\alpha : f(\alpha x) \geq y\}. \qquad (1)$$

The second part of the definition in (1) states that one must make the minimizing criterion as good (small) as possible while maintaining maximizing criterion. Notably, performance bundles C and D are both ideal, namely, the corresponding x value is minimum given the y value. Any further better-off reduction in x for points C or D cannot be achieved without a worse-off reduction in y. That is, there are tradeoffs between these two criteria. In this sense, C and D perform equally; one cannot determine whether C or D performs better. In fact, bundles on the limit are also referred to as Pareto efficient (McGuigan *et al.* [14]).

Now, consider a case with two minimizing criteria ($\mathbf{x} = (x_1, x_2)$) and one maximizing criterion y (Fig. 2). The x-axis is the value for the minimizing-oriented criterion x_1; the y-axis represents the value for another minimizing-oriented criterion, x_2. Particularly, Fig. 2 represents the case of $y = y^o$. Suppose the performance limit, the ideal relationship between $\mathbf{x}$ and a particular y^o, is given as $f(x_1, x_2) = y^o$ (Fig. 2). The shadow area denoted as $L(y^o)$ is the region of $\mathbf{x}$'s, such that $f(\mathbf{x}) \geq y^o$. Any $(\mathbf{x}, y^o)$ in the shadow area but not on $y^o = f(x_1, x_2)$ implies that x_1 and/or x_2 can be better off (smaller) while keeping $y = y^o$. Clearly, the performance represented by point P is not the best. One way to improve the performance of P is to minimize both x_1 and x_2 proportionately while retaining $y = y^o$. Similar to the example presented in Fig. 1, the difference measure between P and ideal performance is OR/OP. A smaller OR/OP represents the worse performance of P. Conversely, point Q is infeasible with a difference measure of $OS/OQ > 1$. Points S and R are at the performance limit of $y = y^o$, i.e., satisfying $y = f(x_1, x_2)$. Both S and R are Pareto efficient such that one cannot determine whether S or R is better; that is, tradeoffs among minimizing-oriented criteria exist. The difference measure (1) can be rewritten as

$$\begin{aligned} D(\mathbf{x}, y) &= \min\{\alpha : f(\alpha\mathbf{x}) \geq y\} \\ &= \min\{\alpha : (\alpha\mathbf{x}, y) \in L(y)\}. \end{aligned} \tag{2}$$

By applying similar arguments, difference measures can be further generalized to multiple maximizing criteria, represented by vector $\mathbf{y}$, as

$$D(\mathbf{x}, \mathbf{y}) = \min\{\alpha : (\alpha\mathbf{x}, \mathbf{y}) \in L(\mathbf{y})\} \tag{3}$$

where $\mathbf{x}$ is the performance vector of m minimizing-oriented criteria and $\mathbf{y}$ is for n maximizing-oriented criteria. The case of $D(\mathbf{x}, \mathbf{y}) = 1$ indicates that performance bundle $(\mathbf{x}, \mathbf{y})$ is feasible and ideal performance is achieved. Thus, $D(\mathbf{x}, \mathbf{y}) < 1$ indicates that $(\mathbf{x}, \mathbf{y})$ can be better off, and $D(\mathbf{x}, \mathbf{y}) > 1$ indicates that $(\mathbf{x}, \mathbf{y})$ is impossible. With a large deviation from 1, the corresponding performance bundle differs significantly from the ideal condition. For demonstration purposes, this work uses minimizing-oriented analysis defined in (1)–(3); similarly, the maximizing-oriented approach can be defined by keeping $\mathbf{x}$ the same and scaling $\mathbf{y}$.

B. Robustness and Alternative Selection

In practice, uncertainty associated with parameter values is a challenge faced by decision makers. A complete lack of knowledge regarding the probability distribution of uncertain parameters likely exists. This study approaches a problem when the joint probability distribution of uncertain parameters is unknown or difficult to obtain. Robust optimization is adopted in the proposed method to produce decisions that have a *robust* objective function value under potentially possible circumstances, i.e., to optimize the worst possible performance. The robust concept is particularly preferred and useful for risk-averse decision makers (Kouvelis and Yu [13]).

Several different methods exist for determining a robust decision among candidates. One such method is the *robust relative decision*, which is the decision that exhibits the best worst case percentage deviation from optimality. We assume that a set of finite scenarios (S) represent different realizations of uncertain parameters. By taking the scenario into account, the concept and notion mentioned, such as (1)–(3), are rewritten with minor modifications. For example, $f_s(x)$, $L(\mathbf{y}|s)$ and $D(\mathbf{x}, \mathbf{y}|s)$ have the same interpretations as $f(x)$, $L(\mathbf{y})$ and $D(\mathbf{x}, \mathbf{y})$, respectively, under a particular scenario $s \in S$. In particular, $D(\mathbf{x}, \mathbf{y}|s)$ represents the difference between performance bundle $(\mathbf{x}, \mathbf{y})$ and performance limit under scenario s, which follows the same principles in (3).

Let A be a set of alternatives and $a \in A$ denote an alternative to be evaluated for the scenarios in set S. In a multicriteria setting, $(\mathbf{x}_a^s, \mathbf{y}_a^s)$ denotes the performance for alternative $a \in A$ under scenario $s \in S$. As discussed earlier, the highest feasible difference measurement $D(\cdot, \cdot)$ equals 1. A robust alternative commonly adopted is to minimize maximum deviation of the difference measurement $D(x_a^s, y_a^s|s)$ from the ideal value,

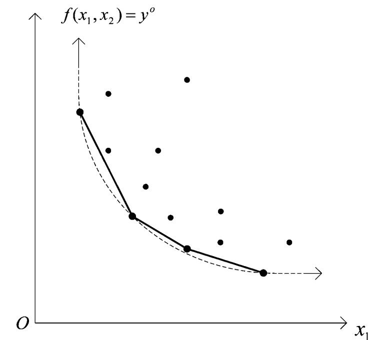

Fig. 3. Estimated performance limit.

1, across all the scenarios in set S. Such a criterion is suitable for the environment in which performance of a selected alternative is evaluated after the uncertain situation is realized. This process captures a notion that the decision is feasible for any potential scenario and can protect a decision maker from performing poorly in a given scenario (Kouvelis and Yu [13]). Decision makers typically search for a robust alternative $a^* \in A$ that performs well across all possible scenarios without attempting to assign an assumed probability distribution to any uncertain parameter via the following optimization problem:

$$\min_{a \in A} \left\{ \max_{s \in S} \left(1 - D(x_a^s, y_a^s|s)\right) \right\}. \tag{4}$$

As a tool for alternative selection given knowledge of the ideal scenario conditions, exaggerated performance can be considered a potential cheating behavior and should be penalized significantly. Notably, (3) provides fraud-proof and assists in filtering out unrealistic proposals. Alternative a is potentially fraudulent given scenario s when $D(\mathbf{x}_a^s, \mathbf{y}_a^s|s) > 1$. Thus, alternative a with $D(\mathbf{x}_a^s, \mathbf{y}_a^s|s) > 1$ is removed from pool A before further data confirmation or any other action; only cases of $D(\mathbf{x}_a^s, \mathbf{y}_a^s|s) \leq 1$ are considered. The relative deviation of alternative a under scenario s, $1 - D(\mathbf{x}_a^s, \mathbf{y}_a^s|s)$, can be interpreted as distance to the "ideal" situation, and deviation clearly only exists when $D(\mathbf{x}_a^s, \mathbf{y}_a^s|s) < 1$.

C. Estimating Performance Limits

Sections II-A and II-B establish the theoretical foundations for robust alternative evaluation and selection under a situation in which the performance limit $f_s(x)$ and feasible region $L(\mathbf{y}|s)$ for scenario s are known. This section further investigates how to handle situations for which $f_s(x)$ and/or $L(\mathbf{y}|s)$ are unavailable, and provides a practical implementation of (3) and (4).

One can estimate the performance of a feasible region or performance limit according to expertise or personal experience; however, such estimation is typically subjective. Here the estimation is based on historical data; that is, the results of knowledge. Function $f_s(x)$ can be estimated by a piecewise linear function. Fig. 3 is one example of the estimation where the dots represent given historical records for a case with two minimizing criteria and one maximizing criterion. In other words, $f_s(x)$ is estimated using the best performance bundles in a given set of performance data.

TABLE I
HYPOTHETICAL PERFORMANCE EXAMPLE

	Record						Alternative	
	B	C	D	E	F	G	$A1$	$A2$
x_1	2	4	6	6	5	8	5	4
x_2	4	8	6	7	6	11	5	8
y_1	3	4	7	8	4	7	7	3
y_2	2	6	6	5	3	7	6	2

To generalize this idea, given a set of observed records, denoted by W^s, for each scenario $s \in S$ representing historical experiences, the difference index for alternative $a \in A$, $D\left(\mathbf{x}_a^s, \mathbf{y}_a^s | s\right)$, is estimated by $\hat{D}\left(\mathbf{x}_a^s, \mathbf{y}_a^s | s\right)$ as follows (Banker *et al.* [1], Charnes *et al.* [2]):

$$\hat{D}\left(x_a^s, y_a^s | s\right) = \min \left\{ \theta : \sum_{\omega \in W^s} \mathbf{x}^\omega \lambda^\omega \leq \theta \mathbf{x}_a^s; \right. \\ \left. \sum_{\omega \in W^s} \mathbf{y}^\omega \lambda^\omega \geq \mathbf{y}_a^s;\ \lambda^\omega \geq 0;\ \omega \in W^s \right\}. \quad (5)$$

For demonstration purposes, implementing (5) for a simple example is illustrated as follows. Consider hypothetical performance data in a database with six records for a particular scenario (Table I), i.e., $W^s = \{B, C, D, E, F, G\}$. Four criteria and two alternatives, $A1$ and $A2$, are evaluated. According to (5), the difference measure for $A1$ is computed as

$$\begin{aligned}
&\hat{D}\left(\mathbf{x}_{A1}^s, \mathbf{y}_{A1}^s | s\right) = \min \theta \\
&s.t.\ 2\lambda_B + 4\lambda_C + 6\lambda_D + 6\lambda_E + 5\lambda_F + 8\lambda_G \leq 5\theta \\
&\quad 4\lambda_B + 8\lambda_C + 6\lambda_D + 7\lambda_E + 6\lambda_F + 11\lambda_G \leq 5\theta \\
&\quad 3\lambda_B + 4\lambda_C + 7\lambda_D + 8\lambda_E + 4\lambda_F + 7\lambda_G \geq 7 \\
&\quad 2\lambda_B + 6\lambda_C + 6\lambda_D + 5\lambda_E + 3\lambda_F + 7\lambda_G \geq 6 \\
&\quad \lambda_B \geq 0, \lambda_C \geq 0, \lambda_D \geq 0, \lambda_E \geq 0, \lambda F \geq 0, \lambda_G \geq 0 \\
&\quad \theta \text{ is free.}
\end{aligned}$$

$\hat{D}\left(\mathbf{x}_{A2}^s, \mathbf{y}_{A2}^s | s\right)$ is computed as follows:

$$\begin{aligned}
&\hat{D}\left(\mathbf{x}_{A2}^s, \mathbf{y}_{A2}^s | s\right) = \min \theta \\
&s.t.\ 2\lambda_B + 4\lambda_C + 6\lambda_D + 6\lambda_E + 5\lambda_F + 8\lambda_G \leq 4\theta \\
&\quad 4\lambda_B + 8\lambda_C + 6\lambda_D + 7\lambda_E + 6\lambda_F + 11\lambda_G \leq 8\theta \\
&\quad 3\lambda_B + 4\lambda_C + 7\lambda_D + 8\lambda_E + 4\lambda_F + 7\lambda_G \geq 3 \\
&\quad 2\lambda_B + 6\lambda_C + 6\lambda_D + 5\lambda_E + 3\lambda_F + 7\lambda_G \geq 2 \\
&\quad \lambda_B \geq 0, \lambda_C \geq 0, \lambda_D \geq 0, \lambda_E \geq 0, \lambda_F \geq 0, \lambda_G \geq 0 \\
&\quad \theta \text{ is free.}
\end{aligned}$$

Notably, the left side of the inequalities is constructed using database records; only the right side of inequalities represents alternative performance and differs for $A1$ and $A2$. In this example, $\hat{D}\left(\mathbf{x}_{A1}^s, \mathbf{y}_{A1}^s | s\right) = 1.2$ and $\hat{D}\left(\mathbf{x}_{A2}^s, \mathbf{y}_{A2}^s | s\right) = 0.5$, indicating that alternative $A1$ is potentially fraudulent and $A2$ is underperformed.

An $|A| \times |S|$ matrix consisting of $D\left(\mathbf{x}_a^s, \mathbf{y}_a^s | s\right)$ is constructed by repeating the same computing procedure. Robust alternative a^* is determined by

$$a^* \equiv \arg\min_{a \in A} \left\{ \max_{s \in S} \left(1 - \hat{D}(x_a^s, y_a^s | s) \right) \right\}. \quad (6)$$

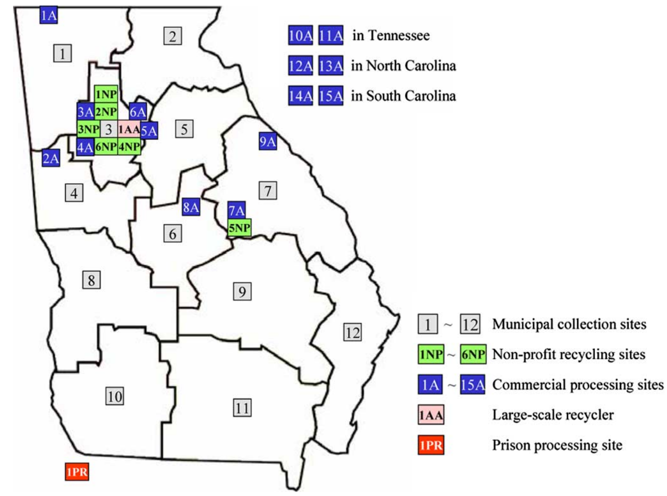

Fig. 4. Potential 35 considered sites in the case study (adapted from Hong *et al.* [11]).

TABLE II
KEY UNCERTAINTY VALUE SETTINGS FOR EIGHT SCENARIOS

Reusable Percentage	Collection Utilization	
	45%	75%
TV: 10%, CPU: 30%, Monitor: 25%	S1	S2
TV: 5%, CPU: 30%, Monitor: 25%	S3	S4
TV: 10%, CPU: 10%, Monitor: 10%	S5	S6
TV: 5%, CPU: 10%, Monitor: 10%	S7	S8

III. CASE STUDY

This case study is based on an e-scrap RPS infrastructure design and demonstrates the use of the proposed robust multi-criteria alternative selection procedure. A decision maker, such as the government, evaluates and selects bids for e-scrap infrastructure design using several estimates of criteria under uncertainty. This work utilizes the dataset presented in Hong *et al.* [11] as input parameters for this case study to demonstrate application of the proposed method.

This study selects a robust alternative infrastructure design to handle the accumulated end-of-life electronic products in the state of Georgia, an area covering approximately 57 906 square miles (149 911 km^2) with an estimated population of 8.4 million. At this initial stage, the main physical inputs to the system are considered obsolete televisions (TVs), computer monitors, and desktop computers (CPUs). We predict that more than 5.5 million pounds of used TVs, 3.3 million pounds of computer monitors, and 1.8 million pounds of CPUs will be scrapped. The potential RPS infrastructure sites are municipal collection sites, nonprofit recycling sites, commercial processing sites, a large-scale recycler, and a prison processing site.

A potential contractor proposes an infrastructure design with several estimates for criteria, such as associated cost, revenue, and amount collected, under several predefined uncertain scenarios. However, a contractor may list an exaggerated measure to increase the likelihood of winning the contract. A major task in the proposed method is to identify the possible fraudulent alternative in which measures claimed by a contractor may not be achievable. Furthermore, the objective of the decision maker is to select a robust alternative for infrastructure design among ten

TABLE III
CRITERIA VALUES OF EACH ALTERNATIVE

		Alternative									
Scenario		A1	A2	A3	A4	A5	A6	A7	A8	A9	A10
S1	Cost	4,943	5,285	4,632	4,179	4,681	5,042	3,954	4,425	4,805	4,574
	Revenue	6,059	6,107	5,641	5,128	5,646	6,132	6,059	5,382	5,771	5,641
	Collection	7,147	7,354	6,479	5,603	6,479	7,275	7,147	5,844	6,696	6,479
S2	Cost	4,896	5,285	4,853	4,554	5,037	4,980	3,943	4,554	5,151	4,986
	Revenue	6,292	6,379	6,122	5,745	6,273	6,320	6,327	5,745	6,393	6,318
	Collection	7,600	7,694	7,336	6,624	7,621	7,621	7,600	6,624	7,710	7,621
S3	Cost	3,835	4,263	3,744	4,078	3,958	3,921	3,068	4,024	3,987	3,725
	Revenue	4,851	4,973	4,654	4,987	4,859	4,912	4,851	4,934	4,882	4,707
	Collection	4,913	5,027	4,711	5,044	4,955	4,955	4,913	5,044	4,918	4,711
S4	Cost	4,741	5,049	4,513	4,158	4,543	4,434	3,793	4,154	4,586	4,437
	Revenue	5,956	5,988	5,614	5,248	5,625	5,625	5,956	5,248	5,666	5,625
	Collection	7,267	7,259	6,624	5,797	6,624	6,624	7,267	5,797	6,624	6,624
S5	Cost	2,327	2,657	2,442	2,001	2,461	2,360	1,877	2,001	2,461	2,376
	Revenue	2,623	2,641	2,623	2,160	2,654	2,636	2,641	2,160	2,654	2,654
	Collection	3,415	3,415	3,415	2,540	3,415	3,415	3,415	2,540	3,415	3,415
S6	Cost	3,074	3,388	3,185	2,497	3,198	3,112	2,459	2,497	3,198	3,110
	Revenue	3,542	3,542	3,542	2,768	3,542	3,542	3,542	2,768	3,542	3,542
	Collection	5,166	5,166	5,166	3,707	5,166	5,166	5,166	3,707	5,166	5,166
S7	Cost	1,942	2,257	2,050	1,614	1,642	1,947	1,552	1,614	1,642	1,948
	Revenue	2,101	2,101	2,112	1,715	1,715	2,101	2,101	1,715	1,715	2,101
	Collection	2,540	2,540	2,540	1,665	1,665	2,540	2,540	1,665	1,665	2,540
S8	Cost	2,953	3,266	3,064	2,504	2,511	2,390	2,360	2,504	2,511	2,406
	Revenue	3,244	3,244	3,244	2,691	2,691	2,666	3,244	2,691	2,691	2,675
	Collection	4,905	4,905	4,905	3,707	3,707	3,707	4,905	3,707	3,707	3,707

Cost and Revenue: Dollars in thousands
Collection: Pounds in thousands

potential alternatives representing different infrastructure configurations. Fig. 4 shows the potential collection and processing sites. This case study considers 12 potential municipal collection sites based on service regions defined by Georgia's Department of Community Affairs (DCA) and 15 potential commercial processing sites (nine in Georgia, two in Tennessee, two in North Carolina, and two in South Carolina) (DCA [8], Hong *et al.* [11]). Additionally, six nonprofit processing sites, one large commercial processing site, and one prison processing site are included in the set of candidate sites. Each facility is an actual refurbishing and/or demanufacturing site located in Georgia or nearby states. The potential site locations also coincide with the population distribution where more than half of Georgia residents live in metropolitan Atlanta.

As mentioned in Section II-B, uncertainty inevitably impacts RPS infrastructure design. For example, system profits due to sales of refurbished products are definitely affected by the uncertain parameter for the estimate of the quality of end-of-life products. The key uncertain parameters in this case study are as follows: 1) utilization of collection infrastructure; 2) percentage of reusable CPUs and monitors; and 3) percentage of reusable televisions (Hong *et al.* [11]). Typically, decision makers can predict the lower and upper bounds of uncertain parameters. A practical approach for generating particular scenarios accounts for combinations of extreme points, but not limited to, within a prediction range of uncertain parameters. Consequently, these three uncertain parameters, with two levels specified for each parameter, result in 2^3 or eight scenarios. Table II lists the eight scenarios in detail. Notably, a tradeoff exists between the number of scenarios and effort when making a decision. Additional scenarios can improve the representation of uncertainties in reality; however, such an increase increases the effort expended in data collection and computations.

A decision maker may be interested in the total amount collected in addition to the measure of total revenue when considering an e-scrap RPS infrastructure design problem. In this case study, maximizing-oriented criteria are total revenue and amount collected; the minimizing-oriented criterion is total cost. The decision maker selects a robust and feasible alternative from ten potential infrastructure designs proposed by contractors. Table III lists the associated measures for cost, revenue, and amounts collected claimed by contractors under each scenario. In real practical cases, these data provided by contractors indicate estimated cost and promised revenue, as well as amounts collected that correspond to possible scenarios.

To evaluate these potential alternatives proposed by contractors, decision makers must estimate the reference performance limit and/or feasible region based on experience. This case study utilizes the model proposed by Hong *et al.* [11] to generate a bunch of reference performance bundles with associated revenues and amounts collected (maximizing criteria) and costs (minimizing criterion). Given a specific total cost, the optimal (feasible) solution for total revenue and amount collected can be obtained by Hong *et al.* [11]. For each scenario, this case study collects 12 performance bundles,[1] which are used to approximate the performance limit. Notably, a larger set of observation points results in better approximation of the performance limit; however, computation time and effort expended during data collection increase.

The performance indices of each alternative under all scenarios in this case study are computed based on (5). Table IV

[1]These data are available at http://nirvana.iem.nctu.edu.tw/wenchih/rpsdata.pdf.

TABLE IV
ROBUST PERFORMANCE OF EACH ALTERNATIVE

Scenario	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10
S1	0.999 (0.001)	0.955 (0.045)	0.975 (0.025)	0.952 (0.048)	0.965 (0.035)	0.995 (0.005)	1.249	0.940 (0.060)	0.968 (0.032)	0.987 (0.013)
S2	0.948 (0.052)	0.889 (0.111)	0.926 (0.074)	0.903 (0.097)	0.922 (0.078)	0.935 (0.065)	1.179	0.903 (0.097)	0.915 (0.085)	0.934 (0.066)
S3	0.925 (0.075)	0.852 (0.148)	0.909 (0.091)	0.894 (0.106)	0.902 (0.098)	0.914 (0.086)	1.156	0.902 (0.098)	0.893 (0.107)	0.917 (0.083)
S4	0.932 (0.068)	0.876 (0.124)	0.903 (0.097)	0.878 (0.122)	0.897 (0.103)	0.919 (0.081)	1.164	0.879 (0.121)	0.891 (0.109)	0.919 (0.081)
S5	0.961 (0.039)	0.844 (0.156)	0.916 (0.084)	0.857 (0.143)	0.912 (0.088)	0.949 (0.051)	1.194	0.857 (0.143)	0.912 (0.088)	0.945 (0.055)
S6	0.971 (0.029)	0.881 (0.119)	0.938 (0.062)	0.896 (0.104)	0.934 (0.066)	0.960 (0.040)	1.214	0.896 (0.104)	0.934 (0.066)	0.960 (0.040)
S7	0.947 (0.053)	0.814 (0.186)	0.899 (0.101)	0.847 (0.153)	0.832 (0.168)	0.944 (0.056)	1.184	0.847 (0.153)	0.832 (0.168)	0.944 (0.056)
S8	0.963 (0.037)	0.871 (0.129)	0.928 (0.072)	0.902 (0.098)	0.900 (0.100)	0.941 (0.059)	1.205	0.902 (0.098)	0.900 (0.100)	0.936 (0.064)
max deviation	0.075	0.186	0.101	0.153	0.168	0.086		0.153	0.168	0.083

summarizes these performance indices. The values in brackets are relative deviations from ideal conditions. Notably, A7 has an index value > 1. As mentioned, this implies that A7 outperforms the best experienced performance, and may also indicate a potential error and/or fraud associated with claimed performance values. Further confirmation and validation should be performed, and, in this case study, A7 is removed from the candidate list. The last row in the bottom of Table IV, except that for A7, lists the maximum relative deviation of all alternatives, which represents the worst case under all scenarios. Notably, A1 has the lowest maximum relative deviation (0.075), indicating that it is the robust selection among candidates based the proposed method. Thus, alternative A1 captures a notion of "risk" that the decision maker wants to protect himself/herself from selecting a very poorly performed alternative in a given scenario.

IV. Conclusion

Given concerns regarding the environmental impact of disposed waste and the economic value associated with recovered materials, efficient reverse logistics systems have become increasingly important. How to best design an effective e-scrap RPS infrastructure is both important and challenging as multiple objectives must be achieved, and uncertainty regarding external system parameters in the real world must be considered. This study presents a novel method for e-scrap RPS design selection that can be applied easily to other applications that face similar challenges. The case study also demonstrates application of the proposed method for properly selecting a RPS design among alternatives.

The proposed alternative selection procedure differs from robust optimization approaches (e.g., Hong *et al.* [11], Realff *et al.* [16]) in the purpose and timing of deployment. The optimization model is used to *generate* an optimal alternative, whereas the proposed method is applied to evaluate and select a relatively optimal alternative from a given pool of alternatives. The alternatives in the candidate pool may be proposed by contractors using various methods including ad-hoc and conventional optimization methods. The proposed method is used as a second stage of RPS infrastructure design, which is generally overseen by government, to select a robust solution from the list generated by methods unknown to those evaluating the solutions.

In public tenders, contractors may only provide a single bundle of criteria values instead of proposing a full set of values for all scenarios. For example, criteria values for the eight scenarios in this case study may be aggregated into one representative value. However, the synthesis process is unknown and case-dependent, and is not addressed in this work. Further investigation can analyze this challenging problem.

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