Fast Heuristics for Designing Integrated E-Waste Reverse Logistics Networks

I-Lin Wang and Wen-Cheng Yang

***Abstract*—This paper investigates a mixed-integer linear programing model that solves an integrated facility location and configuration problem for recycling electronic waste (e-waste). Since different recycled e-waste consume different levels of recycling processes and resources, the capability of processing only one or more categories of recycled e-waste for each candidate facility is considered in addition to its location to maximize the total revenue. Computational experiments based on proposed heuristics are conducted using data collected from Taiwan's recycled e-waste market and show our proposed methods give a high-quality near-optimal solution in a promising time shorter than previous solution methods and CPLEX.**

***Index Terms*—Electronic waste, facility location, heuristics, mixed-integer linear programing, reverse logistics.**

I. Introduction

WITH the growing economy, the increasing amount of disposed goods can induce important environmental issues if they are not properly managed at product end of life. Reverse logistics, the activities to collect and process used products, has been extensively investigated recently to preserve as much of the residual value of used products in a way friendly to the environment. For example, the environmental regulations in Taiwan mandate the manufacturers and importers to take back their products. Manufacturers and importers contribute approximately \$20 USD of disposition fees for each new electronic appliance and computer to a fund established by the Environmental Protection Administration (EPA) of Taiwan. The fund committee is responsible in evaluating the amount of disposition fees and certifying the take-back rate to establish an effective reverse logistics system.

Decisions made by the fund committee may have great affects on the entire reverse logistics system. In particular, changing the disposition fee for a specific category of recycled products may encourage (or discourage) reverse logistics companies to raise (or lower) its take-back rate. Besides specifying the subsidy for recycling specific products, a government may enact regulations to limit or encourage the locations or configurations for specific recycling facilities. To evaluate the performance of a reverse logistics system in its planning stage, a government or a company may first formulate their problem as a mathematical programing problem, solve it, and then perform sensitivity analysis. The design of a reverse logistics system is usually treated as a mixed integer linear programing problem (MIP) which seeks the maximum total revenue or minimum total cost obtained by optimal facility locations and transportation assignments for processing and shipping the recycled products or materials in accordance with the operational capacities and the regulations. The sensitivity analysis for MIP may be conducted by iteratively solving MIPs of the same problem structure but with slightly different settings of coefficients. Unfortunately, solving such a MIP in reasonable time is usually a hard task even using a state-of-the-art optimization software like CPLEX (see ILOG [4]).

Developing a solution method that computes the optimal or near-optimal solutions in shorter time is not only useful for conducting the sensitivity analysis, but also beneficial in solving network design problem under uncertainty. In particular, during the supply chain design phase, the uncertainty in demands and prices should be considered to achieve better management over the planned time horizon. The discounted cash flow analysis incorporated with the decision tree methodologies can be used for evaluating the network design decisions (see Chopra and Meindl [2]) under uncertainty, in which each node in the decision tree corresponds to an MIP. As one solves an MIP at each node in the decision tree and works backwards from future period based on the Bellman's principle, exponentially many MIPs have to be solved which could be a very time-consuming task. In practice, such a strategy analysis may not require all the MIPs to be solved to optimality; thus, fast heuristics to compute for solutions in shorter time will definitely decrease the computational efforts required for conducting the sensitivity analysis or designing the network under uncertainty.

Previous research in reverse logistics network design problem usually only considers universal facilities which can collect or process all kinds of recycled products. Such an assumption is, in fact, not realistic since the major players in recycling industries typically engage in niche markets based on their core competencies. Moreover, some governments (e.g., Taiwan) even make regulations to forbid certain categories of recycled products to be collected or processed by the same company or facility due to safety and environmental concerns, as well as maintaining the competitive market for the recycling industries. Therefore, a more reasonable assumption in designing a reverse logistics network should also consider different configurations of facilities for different categories of recycled products. Using different facility configurations to recycle different categories of

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I-L Wang is with the Department of Industrial and Information Management, National Cheng Kung University, Tainan 701, Taiwan, R.O.C. (e-mail: ilinwang@mail.ncku.edu.tw).

W-C Yang is with the Cell Manufacturing Support Section, Hannstar Display Corporation, Tainan County 741, Taiwan, R.O.C.

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recycled e-waste is a common practice in Taiwan's e-waste recycling industry. For example, suppose there are two categories of recycled e-waste (e.g., category 1: TV, refrigerator, washing machine, and air condition; category 2: computer, printer and scanner), for a candidate facility location, one may either choose not to build any facility at all, or build a facility with configuration for processing the recycle e-waste of category 1, of category 2, or of both categories. In particular, given a candidate location qualified for building a facility that can collect or process exactly ρ of the entire γ categories of recycled products, the facility will have C_ρ^γ possible configurations to be built. Furthermore, one may at most have $C_0^\gamma + C_1^\gamma + \cdots + C_\gamma^\gamma = 2^\gamma$ options to build a facility that can collect or process up to γ categories of recycled products. Such flexibility in constructing different configurations of facilities is very important to achieve a better reverse supply chain management, although it will induce a large number of new variables and constraints.

The major contributions of this paper are twofold. First, besides the optimal facility locations and transportation assignments for recycling e-waste as usually considered in the literature, we also consider the flexibility of facility configurations and seek an optimal facility configuration to be built—whether it only processes a specific category or all categories of recycled e-waste. Second, we propose two solution methods that can compute a near-optimal solution with good quality in a time much shorter than previous solution methods and CPLEX. The rest of this paper is organized as follows. Section II reviews the problems and solution methods in designing reverse logistics networks. In Section III, we propose an MIP to formulate the optimal facility location and configuration problem for a reverse logistics system. Two solution methods are proposed in Section IV to solve the MIP. Section V presents settings of our computational experiments and analysis of the results. Finally, Section VI summarizes and concludes the paper.

II. Literature Review

Some recycled products may require special treatments for hazardous materials produced during the recycling processes. Different products consume different levels of recycling processes, resources, and equipments. Thus, not only should one consider the optimal location for the facilities, but also the type of recycling equipments in the facilities should be considered to achieve better supply chain management. However, most previous research focuses only on the optimal facility location problem.

Shih [11] introduces and analyzes the reverse logistics system for recycling electronic appliances (TVs, refrigerators, washing machines, and air conditioners) and computers in Taiwan. He proposes a reverse logistics network model which contains four types of nodes: 1) a collecting point that collects recycled products; 2) a storage site that serves as a buffer where recycled products may be sorted or classified according to their conditions; 3) a disassembly/recycle plant that disassembles and classifies the four major electronic appliances or computers; and 4) a final treatment and landfill which are the last stage of the disposal process. Each of these four stakeholders (nodes) can claim a subsidy. An MIP model is proposed and real-world parameters

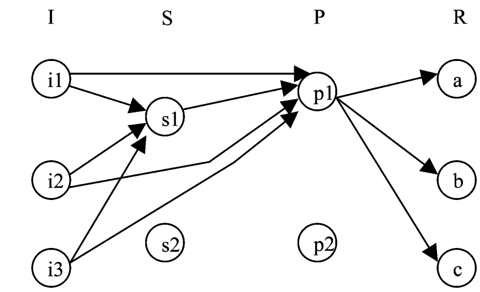

Fig. 1. Reverse logistics network for recycling electronic waste.

and coefficients corresponding to the e-waste recycling industry in Taiwan are also provided in the paper.

Fleischmann *et al.* [3] surveys quantitative models for reverse logistics. Marin and Pelegrin [7] investigates Lagrangian relaxation-based methods to solve a return location problem which identifies the optimal locations for return plants to receive and distribute used or damaged products in minimum total cost. Barros *et al.* [1] give a two-level location model for recycling the construction waste (i.e., sand). The problem is NP-hard and solved by heuristics. Hu *et al.* [5] present a linear cost-minimization model for minimizing the total operating costs of a multi-time-step, multitype hazardous-waste reverse logistics system. Nagurney and Toyasaki [9] construct the multitiered e-cycling network equilibrium model, give a variational inequality formulation, and solve it using the modified projection method. Min *et al.* [8] propose a nonlinear MIP model and a genetic algorithm that can solve the reverse logistics problem involving product returns.

Jayaraman *et al.* [6] study a reverse distribution problem and propose greedy heuristics which combine both a concentration (first proposed by Rosing and ReVelle [10] to solve p-median problems) procedure and an expansion procedure to select good location candidates. Their computational results show the superiority of their heuristic methods to CPLEX for computing a near-optimal solution in short time. Despite the good computational results of their algorithms, we have identified some room for further efficiency improvement. For example, their heuristic expansion (HE) procedure requires too many iterations of computation, which we will aim to reduce without sacrificing the quality of the solution computed. In addition, their procedure CC only considers the ratio of the fixed and operational cost to the facility capacity, whereas the effect of the transportation cost is ignored.

In this paper, we will investigate better heuristics based on the methods proposed by Jayaraman *et al.* [6] on solving a facility location and configuration problem in reverse logistics networks of recycling electronic appliances and computers. Our MIP model is based on the model proposed by Shih [11], whose real-world parameters collected from Taiwan's e-waste recycling industry will also be exploited in our computational experiments. Considering the current practice in Taiwan where there are usually two major categories of recycled e-waste, for each candidate facility location, we give four facility configuration options for a manager: to build a facility for processing the recycled e-waste of category 1, category 2, or both, besides the option of not constructing any facility at all.

III. Problem Formulation

Let I, S, P, and R be the set of collecting points, storage sites, recycle plants, and final treatment sites, respectively. An e-waste reverse logistics network is illustrated in Fig. 1, where a node represents a site in the node set $N = I \cup S \cup P \cup R$ and an arc belongs to the arc set $A = \{I \otimes S\} \cup \{I \otimes P\} \cup \{S \otimes P\} \cup \{P \otimes R\}$. In particular, products for recycling are collected in a node in I, then they are either shipped to a node in S and then to a node in P, or directly to a node in P. Products will be recycled in a node in P (e.g., some disassembling or sorting processes) to obtain sorted materials which are then to be shipped to nodes in R for final treatment or landfill.Parameters for modeling our mixed integer programing problem are listed as follows.

$Y_{\alpha\beta j}$	the amount of recycled products of category j shipped from node α to node β for each arc $(\alpha, \beta) \in A$ and both α and β are of configuration 0 (i.e., they are able to process both categories of recycled products at the same time).
$Z_{\alpha\beta}$	the amount of recycled material from node α to node β for each arc $(\alpha, \beta) \in A$.
S_{sj} and P_{pj}	binary variables to denote whether a new facility s or p of configuration j (0, 1, or 2) is to be built (with value 1) or not (with value 0).
$M_{\lambda j}$	unit subsidy for recycled products of category j in node λ where $\lambda = 1$ for collection point, $\lambda = 2$ for storage site, $\lambda = 3$ for recycle plant.
A_{ij}	a given estimated amount of recycled products of category j in collecting point i
TCIS_j	unit transportation cost for recycled products of category j from a collecting point to a storage site.
TCSP_j	unit transportation cost for recycled products of category j from a storage site to a recycle plant.
TCIP_j	unit transportation cost for recycled products of category j from a collecting point to a recycle plant.
TCPR_r	unit transportation cost for sorted material r from a recycle plant to final treatment and landfill.
$D_{\alpha\beta}$	distance between node α and node β.
$CC_{\lambda j}$	unit operational cost for recycled products of category j in node λ where $\lambda = 1$ for collection point, $\lambda = 2$ for storage site, $\lambda = 3$ for recycle plant.
f_{sj}	fixed cost for a new facility i ($i = s$ or p) of configuration j (0, 1, or 2).
B^1	set of profitable sorted material r in the final treatment and landfill, each unit earns B_r units of money.
B^2	set of useless sorted material r in the final treatment and landfill, each unit costs B_r units of money.
Z_{pr}	amount of sorted material from recycle plant p to final treatment and landfill r.

$$
\begin{aligned}
&\left.\begin{aligned}
\text{MAX} &\sum_i \sum_j M_{1j} \times A_{ij} + \sum_i \sum_s \sum_j M_{2j} \times X_{isj} + \sum_i \sum_{s=n+1}^{q} \sum_j M_{2j} \times Y_{isj} \\
&+ \sum_i \sum_p \sum_j M_{3j} \times X_{ipj} + \sum_i \sum_{p=m+1}^{k} \sum_j M_{3j} \times Y_{ipj} \\
&+ \sum_s \sum_p \sum_j M_{3j} \times X_{spj} + \sum_s \sum_{p=m+1}^{k} \sum_j M_{3j} \times Y_{spj}
\end{aligned}\right\} \text{(Subsidy)} \\
&\left.\begin{aligned}
&- \sum_i \sum_s \sum_j (\text{TCIS}_j \times D_{is} \times X_{isj}) - \sum_i \sum_{s=n+1}^{q} \sum_j (\text{TCIS}_j \times D_{is} \times Y_{isj}) \\
&- \sum_s \sum_p \sum_j (\text{TCSP}_j \times D_{sp} \times X_{spj}) - \sum_s \sum_{p=m+1}^{k} \sum_j (\text{TCSP}_j \times D_{sp} \times Y_{spj}) \\
&- \sum_i \sum_p \sum_j (\text{TCIP}_j \times D_{ip} \times X_{ipj}) - \sum_i \sum_{p=m+1}^{k} \sum_j (\text{TCIP}_j \times D_{ip} \times Y_{ipj}) \\
&- \sum_p \sum_r (\text{TCPR}_r \times D_{pr} \times Z_{pr})
\end{aligned}\right\} \text{(Transportation Cost)} \\
&\left.\begin{aligned}
&- \sum_i \sum_j CC_{1j} \times A_{ij} - \sum_i \sum_s \sum_j CC_{2j} \times X_{isj} \\
&- \sum_i \sum_{s=n+1}^{q} \sum_j CC_{2j} \times Y_{isj} \\
&- \sum_i \sum_p \sum_j CC_{3j} \times X_{ipj} - \sum_i \sum_{p=m+1}^{k} \sum_j CC_{3j} \times Y_{ipj} \\
&- \sum_s \sum_p \sum_j CC_{3j} \times X_{spj} - \sum_s \sum_{p=m+1}^{k} \sum_j CC_{3j} \times Y_{spj}
\end{aligned}\right\} \text{(Operational Cost)} \\
&\left.- \sum_{s=n+1}^{q} \left(\sum_j S_{sj} \times f_{sj} + S_{s0} \times f_{s0} \right) - \sum_{p=m+1}^{k} \left(\sum_j P_{pj} \times f_{pj} + P_{p0} \times f_{p0} \right) \right\} \text{(Fixed Cost)} \\
&+ \sum_{r \in B^1} \sum_p B_r \times Z_{pr} - \sum_{r \in B^2} \sum_p C_r \times Z_{pr}
\end{aligned}
\tag{1}
$$

Q_{pj} total amount of recycled products of category j passing through recycle plant p.

G_{jr} percent of sorted material r obtained from each unit of recycled products of category j.

The mathematical programing formulation for our facility location and design problem is shown in (1) at the bottom of the previous page, **subject to** (2)–(19) shown at the bottom of the page.

The objective function [see (1)] includes the subsidies earned from the recycling processes, transportation costs along all arcs, fixed costs for opening new storage sites and recycle plants, operational costs of all facilities, revenues earned from sorted materials sold in the final treatment sites, and costs to process all the useless materials. The constraints cover flow balance relationships [i.e., flow entering a node plus its supply/demand equals to flow leaving it, see (2)–(7)], facility capacities including both the minimum and maximum designed capacities [see (8)–(13)], and dependency relationships [see (8)–(13)].

In our problem, at most h_1 new storage sites out of the q candidate storage sites in S [see (14)] and at most h_2 new recycle plants out of the k candidate recycle plants in P [see (15)] are considered to be built besides the n original storage sites and m original recycle plants. In addition to the constraints usually appeared in conventional facility location problems such as flow balance [see (2)–(7)] and facility capacity constraints [see (8)–(13)], we further consider the possibility of constructing

$$\sum_s X_{isj} + \sum_{s=n+1}^{q} Y_{isj} + \sum_p X_{ipj} + \sum_{p=m+1}^{k} Y_{ipj} \le A_{ij} \quad \text{for all } i, j \tag{2}$$

$$\sum_i X_{isj} = \sum_p X_{spj} + \sum_{p=m+1}^{k} Y_{spj} \quad \text{for all } s \in [1, n], j \tag{3}$$

$$\sum_i X_{isj} + \sum_i Y_{isj} = \sum_p X_{spj} + \sum_{p=m+1}^{k} Y_{spj} \quad \text{for all } s \in [n+1, q], j \tag{4}$$

$$\sum_i X_{ipj} + \sum_s X_{spj} = Q_{pj} \quad \text{for all } p \in [1, m], j \tag{5}$$

$$\sum_i X_{ipj} + \sum_i Y_{ipj} + \sum_s X_{spj} + \sum_s Y_{spj} = Q_{pj} \quad \text{for all } \ p \in [m+1, k], j \tag{6}$$

$$\sum_j Q_{pj} \times G_{jr} = Z_{pr} \quad \text{for all } p, r \tag{7}$$

$$\text{MIN}S_0 \times S_{s0} \le \sum_i \sum_j X_{isj} \le \text{MAX}S_0 \times S_{s0} \quad \forall s \tag{8}$$

$$\text{MIN}P_0 \times P_{p0} \le \sum_i \sum_j X_{ipj} + \sum_s \sum_j X_{spj} \le \text{MAX}P_0 \times P_{p0} \quad \forall p \tag{9}$$

$$\text{MIN}S_j \times S_{sj} \le \sum_i X_{isj} \le \text{MAX}S_j \times S_{sj} \quad \forall s, \text{and} j \in \{1, 2\} \tag{10}$$

$$\text{MIN}S_0 \times S_{s0} \le \sum_i \sum_j Y_{isj} \le \text{MAX}S_0 \times S_{s0} \quad \forall s \tag{11}$$

$$\text{MIN}P_j \times P_{pj} \le \sum_i X_{ipj} + \sum_s X_{spj} \le \text{MAX}P_j \times P_{pj} \quad \forall p, \text{and} j \in \{1, 2\} \tag{12}$$

$$\text{MIN}P_0 \times P_{p0} \le \sum_i \sum_j Y_{ipj} + \sum_s \sum_j Y_{spj} \le \text{MAX}P_0 \times P_{p0} \quad \forall p \tag{13}$$

$$\sum_{s=n+1}^{q} \sum_j S_{sj} \le h_1 \tag{14}$$

$$\sum_{p=m+1}^{k} \sum_j P_{pj} \le h_2 \tag{15}$$

$$\sum_j S_{sj} \le 1 \quad \forall s \tag{16}$$

$$\sum_j P_{pj} \le 1 \quad \forall p \tag{17}$$

$$\begin{aligned} & X_{ipj} \ge 0, X_{isj} \ge 0, X_{spj} \ge 0, Z_{pr} \ge 0, Y_{ipj} \ge 0, Y_{isj} \ge 0, Y_{spj} \ge 0 \\ & S_{sj} \ge 0, P_{pj} \ge 0, \quad \forall\, i, s, p, j, r \end{aligned} \tag{18}$$

$$S_{sj}, P_{pj} \in [0, 1] \quad \forall\, s, p, j \tag{19}$$

different configurations of new facilities capable of processing different categories of recycled appliances to maximize the facility utilization and total revenue. In particular, considering the current practice in Taiwan, suppose we have two categories of recycled products (e.g., category 1: TV, refrigerator, washing machine, and air condition; category 2: computer, printer, and scanner), and each new facility can be of configuration 1 (or 2) that only processes recycled products of category 1 (or 2), or of configuration 0 that can process both categories [see (16) and (17)]. Different configurations of facilities have different fixed and operational costs, as well as different minimum and maximum processing capacities. These options for building new facilities complicate the problem since the decision to the configuration of a facility would affect not only the total cost and processing capacity, but also the type of arcs connecting to and from the new facilities. In particular, if a storage site (or a recycle plant) is decided to be of configuration 1 (or 2), it can not allow any recycled products of category 2 (or 1) to pass through.

In the flow balance constraints [see (2)–(7)], we associate each arc connecting candidate sites α and β with variables $X_{\alpha\beta j}$ and $Y_{\alpha\beta j}$, since a candidate site may be of configuration 1 or 2 (then $X_{\alpha\beta j}$ is used), or of configuration 0 (then $Y_{\alpha\beta j}$ is used). To formulate these options for building new facilities (i.e., nodes in S and P) together with their associated arcs, we give the mathematical inequalities (8)–(13), (16), and (17), where $\mathrm{MIN}S_j$ $(\mathrm{MIN}P_j)$ defines the minimum capacity, and $\mathrm{MAX}S_j$ $(\mathrm{MAX}P_j)$ is for the maximum capacity of a new storage site (recycle plant) of configuration j. Inequalities (16) and (17) restrict the new facility to be either of configuration 0, 1, or 2 but not at the same time.

Since we give more options than conventional facility location models for each candidate site to be constructed, our formulation will induce a larger number of variables and constraints and thus become more difficult to solve. In order to efficiently solve our proposed model in shorter time without sacrificing the solution qualities, we investigate new heuristics based on the methods proposed by Jayaraman *et al.* [6].

IV. Solution Methods

Our problem is an NP-hard mixed integer linear programing problem; thus, we exploit the heuristics developed by Jayaraman *et al.* [6] and modify part of their procedures to get better solutions in shorter time. In particular, we give four procedures: 1) random selection (RS); 2) heuristic concentration (HC); 3) modified heuristic expansion (MHE); (4) modified CC (MCC) to solve our problem. Among these four procedures, the RS and HC procedures are imported from Jayaraman *et al.* [6] with slight modifications in some parameters such as the number of candidate sites to be ranked and selected, whereas the other two new procedures MHE and MCC are modified from the procedures HE and CC of Jayaraman *et al.* [6], respectively.

A. RS + HC + MHE Algorithm

Our first algorithm contains three procedures. In particular, RS iteratively solves smaller min-cost flow subproblems with randomly selected candidate sites, where each subproblem seeks the best transportation assignments between the selected candidate sites that minimize the total facility and transportation costs. Since each subproblem corresponds to an easier linear programing (LP) problem, we run this procedure for b times (e.g., $b = 100$), and rank the sites ever appeared in the optimal solutions for these smaller LP subproblems. Intuitively, a candidate site that appears more often in the optimal solution sets of RS may tend to appear in the optimal solution of the original problem. HC then selects sites appeared more often in the solution sets of RS, solves a small MIP to determine the optimal candidate sites among those selected candidate sites, and then updates the optimal solution obtained in the procedure. To prevent possible bias caused by the small MIP solved in HC, procedure MHE further expands the scale of candidate sites based on HCs solution set, and then iteratively adds new candidate sites to the small MIP and solves the MIP of larger size until no further improvement in the objective function is occurred. Our MHE requires much fewer iterations and shorter time than its original version HE, as proposed by Jayaraman *et al.* [6]. Even better, our computational results show our method (RS + HC + MHE) can obtain a solution of similar quality in shorter time than the method (RS + HC + HE) proposed by Jayaraman *et al.* [6].

Here we give the procedures of RS as illustrated in the following steps 1–4.

Random selection (RS)

1) Randomly select h_1 storage sites and h_2 recycle plants as candidate sites (h_1 and h_2 are predefined parameters).
2) Solve the problem (i.e., a min-cost flow subproblem) to optimality, save the best solution and its configuration.
3) Repeat step 1–2 for b times (e.g., $b = 100$), denote the number of storage sites and recycle plants in the best of these b solution sets to be P^* and Q^*, respectively. Also, save the best t (e.g., $t = 8$) solution sets among the entire b solution sets.
4) Record and rank the frequency for each storage site and recycle plant appeared in the entire b solution sets.

We then continue the next procedure HC as illustrated in the following steps 5–6.

Heuristic concentration (HC)

5) In addition to the current best P^* storage sites and Q^* recycle plants in the best solution set obtained in Step 3, include the best additional $h_1 + 6 - P^*$ storage sites and $h_2 + 6 - Q^*$ recycle plants from the ranked candidate list appeared in the best t solution sets obtained in step 3 to the new candidate sites.
6) Solve the small MIP with the selected $h_1 + 6$ candidate storage sites and $h_2 + 6$ candidate recycle plants to optimality. Update the best solution and its configuration of P^{**} storage sites and Q^{**} recycle plants.

Finally we execute procedure MHE as illustrated in the following steps 7–10.

Modified heuristic expansion (MHE)

7) In addition to the current best P^{**} storage sites and Q^{**} recycle plants in the solution obtained in Step 6,

include the best additional $h_1 + 6 - P^{**}$ storage sites and $h_2 + 6 - Q^{**}$ recycle plants from the ranked candidate list obtained in step 4 to the new candidate sites.
8) Solve the small MIP with the selected $h_1 + 6$ candidate storage sites and $h_2 + 6$ candidate recycle plants to optimality. Update the best solution and its configuration.
9) Repeat steps 7 and 8 until all storage sites and recycle plants have been checked.
10) Report the best solution found in step 9.

Our RS and HC procedures follow the same steps as proposed by Jayaraman *et al.* [6] except the following changes

1) Our RS save the best t solution sets among the entire b solution sets and use these best t solution sets as a good start for HC, whereas the original RS sets $t = 5\%{}^*b$
2) Our HC solves the MIP with the selected $h_1 + 6$ candidate storage sites and $h_2 + 6$ candidate recycle plants, whereas the original HC use h_1+2 candidate storage sites and h_2+2 candidate recycle plants.

The effects of these changes in parameters are rather case-dependent and have no particular theoretical implication. In our computational experiments, we use the settings $t = 8$ and $b = 100$. We decide to have more candidate sites in our HC procedure than its original version since the MIP in our HC is still of small size and easily solvable. Furthermore, although our RS + HC may take slightly more time than their original versions, we are able to compute a better solution to start with MHE. The quality of the initial solution for MHE could dramatically cut off the computational efforts required in MHE. This is especially beneficial since MHE usually consumes the most computational time in our experiments.

The original HE procedure by Jayaraman *et al.* [6] is initialized by the best P^{**} candidate storage sites and Q^{**} candidate recycle plants obtained from HC. It solves an MIP which keeps the original best candidate sites but with additional one candidate storage site or one candidate recycle plant. Different MIPs using different additional candidate sites are solved until all the candidate sites have ever been included. The best-found solution will then be used as new initial candidate sites and then different MIPs using different additional candidate sites (adding one candidate storage site or one recycle plant) are solved repeatedly until all the candidate sites have ever been included. These steps are repeated until no better solution is found. In general, the original HE could take a lot of computational efforts, especially when P^{**} and Q^{**} are much smaller than h_1 and h_2, respectively. In our computational experiments, we have experienced such a computational burden. Therefore, we decide to give a moderate number of additional candidate sites (i.e., additional $h_1 + 6 - P^{**}$ storage sites and $h_2 + 6 - Q^{**}$ recycle plants) and exploit the ranked information obtained in step 4. Our modification does dramatically decrease the computational efforts in seeking better candidate sites, compared with the original HE procedure. Our modification is also very effective for solving larger problems. For example, as illustrated in Fig. 2, the original RS + HC + HE method spends more time in computing a near-optimal solution for our problem set 2, whereas CPLEX runs much faster than RS + HC + HE to compute an exact optimal solution. This makes the original RS + HC + HE (and especially HE) unattractive since the purpose of a heuristic

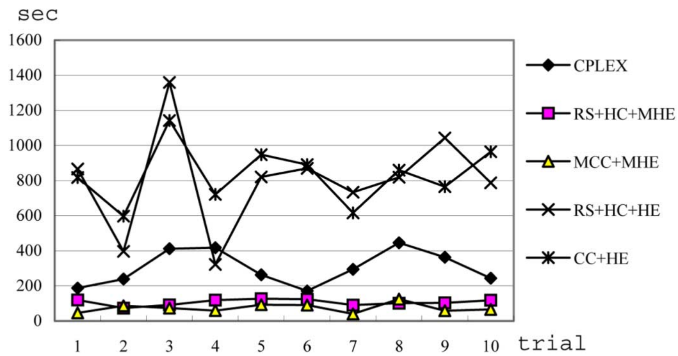

Fig. 2. Comparison in computational time for ten random cases of problem set 1 using five algorithms: CPLEX, RS+HC+MHE, MCC+MHE, RS+HC+HE, and CC + HE.

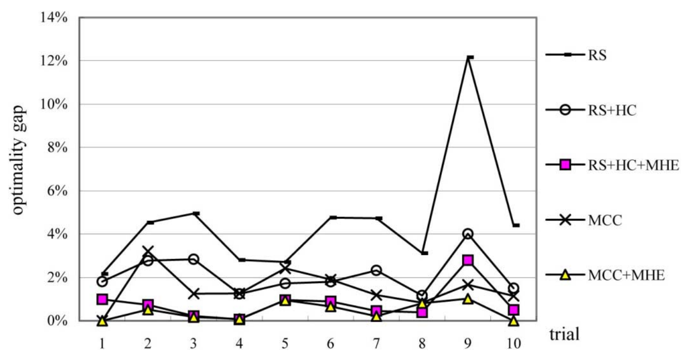

Fig. 3. Comparison in optimality gap with respect to CPLEX for ten random cases of problem set 1 using five algorithms: RS, RS + HC, RS + HC + MHE, MCC, and MCC + MHE.

is to compute a near-optimal solution in a time much shorter than any method (e.g., CPLEX) that computes for an exact optimal solution. On the other hand, our RS+HC+MHE heuristic does compute for a near-optimal solution (see Fig. 3) in a time much shorter than CPLEX, which shows the effectiveness of our heuristics.

Besides the iterative application of RS, HC, and MHE, we also propose the following procedures which may save more time with satisfactory results.

B. *MCC + MHE Algorithm*

Besides using RS and HC, Jayaraman *et al.* [6] also propose another procedure named CC which considers the unit capacity cost induced by the fixed and operational cost for each facility. In particular, CC calculates the ratio of the total fixed and operational cost to the capacity for each facility, and then selects the facilities with smaller unit capacity cost as a starting point to apply their HE procedure.

Here, we further modify the original CC by including all the transportation costs associated with a facility into consideration and propose a modified CC procedure named MCC as illustrated in the following steps 1–3.

Modified procedure CC (MCC)

1) Rank all storage sites and recycle plants by the total cost (fixed, operational, and transportation) per unit capacity.
2) Select $h_1 + 4$ storage sites and $h_2 + 4$ recycle plants with the cheapest cost per unit capacity.
3) Solve the problem to optimality.

TABLE I
FIVE TEST PROBLEM SETS AND THEIR TOPOLOGY SETTINGS

Problem Set	$\|I\|$	$\|S\|=q$	h_1	$\|P\|=k$	h_2
1	40	20	3	25	5
2	60	30	4	35	6
3	70	40	5	45	7
4	100	50	6	55	8
5	120	60	6	65	8

Our MCC procedure does give smaller optimality gap than CC (see Section V for details) that validates the fact that our modification does serve its purpose.

The computational results and analysis are discussed in Section V.

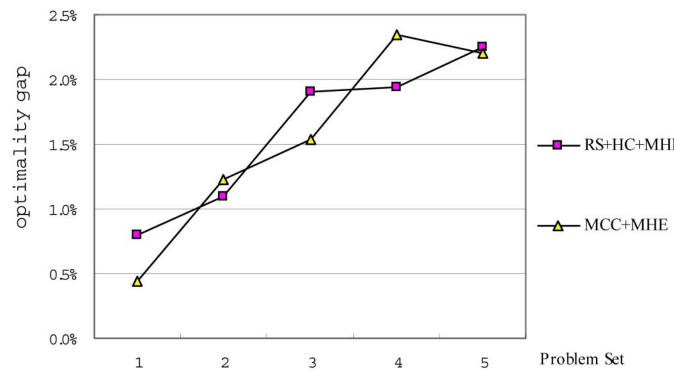

Fig. 4. Comparison in averaged optimality gap with respect to CPLEX for five problem sets using two algorithms: RS + HC + MHE and MCC + MHE.

V. COMPUTATIONAL RESULTS AND ANALYSIS

We use five test problem sets with network topology settings as listed in Table I. All cases start with only one existing storage site (i.e., $n = 1$) and one recycle plant (i.e., $m = 1$), and the seek to construct up to h_1 new storage sites among the q candidate storage site locations and up to h_2 new recycle plans among the k candidate recycle plants so that the total revenue is maximized. Five problem sets have been tested. For each problem set, we generate ten random cases (trials) of the same topology setting but different associated coefficients (e.g., cost, capacity, subsidy, ..., etc). We average the performance (i.e., the computational time and solution quality) of each method for the ten random cases of the same problem set configuration. The coefficients are reasonably estimated according to the real-world data collected in Taiwan's recycled electronic industries as well as the information collected by Shih [11]. The tests were conducted using Visual C++, CPLEX 6.5.1 callable library on an Intel Pentium 4 machine with 3.20-GHz CPU and 1-GB RAM.

On average, it takes 802 s to solve problem set 1 by RS+HC+HE algorithm and 832 s by CC+HE, whereas 304 s by CPLEX. The long computational times spent by RS+HC+HE and CC+HE make these two methods proposed by Jayaraman *et al.* [6] unattractive in all of our computational tests. On the other hand, as illustrated in Fig. 2, the average time for solving problem set 1 by our proposed methods, RS + HC + MHE (107 s) and MCC + MHE (74 s), are much shorter than that by CPLEX (304 s). Fig. 2 also shows that HE slows down the methods RS + HC + HE and CC + HE by Jayaraman *et al.* [6], whereas our MHE successfully cuts down the computational time as expected. In general, for larger problems (e.g., problem 2), our methods RS + HC + MHE (879 s) and MCC + MHE (533 s) save even more time than the RS + HC + HE (3625 s) and CC + HE (3716 s) by Jayaraman *et al.* [6].

When solving a case, let Z^* denote the optimal objective value obtained by CPLEX, and Z_w^* be the objective value obtained by a solution method w. We define the optimality gap for the solution method w to be $|Z^* - Z_w^*|/Z^*$ and use it as a performance evaluation parameter. A good solution method should give a solution with small optimality gap. Fig. 3 shows the optimality gap for different methods in solving the ten random cases of problem set 1. In particular, the optimality gap of RS (with average gap 4.64%) can be improved by RS+HC (with average gap 2.12%), which can be further improved by RS+HC+MHE (with average gap 0.798%). This result shows that the solution computed by RS and HC requires further polishing, and MHE does successfully boost the quality of the heuristic solution. On the other hand, the solution quality by MCC (with average gap 1.49%) can also be improved when it is used in conjunction with MHE (with average gap 0.44%).

Although not shown in Fig. 3, the original CC procedure has larger average gap (3.92%) than the average gap of MCC (1.49%), which validates our modification on MCC does serve its purpose. Moreover, even if the solution quality of CC + HE (with average gap 0.19%) is slightly better than the solution quality of MCC+MHE (with average gap 0.44%), the computational time of CC + HE (832.24 s) is much longer than MCC + MHE (73.68 s) which makes the tradeoff of using CC + HE unattractive.

Fig. 3 also shows the optimality gaps by RS + HC + MHE (0.798%) and MCC + MHE(0.44%) are both satisfactorily small. Thus, our proposed methods do compute a solution of good quality in short time. Similar trends in performance in both the computational time and optimality gap can also be observed in the tests on problem set 2, 3, 4, and 5. Here, we only give the detailed results of problem set 1 for illustration (see Figs. 2 and 3).

For larger problems (e.g., problem 2), our methods RS + HC + MHE (with average optimality gap 0.94%) and MCC + MHE (with average optimality gap 0.86%) have slightly larger optimality gap than the RS + HC + HE (0.52%) and CC + HE (0.48%). However, the save in the running time of our methods has more significant advantages than the heuristics by Jayaraman *et al.* [6]. Such a tradeoff is very important when a large number of MIPs have to be solved in the process of conducting sensitivity analysis or evaluating network design decisions under uncertainty.

Fig. 4 shows the average optimality gap of our methods for solving five problem sets. It is difficult to judge which of our methods (i.e., RS + HC + MHE and MCC + MHE) is better in terms of optimality gap. Nevertheless, Fig. 5 shows our MCC + MHE takes less computational time than RS + HC + MHE in our experiments, because RS+HC takes longer time than MCC. This shows that a heuristic based on simple and intuitive ideas (e.g., MCC) may still be competitive. Moreover, understanding the nature of a problem may help design a simple heuristic,

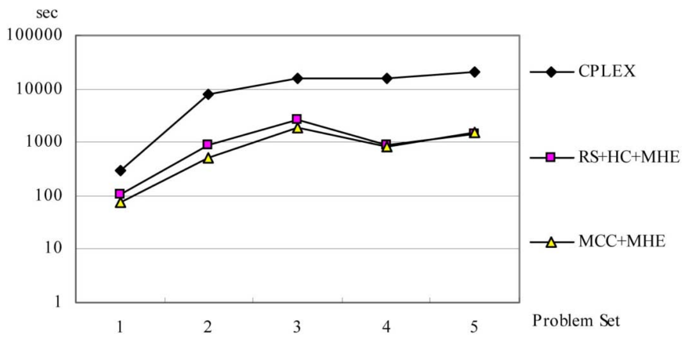

Fig. 5. Comparison in averaged computational time for five problem sets using three algorithms: CPLEX, RS + HC + MHE, and MCC + MHE.

which may even sometimes be able to beat other complicated methodologies.

In summary, our proposed heuristics successfully shorten the computational time required by previous heuristics and CPLEX. The solution quality obtained by our methods is also very good, which makes our methods especially suitable for solving difficult reverse logistics network design problems.

VI. Conclusion

In this paper, we have given a new mixed integer linear programing model that considers both the location and configuration for a new facility to maximize the overall utilization and revenue for designing an e-waste reverse logistics network. Our mathematical model is based on the common practice of the e-waste recycling industry in Taiwan where different facility configurations are used to recycle different categories of recycled e-waste. Although only two categories of recycled products are considered in our model, our mathematical modeling techniques can be further generalized to the cases of more categories with slight modifications. This consideration of facility configuration is not only practical but also very important in the network design phase since more flexibility can be obtained to achieve a better reverse supply chain management.

Sensitivity analysis and evaluations on the decisions of designing reverse logistics networks under uncertainty are important tasks in the management level, where a large number of difficult MIPs have to be solved in short time. We have proposed two algorithms (RS+HC+MHE and MCC+MHE) to successfully compute a solution of good quality in shorter time, compared with previous heuristics and the exact optimal solution methodologies. Our computational experiments validate the effectiveness and efficiency of our proposed algorithms, and also suggest the advantage of understanding the problem nature in designing simple and good heuristics.

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I-Lin Wang received the M.S. degree from the Operations Research Center, Massachusetts Institute of Technology, Cambridge, in 1996 and the Ph.D. degree from the School of Industrial and Systems Engineering, Georgia Institute of Technology, Atlanta, in 2003.

He has been an Assistant Professor in the Department of Industrial and Information Management, National Cheng Kung University, Tainan, Taiwan, R.O.C, since 2003. His research areas include the design and analysis of optimization algorithms, with applications in the supply chain management, network flows optimization, telecommunications, and bioinformatics. He has also worked for the research laboratory of the Fujitsu Company, Tokyo, Japan, as a Foreign Researcher in 1997.

Wen-Cheng Yang received the M.S. degree from the Department of Industrial and Information Management, National Cheng Kung University, Tainan, Taiwan, R.O.C., in 2005.

He currently works as a Senior Engineer in the Cell Manufacturing Support Section, Hannstar Display Corporation, Tainan.