

A stochastic network design of bulky waste recycling – a hybrid harmony search approach based on sample approximation

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Abstract Facing supply uncertainty of bulky wastes, the capacitated multi-product stochastic network design model for bulky waste recycling is proposed in this paper. The objective of this model is to minimize the first-stage total fixed costs and the expected value of the second-stage variable costs. The possibility of operation costs and transportation costs for bulky waste recycling is considered while making the first-stage decisions about the network configuration. Integrating harmony search with sample approximation approach, a meta-heuristic is elaborated to solve the stochastic network design problem of bulky waste recycling, i.e. to decide where bulky waste recycling centers should be opened, and to determine which disposition procedure should be introduced. Several numerical examples are utilized to demonstrate the validness of the harmony-search-based sample approximation algorithm (HS-SAA). In addition, the HS-SAA is compared to a genetic algorithm previously applied to the same problem. HS-SAA has advantages in the solution quality.

Keywords Stochastic Network Design, Harmony Search, Sample Approximation Algorithm, Reverse Logistics.

1 Introduction

Recycling of products and materials has received increasing attention recently due to a growing concern for environmental protection. A concept of material cycles gradually replaces a “one way” perception of economy. Waste reduction has become a major concern in industrialized countries. In Taiwan, the recycling rate of municipal solid waste is 41.96%, but the bulk waste recycling rate is only 0.59% in 2008. In the past, bulky wastes were often disposed of by incineration or landfill. Such disposal would increase environmental burdens. In fact, some bulk wastes may still be reused after minor repairs. Even if they are beyond repairs, useful resources such as plastics, metals or wood may still be recovered after they are disassembled for recycling. Taiwan’s Environmental Protection Administration (TEPA) statistics show that in 2007, 181,795 tons of bulk wastes were collected, average 498 tons per day. Of the bulk waste collected, 65.74% is waste furniture, 25.53% being garden trimming, and the rest contains some useable plastics and metals. In order to reduce resource consumption and create a sustainable resource utilization society, an exclusive bulky waste recycling system is urgently needed.

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Bulky wastes are not suitable for regular garbage collection because of their size and/or weight. There are many types of bulky wastes, e.g. disused furniture, bicycles, household electric appliances, mattresses, waste upholstery, and lopping. By means of disposition procedures with different recycling options, bulky wastes become different types of recycling productions, including reused products, reused parts, recycled materials, and valueless materials. For example, disused furniture, abandoned bicycles, and disused household electric appliances can be repaired, refurbished, or remanufactured by the corresponding exclusive disposition procedure. Except for antiquated mattresses, most bulky wastes can be disassembled by a universal disposition procedure. Product characteristics of bulky wastes recycling are given in Table 1. Disposition procedures for different types of bulky wastes are shown in Figure 1.

Table 1 Product characteristics of bulky wastes recycling

Category of bulky wastes	Economic value	Recycling options
Disused furniture	Valuable as a product or only few components	Repair, refurbishing, cannibalization, recycling
Abandoned bicycles	Valuable as a product or only few components	Repair, refurbishing, cannibalization, recycling
Discarded household electric appliances	Valuable as a product or only few components	Repair, refurbishing, cannibalization, recycling
Antiquated mattresses	Valuable as only few components	Cannibalization, recycling
Waste upholstery	Valuable as only few components	Cannibalization, recycling
Garden trimming	Valuable as only few components	Recycling

The efficient implementation of bulky wastes recycling requires appropriate distribution network structures. A recycling network of bulky wastes is composed of facilities and transportation flows between facilities. These facilities perform different roles as collection points, bulky waste recycling centers, reuse or refurbishment exchanges and final disposal sites. The bulky waste distribution is composed of three subprocedures, as shown in Figure 2. At first, the bulky waste is delivered from an occurrence point to a bulky waste recycling center. Through waste disposition, reused product, reused parts, or recycled materials are valuable outputs to a bulky waste recycling center. They are delivered to the corresponding reuse or refurbishment market to earn revenue. Valueless final wastes are delivered to a final disposal site.

Moreover, there is high uncertainty regarding quantity, quality, location and timing of returns in the bulky waste recycling problem. Supply uncertainty puts heavy burdens on the robustness of the network designs. The decisions implied in network design of bulky wastes recycling problem are:

1. To determine the number and the locations of bulky waste recycling centers;
2. To determine the disposition procedures and capacities of bulky waste recycling centers;

To allocate the flows of bulky wastes reused commodity, and final wastes between all facilities.

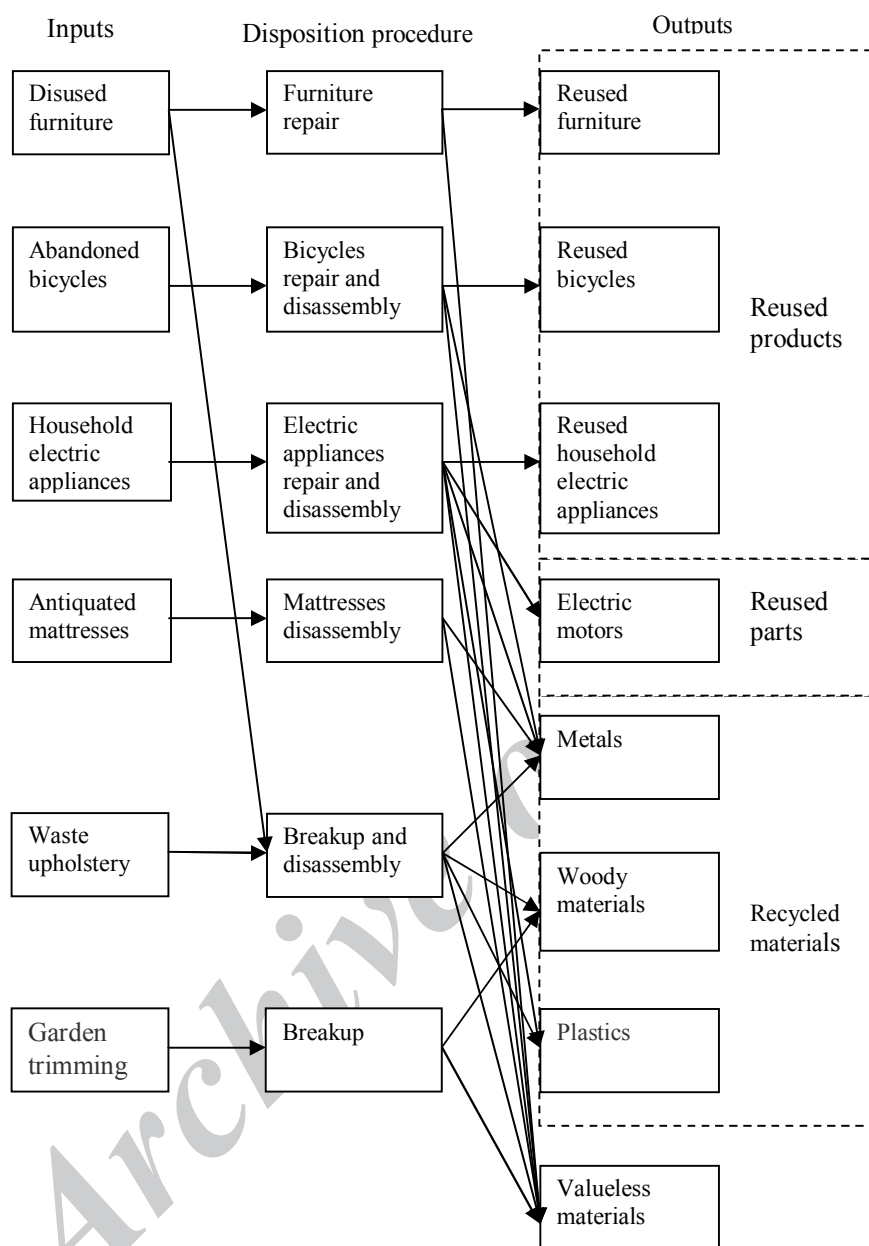


Fig. 1 Disposition procedures for bulky wastes recycling

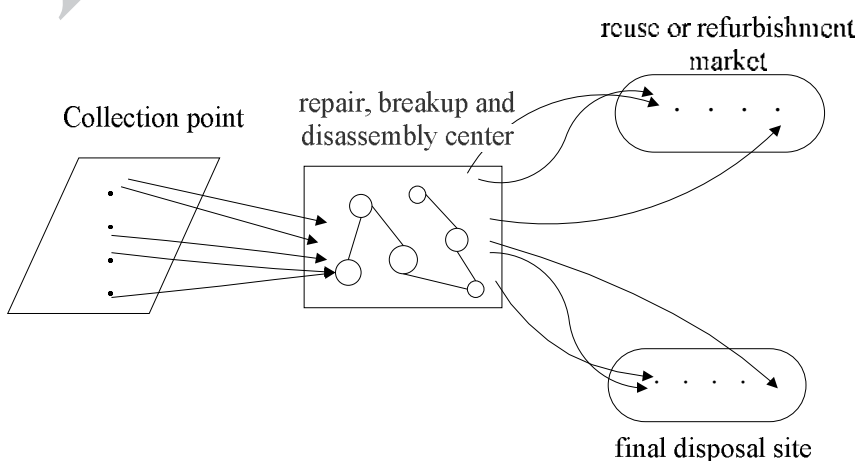


Fig. 2 A bulky waste recycling network

Facing strong supply uncertainty of bulky wastes, we apply stochastic programming techniques to the network design of the bulky waste recycling problem. A metaheuristic is elaborated to solve this problem. The rest of this paper is organized as follows: In section 2, a literature review on the stochastic network design of bulky wastes problems and harmony search are presented. Next in section 3, the mathematical formulation of this network design of the bulky waste recycling problem is given. A metaheuristic which integrates sample approximation approach with harmony search algorithm is described in section 4. Then, some experiments, results, and the comparative study with the genetic algorithm are presented and discussed, in section 5. Finally, section 6 covers our conclusion and suggestion.

2 Literature review

2.1 Bulky wastes recycling

In the past, the researches about bulky wastes recycling are concerned with material recycling from rather low value products, e.g. sand recycling [1], recycling of steel by-products [2], and carpet recycling [3]. Shih [4] proposes a MILP model to optimize the infrastructure design and the reverse network flow for the recovery of electrical appliances and computers. Krikke et al. [5] developed a mixed integer program to determine the locations of shredding and melting facilities for the recovery and disposal of used automobiles. Jayaraman et al. [6] present a MIP to determine the optimal number and locations of remanufacturing facilities for electronic equipment. Jayaraman et al. [7] extend their previous study to solve the two-level hierarchical location problem which involves the reverse logistics operations of hazardous products. Lee and Dong [8] develop an MILP model for integrated logistics network design for end-of-lease computer products. A simple network with a single production center is considered and a given number of hybrid distribution-collection facilities to be opened. They solve this model by using tabu search. But in the published literatures on the design of reverse distribution network, only one type, recovery, recycling or remanufacturing, has been considered. However a bulky wastes recycling system should encompass repairing, cannibalizing, and recycling options simultaneously because there are various types of bulky wastes; it is more complicated than the above-mentioned researches.

To our knowledge, applying stochastic programming theory, related research about bulky wastes recycling is rare. Realff et al. [9-10] extend the research of Ammons et al. [11] and apply the robust programming approach to the network design problem of carpet recycling. Listes and Dekker [12] present a stochastic programming based approach to the case study of sand recycling network design problem which is first proposed by [1]. In this approach, the uncertainty is related to the quality and demand sources, i.e. from which locations the sand to be recycled. However this research for network design under uncertainty can only address a modest number of scenarios for the uncertain problem parameters.

Chang and Wu [13] first apply stochastic programming techniques to propose a stochastic network design model for the bulky waste recycling problem with the uncertainty of occurrence locations and of quantity. A genetic algorithm (GA) integrating with sampling approximation approach is developed. The applicability of the proposed stochastic model and the efficiency of the proposed solution approach are demonstrated in a computational study mimicking the real-world example.

2.2 Stochastic supply network design

The application of stochastic programming to network design problems is however a challenging research subject. Research addressing comprehensive design of forward supply chain networks under uncertainty is significantly smaller in number than deterministic supply chain networks. We refer the interested reader to the surveys in [14].

Salema et al. [15] propose a generalized model for the capacitated multi-product reverse logistics network model in which the uncertainty in the demand and return flows is considered through the use of a multi-scenario approach. Their model is based on the recovery network model proposed by [16] and allows the simultaneous definition of the optimal distribution and recovery networks. The forward flows and reverse flows are integrated by means of a balance constraint that assures, for each factory, that its total return is not greater than its total production. However, the computational burden is expected to grow accordingly as the problem size increases.

Lee et al. [17] propose a stochastic programming-based approach in which a deterministic model for product recovery network design can be extended to account for uncertainties explicitly. The supply of returned products, the demand of forward products and the reusable rate of returned product are regarded as stochastic parameters with known distribution. A solution algorithm integrating the sampling method, proposed by [18], with an acceleration strategy is developed.

El-Sayed et al. [19] propose a multi-stage stochastic mixed integer linear programming model to formulate a multi-period multi-echelon forward-reverse logistics network design under uncertainty. Customers' locations are known and fixed with stochastic demands. The returned quantities are stochastic and depend on the customers' demands.

It is worth noting that the supply of returned products, the demand of forward products and the reusable rate of returned product are the common uncertainty but the locational uncertainty of returned products and forward products aren't considered in the published studies.

2.3 Harmony search

Harmony search (HS) proposed by Geem et al. [20] is a recently developed meta-heuristic optimization algorithm. It is inspired by the natural musical performance process that occurs when a musician searches for a better state of harmony. In the HS algorithm, the solution vector is analogous to the harmony in music, and the local and global search schemes are analogous to musician's improvisations. Compared to other meta-heuristics in the literature, the HS algorithm offers a simple concept, few parameters, easy implementation, fewer mathematical requirements, and does not require initial value settings of the decision variables [21].

The HS algorithm has been very successful in a wide variety of discrete optimization problems, including the traveling salesperson problem [20], tour routing [22], Sudoku puzzle solving [23], water network design [24, 25], dam operation [26], vehicle routing [27], structural design [28, 29], Ecological conservation [30, 31], power economic dispatch [32], and urban road network design [33]. HS as a solution procedure has been recently used in a number of researches, but it has not been used to solve stochastic network design problems before.

On the other hand, many studies explore theoretical foundations of the HS algorithm,

such as stochastic derivative [34], stochastic co-derivative [35], exploratory power [36], distributed HS [22], multi-modal HS [37], and parameter-setting-free/adaptive HS [38, 39]. Theoretical foundations of the HS algorithm have gradually competed.

Moreover, numerical comparisons demonstrate that evolution in the HS algorithm is faster than in GA [21, 40]. The main difference between GA and HS is that HS makes a new harmony vector from all existing harmony vectors in the harmony memory, while GA makes the new chromosome vector only from two of the existing chromosome vectors. Moreover, HS can independently consider each component variable in a vector while it generates a new harmony vector whereas GA cannot because it has to keep the structure of a gene [38].

3 A mathematical model

3.1 Basic assumptions

Without loss of generality, here are some of the assumptions being made:

1. There are two kinds of uncertainty source existing in the supply of bulky wastes. One is unpredictable, e.g. locations and timing of returns; the other is predicted using historical recycling data, e.g. quantity and quality. In this study, we only explore the uncertainty of occurrence locations and of quantity. We regard the coordinates of occurrence points of bulky wastes as discrete random variables. The quantity of bulky wastes follows a discrete probability distribution. In this study we employ a scenario-based approach to model such conditions.
2. Assume there are K supply scenarios of bulky wastes. For a particular scenario k , the supply scenarios of bulky wastes can be stated as $\{n_i^x(k), n_i^y(k), P_{in}(k)\}$, where $n_i^x(k), n_i^y(k)$ represents the X-Y coordinates of occurrence point i under supply scenario of bulky wastes k , and $P_{in}(k)$ represents the quantity of bulky wastes generated at occurrence point i and needed the treatment of disposition procedure n under supply scenario of bulky wastes k .
3. All kinds of costs in the bulky wastes recycling system are linear, including land costs, facility and equipment costs, disposition operation costs, and transportation cost.
4. The locations of candidate sites of bulky waste recycling centers are known.
5. Equipment of disposition procedure is limited by minimum treatment requirements from the point of economy of scale consideration. In general, disposition procedures have their treatment capacity.
6. The locations of reuse markets are given. Because the reuse market of bulky wastes recycling is not mature, the demand side is not considered.
7. The locations of final disposal sites are given. Related to treatment capacity of disposition procedures, there is no need to consider capacity limits of final disposal sites.

3.2 Notations

The meaning of sets and parameters in this model are given as follows:

G : the set of reused commodities

$I(k)$: the set of occurrence points under generation scenario k of bulky wastes

- N_s : the set of disposition procedures which are suitable to be set up at the candidate sit s of bulky waste recycling centers
- M_g : the set of markets of reused commodity g
- R : the set of final disposal sites
- S : the set of candidate sites of bulky waste recycling centers
- B : a big number
- c_{is}^1 : the unit transportation cost between occurrence point i and candidate site s of bulky waste recycling centers
- c_{sgm}^2 : the unit transportation cost of reused commodity g between candidate site s of bulky waste recycling centers and the market m for reused commodity g
- c_{sr}^3 : the unit transportation cost between candidate site s of bulky waste recycling centers and the final disposal site r
- c_{sn} : the unit operation cost of bulky waste treated by disposition procedure n at candidate site s of bulky waste recycling centers
- $d_{is}^1(k)$: under generation scenario k of bulky wastes, the transportation distance between occurrence point i and candidate site s of bulky waste recycling centers
- d_{sgm}^2 : the transportation distance of reused commodity g between candidate site s of bulky waste recycling centers and market m for reused commodity g
- d_{sr}^3 : the transportation distance between candidate site s of bulky waste recycling centers and final disposal site r
- f_{sn}^1 : the land cost of setting up disposition procedure n at the candidate site s of bulky waste recycling centers
- f_{sn}^2 : the facility and equipment costs of setting up disposition procedure n at the candidate site s of bulky waste recycling centers
- K : the number of elements in the set of generation scenarios of bulky wastes
- $P_{in}(k)$: under generation scenario k of bulky wastes, the quantity of bulky waste generated at occurrence point i and needed the treatment of disposition procedure n
- U_{sn} : maximal treatment capacity of disposition procedure n of the candidate site s of bulky waste recycling centers
- L_{sn} : minimal treatment capacity of disposition procedure n of the candidate site s of bulky waste recycling centers
- δ_{ng} : a transformation rate which is the ratio of the weight of bulky waste to the weight of reused commodity g through the disposition procedure n ; $0 \leq \delta_{ng} \leq 1$
- δ'_n : a transformation rate which is the ratio of the weight of bulky waste to the weight of final waste through the disposition procedure n ; $0 \leq \delta'_n \leq 1$
- Decision variables are defined as follows:
- $X_{isn}(k)$: under generation scenario k of bulky wastes, the quantity of bulky waste which is generated at occurrence point i is treated by the disposition procedure n at the candidate site s of bulky waste recycling centers

$X'_{sgm}(k)$: under generation scenario k of bulky wastes, the quantity of reused commodity g which is treated at the candidate site s of bulky waste recycling centers is sent to the market m of reused commodity g

$X''_{sr}(k)$: under generation scenario k of bulky wastes, the quantity of final wastes which is treated at the candidate site s of bulky waste recycling centers is sent to the final disposal site r

$Y_{isn}(k)$: 0-1 integer variable, its value is 1 if the bulky waste generated at occurrence point i is treated by disposition procedure n which is set up at the candidate site s of bulky waste recycling centers under generation scenario k of bulky wastes; otherwise, its value is 0.

Z_{sn} : 0-1 integer variable, its value is 1 if the disposition procedure n is set up at the resource recycling center s ; otherwise, its value is 0.

3.3 Model formulation

Facing supply uncertainty of bulky wastes, the capacitated multi-product stochastic network design model for bulky waste recycling is proposed as follows:

$$\begin{aligned} \text{Min} \quad OBJ = & \sum_{s \in S} \sum_{n \in N_s} (f_{sn}^1 \times Z_{sn}) + \sum_{s \in S} \sum_{n \in N_s} (f_{sn}^2 \times Z_{sn}) + \\ & \frac{1}{K} \left\{ \sum_{k \in K} \sum_{s \in S} \sum_{n \in N_s} c_{sn} \sum_{i \in I(k)} X_{isn}(k) \right\} + \frac{1}{K} \left\{ \sum_{k \in K} \sum_{i \in I(k)} \sum_{s \in S} c_{is}^1 d_{is}^1(k) \sum_{n \in N_s} X_{isn}(k) \right\} + \\ & \frac{1}{K} \left\{ \sum_{k \in K} \sum_{s \in S} \sum_{g \in G} \sum_{m \in M_g} c_{sgm}^2 d_{sgm}^2(k) X'_{sgm}(k) \right\} + \frac{1}{K} \left\{ \sum_{k \in K} \sum_{s \in S} \sum_{r \in R} c_{sr}^3 d_{sr}^3(k) X''_{sr}(k) \right\} \end{aligned} \quad (1)$$

s.t.

flow conservation constraints

$$\sum_{n \in N} \delta_{ng} \sum_{i \in I(k)} X_{isn}(k) = \sum_{m \in M_g} X'_{sgm}(k) \quad \forall s \in S, g \in G, k \in K \quad (2)$$

$$\sum_{n \in N} \delta'_n \sum_{i \in I(k)} X_{isn}(k) = \sum_{r \in R} X''_{sr}(k) \quad \forall s \in S, k \in K \quad (3)$$

$$\sum_{s \in S} X_{isn}(k) = P_{in}(k) \quad \forall i \in I(k), n \in N, \forall k \in K \quad (4)$$

Facility capacity constraints

$$\sum_{i \in I(k)} X_{isn}(k) \leq U_{sn} \cdot Z_{sn} \quad \forall s \in S, n \in N_s, k \in K \quad (5)$$

$$\sum_{i \in I(k)} X_{isn}(k) \geq L_{sn} \cdot Z_{sn} \quad \forall s \in S, n \in N_s, k \in K \quad (6)$$

Rational assignment constraints

$$\begin{aligned} \sum_{i \in I(k)} Y_{isn}(k) & \leq B \cdot Z_{sn} \quad \forall s \in S, n \in N_s, k \in K \\ Z_{sn} & \leq \sum_{i \in I(k)} Y_{isn}(k) \quad \forall s \in S, n \in N_s, k \in K \end{aligned} \quad (8)$$

$$X_{isn}(k) - B[Y_{isn}(k) - 1] \geq P_{in}(k) \quad \forall i \in I(k), s \in S, n \in N, k \in K \quad (9)$$

$$X_{isn}(k) + B[Y_{isn}(k) - 1] \leq P_{in}(k) \quad \forall i \in I(k), s \in S, n \in N, k \in K \quad (10)$$

$$\sum_{s \in S} Y_{isn}(k) \leq P_{in}(k) \quad \forall i \in I(k), n \in N, k \in K \quad (11)$$

$$B \sum_{s \in S} Y_{isn}(k) \geq P_{in}(k) \quad \forall i \in I(k), n \in N, k \in K \quad (12)$$

Domain constraints

$$Y_{isn}(k) \in \{0,1\} \quad \forall i \in I(k), s \in S, n \in N, k \in K \quad (13)$$

$$Z_{sn} \in \{0,1\} \quad \forall s \in S, n \in N \quad (14)$$

$$X_{isn}(k) \geq 0 \quad \forall i \in I(k), s \in S, n \in N, k \in K \quad (15)$$

$$X'_{sgm}(k) \geq 0 \quad \forall s \in S, g \in G, m \in M, k \in K \quad (16)$$

$$X''_{sr}(k) \geq 0 \quad \forall s \in S, r \in R, k \in K \quad (17)$$

Whether a bulky waste recycling center should be opened at each candidate site, and which disposition procedure should be introduced at each candidate site are decided before the uncertain generation of bulky waste are realized. Once the actual generations of bulky waste are known, the transportation plans for bulky waste, reused commodity and final wastes can be made without difficulty. According to the above-mentioned decision sequence, the distribution network design model of bulky wastes with generation scenarios is formulated as a two-stage stochastic programming model. The objective of this model is to minimize the first-stage total fixed costs and the expected value of the second-stage variable costs. In other words, the possibility of operation costs and transportation costs for bulky waste recycling is considered while making the first-stage decisions about the network configuration. The first and the second term of Eq. (1) are the first-stage total fixed costs, including the total land costs and total facility and equipment costs. The rests of Eq. (1) are the second-stage expected total costs, including the expected operation costs and expected transportation costs. The second-stage total expected costs can be called recourse cost. Note that the obtained solution for this model is not optimal for individual scenarios, but it gives the network structure for the worst possible scenario.

Eqs. (2)~(4) are flow conservation constraints. Eq. (2) indicates that under generation scenario k of bulky waste, the total inflows of bulky wastes needed the treatment of disposition procedure n and transported from all occurrence points to the candidate site s of repair, breakup, and centers can be transformed into the total outflows of reused commodity g from this candidate site to all used product markets according to the transformation rate δ_{ng} . Eq. (3) requests that under distribution scenario k of bulky waste, the total inflows of bulky wastes needed the treatment of disposition procedure n and transported from all occurrence points to the candidate site s of bulky waste recycling centers can be transformed into the total outflows of final wastes from this candidate site to all final disposal sites according to the transformation rate δ'_n . Eq. (4) ensures that under generation scenario k of bulky waste, the total treatment quantity for disposition procedure n assigned to all candidate sites of bulky waste recycling centers must be equal to the quantity of bulky waste generated at occurrence point i and needed this treatment of disposition procedure. Note the coefficient of the objective function, $d_{is}^1(k)$, and the right-hand-side value of constraints (3), and (9)~(12), $P_{in}(k)$, are scenario-based random parameters of this stochastic programming model. Eqs. (5) ~ (8) define the relation of the first-stage variables and the second-stage variables. They are the recourse functions of this stochastic programming model.

Eqs. (5) and (6) are facility capacity constraints. They limit the assigned quantity of bulky wastes to a feasible range of treatment capacity for disposition procedure n at candidate site s under generation scenario k of bulky wastes.

Eq. (7) ~ (12) are rational assignment constraints. They can eliminate unreasonable assignments of bulky wastes. Eq. (7) ensures that the bulky wastes treated by the disposition procedure n can be sent to this candidate site s only if this disposition procedure is decided to set up at this candidate site. Eq. (8) prevents the unreasonable assignment, that is, if no bulky waste is assigned to this candidate site of bulky waste recycling centers to have specific disposition procedure treatment under any generation scenario of bulky wastes, such a disposition procedure should not be set up at this candidate site of bulky waste recycling center.

Eqs. (9) and (10) limit that if the assignment stands, $Y_{isn}(k) = 1$, all of the bulky waste at occurrence point i should be transported to the candidate site s of bulky waste recycling centers to have the treatment of disposition procedure n under the generation scenario k of bulky waste. Note that they are extraordinary constraints of this network design model. Such a transport way is more suitable and helpful to track the reverse logistics of bulky wastes.

Eqs. (11) and (12) restrain that it is unnecessary to decide where the bulky waste should be disposed if there is no bulky waste at this point under such a specific generation scenario of bulky waste. Eqs. (13) ~ (17) are domain constraints. Eqs. (13) and (14) define that $Y_{isn}(k)$ and Z_{sn} are 0-1 integer variables. Eqs. (15) ~ (17) define that $X_{isn}(k)$, $X'_{sgm}(k)$, and $X''_{sr}(k)$ are non-negative variables.

4 A solution algorithm

Stochastic integer models are well-known for their computational intractability. Without any doubts, the network design problem of bulky wastes recycling discussed in this paper is NP-hard. The total number of different solutions to be examined is very large, even for rather small problems. Since the exact evaluation is difficult or even impossible, the expected objective value is often approximated through sample averaging. A lower statistical bound and an upper statistical bound for the optimal value of expected total costs are estimated by following the iterative procedures of sample average approximation [41].

Once the sample is generated, a deterministic algorithm can solve the stochastic problem. Recently, harmony search algorithm has received much attention for its implementation advantages and fewer parameters are required. In this study, a harmony search based sample approximation algorithm (HS-SAA) is developed.

The rest of this section is organized as follows. First, the framework of the HS-SAA is explained. Then, the harmony search based algorithm developed for the network design of bulky wastes recycling problem is presented in detail.

4.1 Framework of HS-SAA

The detailed steps of the solution algorithm are as follows

- Step 1: Specify the parameters of sample approximation algorithm: the number of independent samples (V), the number of supply scenarios of bulky wastes (K, K'), and the stopping criterion (gap).

Step 2. Generate V independent samples of supply scenarios of bulky wastes:

$$\left\{n_i^x(1), n_i^y(1), P_{in}(1)\right\}^1, \dots, \left\{n_i^x(k), n_i^y(k), P_{in}(k)\right\}^1, \dots, \left\{n_i^x(K), n_i^y(K), P_{in}(K)\right\}^1$$

$$\dots\dots\dots$$

$$\left\{n_i^x(1), n_i^y(1), P_{in}(1)\right\}^V, \dots, \left\{n_i^x(k), n_i^y(k), P_{in}(k)\right\}^V, \dots, \left\{n_i^x(K), n_i^y(K), P_{in}(K)\right\}^V$$

The sample size is K .

Step 3. Utilize the proposed harmony search based algorithm to solve the network design of the bulky wastes recycling problem. Let $(\hat{Z}, \hat{Y}, \hat{X}, \hat{X}', \hat{X}'')$ and \widetilde{OBJ}^v be the optimal solution and the optimal objective value for each supply scenario.

Step 4. Compute a lower statistical bound \overline{OBJ} for the optimal expected objective value OBJ^* .

$$\overline{OBJ} = \frac{1}{V} \sum_v \widetilde{OBJ}^v \quad (18)$$

Step 5. Compute an upper statistical bound \widetilde{OBJ} for the optimal expected objective value OBJ^* .

Step 5.1: Choose a feasible solution $\{\tilde{Z}_{sn}\}$ of the first stage problem from the above computed solutions $\{\hat{Z}_{sn}\}^v$.

Step 5.2: Generate an independent sample of supply scenario of bulky wastes: $\{n_i^x(1), n_i^y(1), P_{in}(1)\}, \dots, \{n_i^x(k), n_i^y(k), P_{in}(k)\}, \dots, \{n_i^x(K'), n_i^y(K'), P_{in}(K')\}$. The sample size is K' . Typically, K' is much larger than the sample size K used to solve the SAA problems.

Step 5.3: Perform the proposed heterogeneous flow assignment algorithm and harmony repair operations to solve the second stage problem. Let $(\tilde{Y}, \tilde{X}, \tilde{X}', \tilde{X}'')$ be the solution.

Step 5.4: Estimate the true objective value \widetilde{OBJ} of this solution $(\tilde{Z}, \tilde{Y}, \tilde{X}, \tilde{X}', \tilde{X}'')$ as follows:

$$\min \widetilde{OBJ}(\tilde{Z}, \tilde{Y}, \tilde{X}, \tilde{X}', \tilde{X}'') = \sum_{s \in S} \sum_{n \in N_s} (f_{sn}^1 \cdot \tilde{Z}_{sn}) + \sum_{s \in S} \sum_{n \in N_s} (f_{sn}^2 \cdot \tilde{Z}_{sn}) +$$

$$\frac{1}{K'} \left\{ \sum_{k \in K} \sum_{s \in S} \sum_{n \in N_s} c_{sn} \sum_{i \in I(k)} \tilde{X}_{isn}(k) \right\} + \frac{1}{K'} \left\{ \sum_{k \in K} \sum_{i \in I(k)} \sum_{s \in S} c_{is}^1 d_{is}^1(k) \sum_{n \in N_s} \tilde{X}_{isn}(k) \right\} +$$

$$\frac{1}{K'} \left\{ \sum_{k \in K} \sum_{s \in S} \sum_{g \in G} \sum_{m \in M_g} c_{sgm}^2 d_{sgm}^2(k) \tilde{X}'_{sgm}(k) \right\} + \frac{1}{K'} \left\{ \sum_{k \in K} \sum_{s \in S} \sum_{r \in R} c_{sr}^3 d_{sr}^3(k) \tilde{X}''_{sr}(k) \right\} \quad (19)$$

Step 6. Compute the estimate of the optimality gap of the solution $(\tilde{Z}, \tilde{Y}, \tilde{X}, \tilde{X}', \tilde{X}'')$.

$$gap(\tilde{Z}, \tilde{Y}, \tilde{X}, \tilde{X}', \tilde{X}'') = \widetilde{OBJ}(\tilde{Z}, \tilde{Y}, \tilde{X}, \tilde{X}', \tilde{X}'') - \overline{OBJ} \quad (20)$$

Step 7. If the optimality gap is small enough, then the solution $(\tilde{Z}, \tilde{Y}, \tilde{X}, \tilde{X}', \tilde{X}'')$ is the best solution of the second stage problem; otherwise, increase the number of sample V , K , and/or K' and go to Step 2.

4.2 Harmony search based algorithm

For being applied to the stochastic network design problem of bulky wastes recycling, the structure of the original HS algorithm is modified. First, randomly generate a harmony vector to represent the network configuration of bulky wastes recycling; check whether all disposition procedures of bulky wastes are installed. A disposition procedure should be set up at one site of resource recycling. In addition, there are minimal and maximal capacities of disposition procedures, and some kind of harmony repair operations is needed to maintain the feasibility of a harmony vector.

Second, because of the high uncertainty in generation of bulky wastes, a large sampling size is helpful to achieve a good approximation but harmful to computation speed. We attempt to bring the computation burdens under control and maintain a high-level quality of solution. The main idea of our approach is to introduce “elitist selection” into the proposed algorithm. Elitist selection is a variant of the general process of constructing a new population in the genetic algorithm. It allows some of the better organisms from the current generation to carry over to the next, unaltered. Some of the better harmonies from the current improvisation are carried over to the next, with the result that the expected total costs of these better and unaltered harmonies can be evaluated again by utilizing another set of generation scenarios of bulky wastes. As the cumulated number of generation scenarios of bulky wastes increases, a better approximation value of expected total costs of the second stage problem can be obtained.

4.2.1 Harmony memory

The harmony memory (HM) is a memory location where all the solution vectors (sets of decision variables) and corresponding objective function values are stored. HM is similar to the genetic pool in the genetic algorithms. Because bulky wastes recycling problem is full of high uncertainties, we only can approximate the objective function value

Once the decision variables of the first stage problem are determined, the expected objective value of the second stage problem can be evaluated by *sample approximation algorithm* (Chang et al., 2007). Thus this HM matrix is filled with as many randomly generated the first-stage solution vectors $\{Z_{sn}^j\}$ as the harmony memory size $|S| \times |N|$. For example, there are four candidate sites of bulky waste recycling centers. Five disposition procedures can be chosen. The structure of harmony memory is shown in Figure 3.

1	0	0	0	1	...	0	0	0	0	0	OBJ^1
1	0	0	0	1	...	0	0	0	1	0	OBJ^2
...
Z_{11}^j	Z_{12}^j	Z_{13}^j	Z_{14}^j	Z_{15}^j	...	Z_{41}^j	Z_{42}^j	Z_{43}^j	Z_{44}^j	Z_{45}^j	OBJ^j
...
1	0	0	1	1	...	0	0	0	1	0	OBJ^{HMS-1}
1	0	0	0	1	...	1	0	0	1	0	OBJ^{HMS}

Fig. 3 Structure of Harmony Memory

4.2.2 Step-by-step procedures

According to the above explanations, the detailed procedures of HS-SAA are as follows.

Step 1: Parameters Setting

Specify the HS algorithm parameters: harmony memory size (HMS), harmony memory considering rate (HMCR), the number of improvisations (NI), generation gaps rate (GGR), and pitch adjusting rate (PAR).

Step 2. Initialize the harmony memory

Step 2.0: Let $j = 1$.

Step 2.1: Randomly generate *HMS* harmony vectors of the recycling network configuration.

Step 2.2: Calculate the first-stage total costs for building each harmony vector $\{Z_{sn}\}^j$,

$$TC1^j = \sum_{s \in S} \sum_{n \in N_s} (f_{sn}^1 \times Z_{sn}^j) + \sum_{s \in S} \sum_{n \in N_s} (f_{sn}^2 \times Z_{sn}^j). \quad (21)$$

Step 2.3: Generate a sample of supply scenarios of bulky wastes:

$$\{n_i^x(1), n_i^y(1), P_{in}(1)\}, \dots, \{n_i^x(k), n_i^y(k), P_{in}(k)\}, \dots, \{n_i^x(K), n_i^y(K), P_{in}(K)\}$$

The sample size is K .

Step 2.4: According to the harmony vector $\{Z_{sn}\}^j$, utilize the proposed heterogeneous flow assignment algorithm and harmony repair operations, which are proposed in the next sections, to solve the second stage problem for each supply scenario of bulky wastes, $\{X_{isn}(k)\}^j$, $\{X'_{sgm}(k)\}^j$, $\{X''_{sr}(k)\}^j$, and $\{Y_{isn}(k)\}^j$.

Step 2.5: Calculate the penalty costs for violating capacity constraints

Verify that flow solutions $\{X_{isn}(k)\}^j$ satisfy the minimum or maximum requirements, that is, Eqs. (5) and (6). If these flow solutions are infeasible, then the penalty cost is added to the objective function values for supply scenario k of bulky wastes:

$$PC(k)^j = \sum_{s \in S} \sum_{n \in N_s} \alpha_{sn} \left[U_{sn} \cdot Z_{sn}^j - \sum_{i \in I(k)} X_{isn}^j(k) \right] + \sum_{s \in S} \sum_{n \in N_s} \beta_{sn} \left[\sum_{i \in I(k)} X_{isn}^j(k) - L_{sn} \cdot Z_{sn}^j \right] \quad (22)$$

where α_{sn} and β_{sn} are the unit penalty costs for breaking the constraints of the maximal and minimal treatment capacity.

Step 2.6: Calculate the second-stage expected total costs of the harmony vector $\{Z_{sn}\}^j$ including any penalty cost.

$$TC2^j = \frac{1}{K} \left\{ \sum_{k \in K} \sum_{s \in S} \sum_{n \in N_s} c_{sn} \sum_{i \in I(k)} X_{isn}(k) \right\} + \frac{1}{K} \left\{ \sum_{k \in K} \sum_{i \in I(k)} \sum_{s \in S} c_{is}^1 d_{is}^1(k) \sum_{n \in N_s} X_{isn}(k) \right\} + \frac{1}{K} \left\{ \sum_{k \in K} \sum_{s \in S} \sum_{g \in G} \sum_{m \in M_g} c_{sgm}^2 d_{sgm}^2(k) X'_{sgm}(k) \right\} + \frac{1}{K} \left\{ \sum_{k \in K} \sum_{s \in S} \sum_{r \in R} c_{sr}^3 d_{sr}^3 X''_{sr}(k) \right\} \quad (23)$$

Step 2.7: Calculate the objective function value of each harmony vector, $OBJ^j = TC1^j + ETC2^j$.

Step 2.8: Among HMS harmony vectors of this iteration, let the harmony vector $\{Z_{sn}\}^j$ with the lowest objective function value \underline{OBJ}^j be the j -th component of the initial HM.

Step 2.9: If j is less than HMS , then let $j = j + 1$ and go to Step 2.1.

Step 2.10: The initial harmony memory is created.

$$HM = \left\{ \begin{array}{cc} \underline{Z}^1 & \underline{OBJ}^1 \\ \dots & \dots \\ \underline{Z}^j & \underline{OBJ}^j \\ \dots & \dots \\ \underline{Z}^{HMS} & \underline{OBJ}^{HMS} \end{array} \right\} \quad (24)$$

Step 3. Elitist selection

According to the objective function value, sort the harmony memory in ascending order. Select $GGR \times HMS$ harmony vectors with the least objective function values as elitists and let them go to the next iteration directly. The rest of the harmony vectors are put into the HM range and considered as improvisation material of the next operation.

Step 4. Improvise new harmony vectors

Based on four rules (memory consideration, random selection, conditional pitch adjustment, and harmony repair), the l -th decision value of a new harmony vector $\{Z_{sn}\}^{new}$ is generated in turn until $(1-GGR) \times HMS$ new harmony vectors are formed.

Step 4.1: Let $l = 1$

Step 4.2: Memory consideration

Step 4.2.1: Randomly generate a number r_1 , where $0 \leq r_1 \leq 1$.

Step 4.2.2: If $r_1 \leq HMCR$, the l -th value of the decision variable Z_{sn}^{new} is chosen from any value in the HM range; otherwise, go to Step 4.3.

$$Z_{sn|l}^{new} \in \left\{ Z_{sn}^{GGR \times HMS + 1}, Z_{sn}^{GGR \times HMS + 2}, \dots, Z_{sn}^{HMS} \right\} \quad \text{if } r_1 \leq HMCR \quad (25)$$

Step 4.2.3: Conditional pitch adjustment

Randomly generate a number r_2 , where $0 \leq r_2 \leq 1$. If $r_2 \leq PAR$, the l -th value of the decision variable Z_{sn}^{new} switches between 0 and 1. That is, let Z_{sn}^{new} equal 1 if its previous value is 0, and let Z_{sn}^{new} equal 0 if its previous value is 1.

$$Z_{sn|l}^{new} = \begin{cases} 0, & \text{if } r_2 > PAR, \sum_n Z_{sn} \geq 1, Z_{sn|l} = 1 \\ 1, & \text{if } r_2 > PAR, \sum_n Z_{sn} \geq 1, Z_{sn|l} = 0 \end{cases} \quad (26)$$

Step 4.3: Random selection

Randomly assign the value of 0 or 1 to the l -th value of the decision variable Z_{sn}^{new} .

$$Z_{sn|l}^{new} \in \{0, 1\} \quad \text{if } r_1 > HMCR \quad (27)$$

Step 4.4: If all values of a new harmony vector are generated, go to Step 4.5; otherwise, let $l = l + 1$ and go to Step 4.2.

Step 4.5: If all $(1-GGR) \times HMS$ new harmony vectors are generated, go to Step 5; otherwise, go to Step 4.1.

Step 5. Assessment of harmony vectors

Step 5.1: Generate a sample of supply scenarios of bulky wastes:

$$\{n_i^x(1), n_i^y(1), P_{in}(1)\}, \dots, \{n_i^x(k), n_i^y(k), P_{in}(k)\}, \dots, \{n_i^x(K), n_i^y(K), P_{in}(K)\}$$

The sample size is K .

Step 5.2: Let $j = 1$.

Step 5.3: Calculate the first-stage total costs for building the harmony vector $\{Z_{sn}^j\}$,

$$TC1^j = \sum_{s \in S} \sum_{n \in N_s} (f_{sn}^1 \times Z_{sn}^j) + \sum_{s \in S} \sum_{n \in N_s} (f_{sn}^2 \times Z_{sn}^j). \quad (28)$$

Step 5.4: According to the harmony vector $\{Z_{sn}^j\}$, utilize the proposed heterogeneous flow assignment algorithm and harmony repair operations to solve the second stage problem for each supply scenario of bulky wastes, $\{X_{isn}(k)\}^j$, $\{X'_{sgm}(k)\}^j$, $\{X''_{sr}(k)\}^j$, and $\{Y_{isn}(k)\}^j$.

Step 5.5: Calculate the penalty costs for violating capacity constraints

Verify that flow solutions $\{X_{isn}(k)\}^j$ satisfy the minimum or maximum requirements, that is, Eqs. (5) and (6). If these flow solutions are infeasible, then the penalty cost is added to the objective function values for supply scenario k of bulky wastes:

$$PC(k)^j = \sum_{s \in S} \sum_{n \in N_s} \alpha_{sn} \left[U_{sn} \cdot Z_{sn}^j - \sum_{i \in I(k)} X_{isn}^j(k) \right] + \sum_{s \in S} \sum_{n \in N_s} \beta_{sn} \left[\sum_{i \in I(k)} X_{isn}^j(k) - L_{sn} \cdot Z_{sn}^j \right] \quad (29)$$

where α_{sn} and β_{sn} are the unit penalty costs for breaking the constraints of the maximal and minimal treatment capacity.

Step 5.6: Calculate the second-stage expected total costs of the harmony vector $\{Z_{sn}^j\}$ including any penalty cost.

$$TC2^j = \frac{1}{K} \left\{ \sum_{k \in K} \sum_{s \in S} \sum_{n \in N_s} c_{sn} \sum_{i \in I(k)} X_{isn}(k) \right\} + \frac{1}{K} \left\{ \sum_{k \in K} \sum_{i \in I(k)} \sum_{s \in S} c_{is}^1 d_{is}^1(k) \sum_{n \in N_s} X_{isn}(k) \right\} +$$

$$\frac{1}{K} \left\{ \sum_{k \in K} \sum_{s \in S} \sum_{g \in G} \sum_{m \in M_g} c_{sgm}^2 d_{sgm}^2(k) X'_{sgm}(k) \right\} + \frac{1}{K} \left\{ \sum_{k \in K} \sum_{s \in S} \sum_{r \in R} c_{sr}^3 d_{sr}^3 X''_{sr}(k) \right\} + \frac{1}{K} PC(k)^j \quad (30)$$

Step 5.7: Calculate the objective function value of the harmony vector $\{Z_{sn}^j\}$,

$$OBJ^j = TC1^j + ETC2^j.$$

Step 5.8: If j is less than HMS, then let $j = j + 1$ and go to Step 5.3.

Step 6. Update the harmony memory

Step 6.1: According to the objective function value, sort the harmony memory in ascending order.

Step 6.2: Let $j = 1$.

Step 6.3: The new harmony vector $\{Z_{sn}^j\}$ replaces the previous harmony vector in the HM only if the objective function value OBJ^j is better than that of the previous harmony vector in the HM.

Step 6.4: If j is less than HMS, then let $j = j + 1$ and go to Step 6.2.

Step 7. Check the stopping criterion

If *Iteration* is less than *NI* (termination criterion), Steps 3~6 are repeated and let *Iteration* = *Iteration* + 1. Otherwise output the best solution and stop.

4.2.3 Heterogeneous flow assignment

We apply the shortest-first principle to assign bulky waste flows $X_{isn}(k)$, final waste flows $X_{sr}''(k)$, and used material flows $X'_{sgm}(k)$ into the bulky waste recycling network without considering capacity constraints. Note that the conservation of different kinds of flows holds via transformation rates. We name this procedure "heterogeneous flow assignment."

First, assign all bulky waste at occurrence point i $P_{in}(k)$ to the nearest bulky waste recycling center \hat{s} that has the treatment of disposition procedure n . That is, $X_{isn}(k) = P_{in}(k)$. Repeat the bulky waste assignment for the next occurrence point until the task completes. Second, utilizing related transformation rates δ_{sg} and total amounts of different kinds of bulky wastes from all occurrence points, the amount of the reused commodity g at the bulky waste recycling center s is calculated. That is, $\sum_{n \in N} \delta_{ng} \sum_{i \in I(k)} X_{isn}(k)$.

Next, assign all of the reused commodity g at this bulky waste recycling center s to the nearest market of the reused commodity \hat{m} . That is, $X'_{sgm}(k) = \sum_{n \in N} \delta_{ng} \sum_{i \in I(k)} X_{isn}(k)$. Repeat the reused commodity assignment for the next bulky waste recycling center until the task completes. Then, utilizing transformation rates δ'_n and total amounts of different kinds of bulky wastes from all occurrence points, the amount of final wastes at this bulky waste recycling center s is calculated. That is, $\sum_{n \in N} \delta'_n \sum_{i \in I(k)} X_{isn}(k)$. Finally, assign all of the final wastes at this bulky waste recycling center s to the nearest final disposal site \hat{r} . That is, $X_{sr}''(k) = \sum_{n \in N} \delta'_n \sum_{i \in I(k)} X_{isn}(k)$. Repeat the final waste assignment for the next center until the task completes.

The detailed procedures are as follows:

Substep 1. Calculate the distance costs $\{c_{sgm}^2 d_{sgm}^2\}$ between all candidate sites of bulky waste recycling centers and markets for reused commodities.

Substep 2. Calculate the distance costs $\{c_{sr}^3 d_{sr}^3\}$ between all candidate sites of bulky waste recycling centers and final disposal sites.

Substep 3. Calculate the distance costs $\{c_{is}^1 d_{is}^1(k)\}$ between all occurrence points and candidate sites of bulky waste recycling centers under the supply scenario k .

Substep 4. Flow assignment and transformation for X, X', X''

According to the previous mentioned heterogeneous flow assignment rule, determine the flow solutions $\{X_{isn}(k)\}$, $\{X'_{sgm}(k)\}$ and, $\{X_{sr}''(k)\}$ under the supply scenario k of bulky wastes.

4.2.4 Harmony repair operation

Verify the inflows volume of each candidate site for the bulky waste recycling centers to determine whether they satisfy the capacity requirements. If not, then two harmony repair operations are adopted to revise the decision variables of the first-stage model. Rearrange bulky waste flows, final waste flows, and used material flows by performing the heterogeneous flow assignment procedure.

Harmony Repair Operation 1

If the total quantity of various bulky wastes needing the treatment of disposition procedure n is less than the sum of minimal treatment capacity of this disposition procedure at all open candidate sites, then disposition procedures at some candidate sites should be closed. The first priority goes to the candidate sites at which only this disposition procedure is set up; the second priority goes to the candidate sites at which this disposition procedure and others are set up. According to the priority list, candidate sites are canceled until the constraint of the minimal capacity stands or until only one candidate site is left. Note that the minimal capacity of a disposition procedure is violated if the latter occurs.

Harmony Repair Operation 2

If the total quantity of various bulky wastes needing the treatment of disposition procedure n is greater than the sum maximal treatment capacity of this disposition procedure at all open candidate sites, then the disposition procedures at some candidate sites should be set up. The first priority goes to candidate sites at which this disposition procedure is not set up, but others are set up; the second priority goes to closed candidate sites. According to the priority list, candidate sites are opened until the constraint of the maximal capacity stands or until all candidate sites are open. Note that the maximal capacity of a disposition procedure is violated if the latter occurs.

5 Numerical Experiments

This section describes the findings of the model implementation. We will describe the characteristics of the test problem, offer implementation details, and demonstrate the sensitivity analysis. All tests were run on personal computers with an ACPI multiprocessor PC with an Intel Core 2 Duo E6750 CPU @2.66 GHz 2.00 GB of RAM.

5.1 Data and implementation

There are 50/100/150/200 potential occurrence points of bulky waste lie within an X-Y coordinate plane. Their coordinates are generated randomly within $[0,100] \times [0,100]$. The quantity of various kind of bulky waste at each occurrence point is a discrete random variable. There are three generation scenarios, “no occurrence”, “low occurrence”, and “high occurrence”, at each potential occurrence point of bulky waste. The corresponding probabilities are 0.5, 0.25, and 0.25. The detailed data are given in Table 2.

Table 2 Quantity uncertainty of bulky wastes

Type	Quantity of bulky wastes (tons/month)			expected value (tons/month)
	No	Low	High	
Disposition procedure 1	0	700	1400	525
Disposition procedure 2	0	40	80	30
Disposition procedure 3	0	160	320	120
Disposition procedure 4	0	200	400	150
Disposition procedure 5	0	900	1800	675

Five disposition procedures of bulky wastes are set up. The products of various disposition procedures and the transformation rates are shown in Table 3. The coordinates of candidate sites of bulky waste recycling centers are listed in Table 4. Land costs are listed in Table 5. The installation costs and capacities of various disposition procedures are listed in Table 6. The variational costs of different disposition procedures are given in Table 7. In addition, there are five types of reuse or refurbishment markets. The markets for reused products are assumed at bulky waste recycling centers. The coordinates of other reuse or refurbishment markets and three final disposal sites are listed in Table 8.

Table 3 Recovery products of different disposition procedures

Disposition procedure	Recovery product	Transformation rate (%)
#1: to repair disused furniture (70% of the total disused furniture)	Reused furniture	90
	Valueless materials	10
#2: to repair or disintegrate abandoned bicycles	Reused bikes	72
	Metals	18
	Valueless materials	10
#3: to disintegrate antiquated mattress	Metals	75
	Valueless materials	25
#4: to repair or disintegrate electric appliances	Reused household Electric appliances	45
	electric motors	27
	Metals	18
	Valueless materials	10
	Metals	9
#5: to breakup disused furniture (30% of the total disused furniture), waste upholstery and garden trimming	Reused wooden parts	27
	Woody materials	54
	Valueless materials	10

Table 4 X-Y coordinates of candidate sites of bulky waste recycling centers

No. of candidate sites	Candidate site						
	1	2	3	4	5	6	7
3	(15,35)	(47,56)	(37,86)	-	-	-	-
4	(41,42)	(28,25)	(49,90)	(81,23)	-	-	-
5	(15,35)	(47,56)	(88,99)	(81,23)	(42,41)	-	-
6	(41,42)	(28,25)	(49,90)	(81,23)	(55,88)	(62,90)	-
7	(25,45)	(27,26)	(47,96)	(82,13)	(75,61)	(62,90)	(95,91)

unit: km

Table 5 Land costs

No. of Procedures	1	2	3	4	5
land cost	3000	4000	5000	6000	7000

unit: 10^3 NT dollars

Table 6 Installation costs and capacities of different disposition procedures

Disposition procedure	Installation Cost (10^3 NT dollars)	Minimal Treatment Capacity (tons/month)	Maximal Treatment Capacity (tons/month)
#1	1000	2000	30000
#2	500	200	3000
#3	1000	800	15000
#4	1000	1000	15000
#5	20000	4000	85000

Table 7 Variational costs of bulky waste disposition

Disposition procedure	Candidate of bulky waste recycling centers			
	1	2	3	4
#1	565	552	565	558
#2	323	354	360	345
#3	139	123	133	104
#4	300	303	307	318
#5	130	145	126	169

unit: NT dollars/ton

Table 8 Coordinates of reuse or refurbishment markets and final disposal sites

Final facility	(X, Y)		
Markets of reused engines	(30,40)	(30,20)	(50,80)
Markets of recycled metal materials	(30,41)	(80,80)	(95,60)
Markets of reused wooden parts	(42,73)	(60,60)	(67,80)
Markets of recycled wooden materials	(43,43)	(48,20)	(98,96)
Final disposal sites	(43,43)	(30,46)	(57,80)

unit: km

Other input data are listed as follows. The unit transportation cost is 15 NT dollars/ton/km. The penalty for violating the constraint of the maximal/minimal treatment capacity is 1000,000,000/1,000 NT dollars for each disposition procedure.

5.2 Parameters setting of harmony search

In this section, the size of the problem is fixed to 50 potential occurrence points; seven candidate sites of bulky waste recycling centers are considered. Different simulations are performed by varying the HMCR, the GGR, the PAR, the HMS, the K , and the NI. We generate 10 independent samples for lower bound estimation.

5.2.1 Influence of generation gaps rates

Let K , NI , HMS , $HMCR$, and PAR be equal to 50, 600, 50, 0.9, and 0.9, respectively. Results with various values of GGR are shown in Table 9. The CPU time for solving each simulation example is about 140 seconds. The minimum upper statistical bound of the optimal expected objective value is 146,630,800 NT dollars. In this case, the minimum upper statistical bound is obtained within the allowed 600 improvisations when the value of GGR is greater than 0.2. The opposite is not true. This heuristic solution is better than the other two in terms of the upper statistical bound of the optimal expected objective value. This means that elitist selection indeed improves the solution quality of the HS-SAA algorithm.

Table 9 Testing results with various generation gap rates

GGR	Mean of LB	Mean of UB ⁺⁺	gap
0.1	150331200	151480000	0.76%
0.2	147306600	148517800	0.82%
0.3	146333800	146630800	0.20%
0.4	146125100	146630800	0.34%
0.5	146109300	146630800	0.36%

Remarks: V : 10, K : 50, K' : 100000, gap: 2%, HMS : 50, $HMCR$: 0.9, PAR : 0.9, NI : 600

⁺⁺: five repeated tries

5.2.2 Influence of harmony memory considering rates

Let K , NI , HMS , GGR , and PAR be equal to 50, 600, 50, 0.5, and 0.9, respectively. Results with various values of $HMCR$ are shown in Table 10. The CPU time for solving each simulation example is about 140 seconds, too. These results indicate that when the value of $HMCR$ is 0.9, then the minimum upper statistical bound is obtained within the allowed 600 improvisations. This heuristic solution is better than the other two in terms of the upper statistical bound of the optimal expected objective value.

Table 10 Testing results with various $HMCR$ and GGR

HMCR	Mean of LB	Mean of UB ⁺⁺	gap
0.3	147838500	148488200	0.44%
0.6	146592900	147163000	0.39%
0.9	146109300	146630800	0.36%

Remarks: V : 10, K : 50, K' : 100000, gap: 2%, HMS : 50, PAR : 0.9, NI : 600

⁺⁺: five repeated tries

5.2.3 Influence of pitch adjusting rates

We set K , NI , HMS , GGR , and $HMCR$ as 50, 600, 50, 0.5, and 0.9, respectively. The results with various values of PAR are presented in Table 11. The upper statistical bound of the optimal expected objective value is 146,630,800 NT dollars. The results indicate that heuristic solutions can be found within the allowed 600 improvisations whether the value of PAR is 0.3, 0.6, or 0.9.

Table 11 Testing results with various pitch adjusting rates

PAR	Mean of LB	Mean of UB ⁺⁺	gap	Ave. CPU time (sec)
0.3	146102900	146630800	0.36%	140
0.6	146098600	146630800	0.36%	140
0.9	146109300	146630800	0.36%	140

Remarks: V : 10, K : 50, K' : 100000, gap: 2%, HMS: 50, HMCR: 0.9, GGR: 0.5, NI: 600

⁺⁺: five repeated tries

5.2.4 Influence of harmony memory size

Let NI, K , GGR, HMCR, and PAR equal 600, 50, 0.5, 0.9, and 0.9, respectively. The results with various values of HMS are presented in Table 12. The upper statistical bound of the optimal expected objective value is 146,630,800 NT dollars. In this case, the minimum upper statistical bound is obtained within the allowed 600 improvisations when the HMS is greater than 10. As the value of HMS increases, the lower bound of the objective value decreases. In addition, the required CPU time increases almost linearly with the HMS. Thus, HMS should be set to the maximum value if time and memory space permit.

Table 12 Testing results with various harmony memory sizes

HMS	Mean of LB	Mean of UB ⁺⁺	gap	Ave. CPU time (sec)
10	146125100	146630800	0.34%	28
50	146109300	146630800	0.36%	140
90	146020600	146630800	0.42%	262
130	145000000	146630800	1.11%	395
170	144881000	146630800	1.19%	546

Remarks: V : 10, K : 50, K' : 100000, gap: 2%, HMCR: 0.9, PAR: 0.9, GGR: 0.5, NI: 600

⁺⁺: five repeated tries

5.2.5 Influence of the number of supply scenarios

We set NI, HMS, GGR, HMCR, and PAR as 600, 50, 0.5, 0.9, and 0.9, respectively. The results with various numbers of supply scenarios are presented in Table 13. The upper statistical bound of the optimal expected objective value is 146,630,800 NT dollars. Time complexity is an approximately linear function of the number of supply scenarios. In this case, the minimum upper statistical bound is obtained within the allowed 600 improvisations when the number of supply scenarios is greater than 50. However, increasing the number of supply scenarios does not necessarily yield a better approximation of objective value. Thus, the number of supply scenarios should be set large enough within the time constraints of the application.

Table 13 Testing results with various numbers of supply scenarios of bulky wastes

No. of Supply Scenarios	Mean of LB	Mean of UB ⁺⁺	gap	Ave. CPU time (sec)
50	146109300	146630800	0.36%	134
90	145181000	146630800	0.99%	247
130	145459000	146630800	0.80%	356
170	145417000	146630800	0.83%	466

Remarks: V : 10, K : 100000, gap: 2%, HMS: 50, HMCR: 0.9, PAR: 0.9, GGR: 0.5, NI: 600

⁺⁺: five repeated tries

5.2.6 Influence of the number of iterations

Let K , HMS, GGR, HMCR, and PAR equal 50, 50, 0.5, 0.9, and 0.9, respectively. The results with various numbers of iterations are presented in Table 14. The upper statistical bound of the optimal expected objective value is 146,630,800 NT dollars. In this case, the minimum upper statistical bound is obtained within the allowed 100/200/400/600 improvizations. In addition, the required CPU time increases almost linearly with the number of iterations, and NI should be set to the maximum value if time and memory space permit.

Table 14 Testing results with various numbers of iterations

No. of Iterations	Mean of LB	Mean of UB ⁺⁺	gap	Ave. CPU time (sec)
100	146289500	146630800	0.23%	31
200	146263400	146630800	0.25%	54
400	146136500	146630800	0.34%	94
600	146109300	146630800	0.36%	140

Remarks: V : 10, K : 50, K' : 100000, gap: 2%, HMS: 50, HMCR: 0.9, PAR: 0.9, GGR: 0.5

⁺⁺: five repeated tries

5.2.7 Summaries

Based on the above discussion, we find that the HMCR and GGR parameters introduced in the SAA-HS metaheuristics help the algorithm to find globally and locally improved solutions. In addition, the required CPU time increases almost linearly with the number of supply scenarios, the number of iterations, and the harmony memory size. Generally speaking, increasing the number of supply scenarios, the number of iterations, and/or the harmony memory size will improve the solution quality but will increase computation times.

5.3 Comparative study

To evaluate the results generated by the proposed HS-SAA algorithm, a comparative study with the genetic algorithm, proposed by [13], was performed. The HS-SAA also considers several solution vectors simultaneously, in a manner similar to the GA. However, the major difference between the GA and the HS is that the latter generates a new solution vector from

all the existing solution vectors, whereas the former generates a new solution vector from only two of the existing solution vectors.

The results of applying HS-SAA and GA to the four numerical examples described in Section 5.1 are given in Table 15. The HS-SAA and the GA find the same heuristic solution for the numerical example with 50 potential occurrence points. The resulting heuristic solution is two candidate sites of the bulky waste recycling centers, site 1 and 5, are opened. For the other three numerical examples, heuristic solutions found by the HS-SAA are better than the counterparts found by the GA in terms of the upper bound of the optimal expected objective value. The results indicate that the solution quality of the HS-SAA is better than the GA.

Table 15 Testing Results Obtained by GA and HS

No. of Nodes	Algorithm ⁺	Mean of LB	Mean of UB ⁺⁺	Gap	Network Configuration Solution [*]
50	GA	146276300	146630800	0.24%	11111 00000 00000 00000 10000 00000 00000
	HS	145350400	146630800	0.87%	11111 00000 00000 00000 10000 00000 00000
100	GA	265692700	268313800	0.98%	11111 10000 00000 11000 10001 10110 00000
	HS	266523400	266979000	0.17%	11011 00110 10000 10000 11111 00000 00000
150	GA	364689700	368043400	0.91%	11111 10000 11110 10000 11111 00000 00000
	HS	365757286	367171600	0.39%	11111 11000 10000 10000 11111 00000 00000
200	GA	471164750	471180400	0.00%	10111 11010 10110 11111 11010 10001 00000
	HS	469164900	470185400	0.68%	11101 10010 10110 10011 11110 10101 00000

Remarks:

*: each of five digital codes represents whether five disposition procedures are set up or not at this candidate site. 1 means the disposition procedure is set up; 0 means the disposition procedure is not set up

⁺: parameters for SAA: V : 10, K : 250/500/750/1000, K' : 100000, gap: 2%; parameters for GA: Population size: 50, Crossover rate: 0.8, Mutation rate: 0.05, NI: 120; parameters for HS: HMS: 50, HMCR: 0.9, PAR: 0.9, GGR: 0.5, NI: 120

⁺⁺: five repeated tries

6 Conclusions and Suggestions

In this work, the design of a bulky wastes recycling network with uncertainty both in occurrence locations and quantity is studied, while the multiple treatment options and treatment capacity of disposition procedures are taken into account simultaneously. We propose a stochastic mixed integer formulation that is solved using the HS-based sample approximation algorithm to approximate the exact value of expected objective value. A lower statistical bound and an upper statistical bound for the optimal expected objective value are estimated. Numerical examples illustrate the efficiency and practicability of the proposed algorithm.

The HS-based algorithm in this study was modified from its original in several ways:

1. This HS-based algorithm integrates sample approximation approach to evaluate the second-stage expected total costs because the distribution of bulky wastes is uncertain and hardly to be predicated in advance.
2. This HS-based algorithm allows some of the better organisms from the current generation to carry over to the next generation, unaltered. Elitist selection indeed improves the convergence of the HS-based algorithm.

3. In order to solve this stochastic mixed integer model, an efficient initialization scheme is used to construct the initial harmony vectors with a certain level of quality.
4. In coordination with heterogeneous flow assignment, two kinds of harmony repair operations are developed to meet disposition capacity constraints of bulky waste recycling centers.

According to the results of our numerical experiments, a centralized network structure is more suitable to fulfill the need in high processing volumes of bulky waste recycling centers. Testing results also indicate that the proposed HS-SAA is an effective metaheuristics for solving the discussed problem in this study. HMCR and GGR are the principal parameters of the HS-SAA to find globally and locally improved solutions. Increasing the number of iterations and/or the harmony memory size will improve the solution quality but will increase computation times.

The suggestions for future research are given as follows:

1. Combining sample approximation approach with metaheuristics offers a bright application future to solve stochastic network design problem. To mix other metaheuristics and harmony search will further improve the efficiency and quality of solution algorithm.
2. To collect more practical data about the bulky wastes recycling problem such as the probability of bulky wastes generations, transformation rates of disposition procedures, etc. helps demonstrate the practical value of the proposed model's testing.
3. In this study, transportation costs are calculated according to the shortest distance between locations. More accurate distance measurement should be adopted in future works.
4. Economic value may affect centralization/decentralization decisions of bulky waste recycling network. Benefit-based approach can be explored next. To expand and to strengthen the channel of reuse market will promote further the economic benefit and environmental benefit of the whole society.

References

1. Barros, A. I., Dekker, R., Scholten V., (1998). A two-level network for recycling sand: A case study. *European Journal of Operational Research*, 110, 199-214.
2. Spengler T., Puchert H., Penkuhn T., and Rentz O., (1997). Environmental integrated production and recycling management. *European Journal of Operational Research*, 97, 308-326.
3. Louwers, D., Kip, B. J., Peters, E., Souren, F., Flapper, S. D. P., (1999). A facility location allocation model for reusing carpet materials. *Computers and Industrial Engineering*, 36(40), 1-15.
4. Shih, L. H., (2001). Reverse logistics system planning for recycling electrical appliances and computers in Taiwan. *Resources, Conservation and Recycling*, 32(1), 55-72.
5. Krikke, H. R., Kooi, E. J., Schurr, P. C., (1999). Network design in reverse logistics: a quantitative model. In: Stahly P, editor. *New trends in distribution logistics*. Berlin, Germany: Springer, 45-62.
6. Jayaraman, V., Guide, Jr. V. D. R., Srivastava, R., (1999). A closedloop logistics model for remanufacturing. *Journal of the Operational Research Society*, 50, 497-508.
7. Jayaraman, V., Patterson, R. A., Rolland, E., (2003). The design of reverse distribution networks: models and solution procedures. *European Journal of Operational Research*, 150(2), 128-149.
8. Lee, D., Dong, M., (2008). A heuristic approach to logistics network design for end-of- lease computer products recovery. *Transportation Research Part E*, 44, 455-474.
9. Realff, M. J., Ammons, J. C., Newton, D. J., (2000). Strategic design of reverse production systems. *Computers and Chemical Engineering*, 24, 991-996.
10. Realff, M. J., Ammons, J. C., Newton, D. J., (2004). Robust reverse production system design for carpet recycling. *IIE Transactions*, 36(8), 767-776.

11. Ammons, J. C., Realff, M. J., Newton, D. J., (1998). Carpet recycling: determining the reverse production system design. *The Journal of Polymer-Plastics Technology and Engineering*, 8(3), 547-567.
12. Listes, O. L., Dekker, R., (2005). A stochastic approach to a case study for product recovery network design. *European Journal of Operations Research*, 160(1), 268-287.
13. Chang, M. S., Wu, G. S., (2009). Applying genetic algorithm to the stochastic network design problem for bulky waste recovery. *Proceeding of the 20th IASTED International Conference on Modelling and Simulation*, Canada, 331-338.
14. Chang, M. S., Tseng, Y. L., Chen, J. W., (2007). A scenario planning approach for the flood emergency logistics preparation problem under uncertainty. *Transportation Research Part E*, 43, 737-754.
15. Salema, M. I. G., Barbosa-Povoa, A. P., Novais, A. Q., (2007). An optimization model for the design of a capacitated multi-product reverse logistics network with uncertainty. *European Journal of Operational Research*, 179, 1063-1077.
16. Fleischmann, M., Beullens, P., Bloemhof-Ruwaard, J. M., Van Wassenhove, L. N., (2001). The impact of product recovery on logistics network design. *Production and Operations Management*, 10(2), 156-173.
17. Lee, D. H., Dong, M., Bian, W., Tseng, Y. J., (2007). Design of product recovery network under uncertainty, *Transportation Research Record: Journal of the Transportation Research Board*, 2008, 19-25.
18. Santoso, T., Ahmed, S., Goetschalckx, M., Shapiro, A., (2005). A stochastic programming approach for supply chain network design under uncertainty. *European Journal of Operational Research*, 167, 96-115.
19. El-Sayed, M., Afia, N., El-Kharbotly, A., (2010). A stochastic model for forward-reverse logistics network design under risk. *Computers and Industrial Engineering*, 58(3), 423-431.
20. Geem, Z. W., Kim, J. H., Loganathan, G. V., (2001). A new heuristic optimization algorithm: harmony search. *Simulation*, 76(2), 60-68.
21. Pan, Q. K., Suganthan, P. N., Liang, J. J., Tasgetiren, M. F., (2010). A local-best harmony search algorithm with dynamic subpopulations. *Engineering Optimization*, 42(2), 101-117.
22. Geem, Z. W., Tseng, C. L., Park, Y., (2005b). Harmony search for generalized orienteering problem: best touring in China. *Lecture Notes in Computer Science* 3612, 741-750.
23. Geem, Z. W., (2007a). Harmony search algorithm for solving Sudoku. *Lecture Notes in Artificial Intelligence*, 4692, 371-378.
24. Geem, Z. W., Kim, J. H., Loganathan, G. V., (2002). Harmony search optimization: application to pipe network design. *International Journal of Modelling and Simulation*, 22(2), 125-133.
25. Geem, Z. W., (2006). Optimal cost design of water distribution networks using harmony search. *Engineering Optimization*, 38(3), 259-280.
26. Geem, Z. W., (2007b). Optimal scheduling of multiple dam system using harmony search algorithm. *Lecture Notes in Computer Science*, 4507, 316-323.
27. Geem, Z. W., Lee, K. S., Park, Y., (2005a). Application of harmony search to vehicle routing. *American Journal of Applied Sciences*, 2(12), 1552-1557.
28. Lee, K. S., Geem, Z. W., Lee, S. H., Bae, K. W., (2005). The harmony search heuristic algorithm for discrete structural optimization. *Engineering Optimization*, 37(7), 663-684.
29. Lee, K. S., Geem, Z. W., (2004). A new structural optimization method based on the harmony search algorithm. *Computers and Structures*, 82, 781-798.
30. Geem, Z. W., Williams, J. C., (2007). Harmony search and ecological optimization. *International Journal of Energy and Environment*, 1(2), 150-154.
31. Geem, Z. W., Williams, J. C., (2008). Ecological optimization using harmony search. *Proceedings of American Conference on Applied Mathematics*, Harvard University, 148-152.
32. Vasebi, A., Fesanghary, M., Bathaee, S. M. T., (2007). Combined heat and power economic dispatch by harmony search algorithm. *International Journal of Electrical Power & Energy Systems*, 29(10), 713-719.
33. Miandoabchi, E., Farahani, R. Z., Szeto, W. Y., (2012). Bi-objective bimodal urban road network design using hybrid metaheuristics. *Central European Journal of Operations Research*, 20(4), 583-621.
34. Geem, Z. W., (2008). Novel derivative of harmony search algorithm for discrete design variables. *Applied Mathematics and Computation*, 199(1), 223-230.
35. Geem, Z. W., (2011). Stochastic co-derivative of harmony search algorithm. *International Journal of Mathematical Modelling and Numerical Optimisation*, 2(1), 1-12.
36. Das, S., Mukhopadhyay A., Roy A., Abraham A., Panigrahi B. K., (2011). Exploratory power of the harmony search algorithm: analysis and improvements for global numerical optimization. *IEEE Transactions on Systems, Man, and Cybernetics Part B*, 41(1), 89-106.
37. Gao, X. Z., Wang, X., Ovaska, S. J., (2009). Uni-modal and multi-modal optimization using modified harmony search methods. *International Journal of Innovative Computing Information and Control*, 5(10A), 2985-2996.

38. Geem, Z. W., Sim, K. B., (2010). Parameter-setting-free harmony search algorithm. *Applied Mathematics and Computation*, 217(8), 3881-3889.
39. Hasancebi, O., Erdal, F., Saka, M. P., (2010). Adaptive harmony search method for structural optimization. *ASCE Journal of Structural Engineering*, 136(4), 419-431.
40. Lee, K., Geem Z. W., (2005). A new meta-heuristic algorithm for continuous engineering optimization: harmony search theory and practice. *Computer Methods in Applied Mechanics and Engineering*, 194(36-38), 3902-3933.
41. Kleywegt, A. J., Shapiro, A., Homen-De-Mello, T., (2001). The sample average approximation method for stochastic discrete optimization. *SIAM Journal of Optimization*, 12, 479-502.

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