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A bi-objective reverse logistics network analysis for post-sale service

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Abstract

Reverse logistics, induced by various forms of return, has received growing attention throughout this decade. Reverse logistics network design is a major strategic issue. This paper addresses the analysis of reverse logistic networks that deal with the returns requiring repair service. A problem involving a manufacturer outsourcing to a third-party logistics (3PLs) provider for its post-sale services is proposed. First, a bi-objective optimization model is developed. Two objectives, minimization of the overall costs and minimization of the total tardiness of cycle time, are addressed. The facility capacity option at each potential location is treated as a discrete parameter. The purpose is to find a set of non-dominated solutions to the facility capacity arrangement among the potential facility locations, as well as the associated transportation flows between customer areas and service facilities. Then, a solution approach is designed for solving this bi-objective optimization model. The solution approach consists of a combination of three algorithms: scatter search, the dual simplex method and the constraint method. Finally, computational analyses are performed on trial examples. Numerical results present the trade-off relationship between the two objectives. The numerical results also show that the optimization for the first objective function leads to a centralized network structure; the optimization for the second objective function results in a decentralized network structure.

Keywords: Reverse logistics; Third-party logistics; Multi-objective optimization; Scatter search

1. Introduction

Reverse logistics is the process of moving goods from their typical final destination to another point, for the purpose of capturing value otherwise unavailable, or for the proper disposal of the products [1]. For a variety of economic, environmental or legislative reasons, companies have become more accountable for final products, after they sell those products. Reverse logistics is practiced in many industries, including those producing steel, aircraft, computers, automobiles, chemicals, appliances and medical items. The effective use of the reverse logistics can help a company to compete in its industry. Reverse logistics has become increasingly important as a profitable and sustainable business strategy.

There are a number of situations for products to be placed in a reverse flow. Normally, return flows are classified into commercial returns, warranty returns, end-of-use returns, reusable container returns and others [2]. This proposed research primarily concentrates on the post-sale service that deals with warranty returns. After the initial product sale, a

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company must provide support services during the product life cycle. Each return involves activities such as collection of returned products, repair or reprocessing and redistribution.

Effective reverse logistics is believed to result in several direct benefits, including improved customer satisfaction, decreased resource investment levels and reductions in storage and distribution costs [3]. If a reverse logistics system is designed and managed properly, it can be a cost-driving area for improving profitability and customer satisfaction. (The ability to quickly and efficiently handle the return of products for necessary repair can be critical to customer service/satisfaction [4]. To service providers, both service level and total service cost are the major concerns.)

Currently most retailers and manufacturers struggle with the handling and processing of returns internally [1]. While recognizing the importance of reverse logistics, many manufacturers and retailers are considering the outsourcing of reverse logistics and product returns since it is not a strategic core competency of their business. The 3PLs providers have expertise and a broader view of how reverse logistics works because they work with multiple firms and industries. They can leverage their knowledge and software to benefit everyone.

In many situations, the decisions involving the locations, capacities and flows noted above are made difficult by the sheer size (e.g., the number of local stores and warehouses) of the potential network. For example, some major stores such as K-Mart are choosing to outsource their reverse logistics operations to third-party providers like the Genco Distribution System [5], with approximately 94 facilities totaling 26.3 million square feet of space (http://www.genco.com/). High Tech companies like Intermec and Toshiba outsource their repair service to the UPS Supply Chain Solutions (http://www.ups-scs.com/). General Motors, the largest vehicle manufacturer, also calls on UPS to provide warranty parts recovery service. Many companies use NetReturn, an Internet system that FedEx has developed for reverse logistic management, to facilitate their product return process [6]. Many 3PLs such as UPS own both collection facilities (local stores) and warehouses. The large size of these networks implies the use of mathematical programming approaches as described in this paper.

This paper proposes a closed loop reverse logistics network problem. Given that a manufacturer considers taking advantage of a 3PL system for its post-sale service, returned flows start from customer areas, go through distribution network and service facilities, and then go back to customers, accompanied by spare parts flows between manufacturers to the service facilities. The decisions involve: which locations to be chosen for installing repair facilities along with how to allocate the required repair capacities among these locations and how to arrange the transportation flows between collection sites and facility sites.

Almost every important real world problem involves more than one objective [7]. Hence, considering the multiple objectives concurrently is a favorable option for most decision makers. The strategic issue of reverse logistic system design may affect both a company's profitability and the customer service level. This study considers service issues as another objective besides maximization of total profit or minimization of total cost. In particular, two objectives considered are: minimization of the total costs and minimization of the total tardiness of cycle time. This study explores the tradeoffs associated with these two objectives in the reverse logistics network design.

In many real world situations, the size of facilities is a multiple of some fixed value and is therefore represented by a discrete scale. Therefore, with respect to facility capacity arrangement in this reverse logistic research, there can be finite alternatives to allocating total required capacity among the potential locations. Furthermore, the effect of economies of scale on facility capacity investment should be considered. A more centralized strategy can achieve greater benefit of economies of scale. Therefore, optimization of the first objective has a tendency towards centralization in terms of the capacity arrangement. On the other hand, optimization of the second objective has a tendency towards decentralization in term of the capacity arrangement in order to achieve the lowest total tardiness of cycle time.

First, a bi-objective MIP optimization model is developed for the proposed reverse logistic network problem. Then, a solution procedure is designed for solving this bi-objective MIP optimization model. A heuristic algorithm, scatter search (SS), is used to deal with the discrete variables, which represent the capacity arrangement among the potential facility locations. The dual simplex method is applied to obtain the solution for continuous variables, which represent the transportation arrangement. The constraint method [8] is used to attain a set of non-dominated solutions for the reverse logistic network.

Normally, the SS algorithm is used to solve single objective problems. This research extends the application of the SS algorithm to a bi-objective problem.

In the next section of the paper, a literature review involving reverse logistics and 3PLs is presented. In Section 3, a problem concerning a 3PL involving post-sale service is proposed. A bi-objective MIP optimization model associated with the proposed problem is developed. Section 4 discusses the design of a solution approach for the bi-objective MIP optimization model. Section 5 implements the computational analysis on trial examples. Finally, Section 6 presents conclusions.

2. Literature review

2.1. Reverse logistic network design

Reverse logistics is a fairly new concept in logistics and supply chain management; however, it is receiving increasing attention from industries and researchers.

Thierry et al. [9] presented an integrated supply chain framework to demonstrate reverse flows and recovery options such as repair, refurbishing, remanufacturing, recycling, etc. De Brito and Dekker [10] provided a decision framework for reverse logistics in terms of strategic, tactical and operational aspects of the problem. They pointed out that the strategic level decision, the design of the recovery network, has to be decided upon first.

Some researchers put forward strategic factors that need to be considered when designing a reverse logistics network. Minimizing strategic costs is essential for a successful reverse logistics system [11,12,9]. Strategic costs include the costs of equipment for remanufacturing products, the costs for qualified workers, the costs of warehouse facilities and transportation costs. Identifying and fulfilling customer service requirements are other essential issues. This strategic factor should reflect the basic logistics rule of right time, right place, right price and right quantity [13]. Other important factors include product characteristics, market characteristics and resource requirements [2,9].

Many researchers have studied reverse logistic network design for different industries such as the steel industry [14], carpet recycling [15], electronic equipment [16], sand recycling [17], reusable packing [18], distribution networks [19] and a general recovery networks [2]. They each proposed a MILP logistic network model for their studies to minimize overall cost. However, few researchers have considered level of service (e.g., as measured by service cycle time) as another criterion in their reverse logistics network model.

Rogers et al. [1] argued that a critical element to successful reverse logistics management is having short disposition cycle times related to return product decisions, movement and processing. In most cases he examined, the reduction in cycle time directly and positively impacted both the firm's bottom line and its service level. Studies by Dawe [20] indicate that customer returns for warranty repair were not being processed and sent back to customers within the agreed upon time. This became the source of customer complaints despite the customer's satisfaction with the product and the price. Dawe [20] further argued that shortening returns cycle time is important for handling returns well. He also suggested the use of third-party specialists and the incorporation with a repair center.

Manufacturers have an opportunity to improve profitability and margins through reverse logistics. However, the challenge of running a distribution system in forward is difficult; it is still harder for companies to allocate resources to manage the system in reverse [1]. Many companies are not willing to commit their people, system or their limited resources to operate a product return system. Therefore, these companies outsource their reverse logistics operation needs to third-party providers.

The 3PLs business is developed as a result of the emerging demand of advanced logistics services. Typical services outsourced to 3PLs providers are transportation, warehousing, inventory, value-added service, information services and reengineering of the supply chain [21]. There are major advantages associated with 3PLs providers handling the reverse logistics for these companies. First, the 3PLs providers have expertise, sophisticated logistic networks, IT technology and the capability to operate systems efficiently [22,23]. Second, the same assets (investment) of third-party providers can be used in various contractual relationships and thus provide economies of scale when employed [24]. This advantage can lead to the fast recapture of investment capital.

Studies by Lieb et al. [25], Rupnow [26] and other researchers showed the multiple benefits that companies using 3PLs service typically experience. The most frequently cited benefits are cost reduction, improved expertise and access to data, improved operation and customer services, the ability to focus on core competencies and flexibility.

3. A proposed reverse logistics network problem

A reverse logistics network problem is proposed as follows. A manufacturer is considering using the sophisticated network of a 3PL provider to fulfill its post-sales repair service. The 3PL provider already has an established logistic network with advanced information technology, and can provide transportation service for the manufacturer and its customers. Moreover, the established warehouses or distribution centers of the 3PL provider can be considered as potential locations for the installation of repair facilities and the local stores of the 3PL provider can be used as collection sites. The manufacturer has a number of separate plants in different areas, which produce the same category, but maybe different models of products. All of the chosen facility locations provide the same type of repair service.

The customers return the defective products to collection sites, the established 3PL local stores. The 3PL provider immediately transports the returned products to repair facilities. After repair, the products are delivered back to the collection sites soon. Therefore, the transportation of products between collection sites and repair facilities is considered one-by-one. Periodically the replaced defective parts are sent to the plants of the manufacturer for remanufacturing or for other purposes, and the new spare parts are transported to the repair facilities.

Besides the facility locations, another major consideration is the decision on the capacity levels of the repair service facilities in order to achieve both minimal investment and operational costs and maximal customer satisfaction. Hence, important questions include which of the distribution centers of the 3PL provider should be designated for repair service facilities and what capacities should be installed at these chosen locations.

The capacity level of a facility at a location is associated with the number of equipment units installed at the location. One set of equipment units represents the smallest entity that can be installed at a location. Therefore, the capacity level or facility size can be one or a multiple of equipment units. In this paper, the capacity of an equipment unit is referred to as one capacity unit, denoted as b; then, the options for the repair capacity at a facility location can be expressed in a discrete form as: $0, b, 2b, \ldots$ or Nb. If the total required capacity from customers is A. Then, at least the total number of N, where $N = \lceil \frac{A}{b} \rceil$, capacity units must be installed among these potential locations.

There are two extreme configurations on the service network design: one is a decentralized location strategy, by which total capacity of Nb is spread among the potential repair locations; another is a centralized strategy, by which only one location is chosen to install the total capacity of Nb. Other options are in between these two extreme options. With a greater number of locations installed with repair facilities, customers may receive more convenient and quicker service. It is assumed that within a certain amount of cycle time customers are satisfied with the service; and beyond that expected cycle time customers to some extent are unsatisfied with the service. Thus, in this research, the total tardiness of cycle time is used to measure the customer's satisfaction level of the post-sales service.

Design of the reverse logistic network may involve a trade-off relationship between the total costs and the total tardiness of cycle time. For example, in some cases, the companies may need to open more facility locations in order to decrease the total tardiness of cycle time and fulfill higher customer satisfaction, which may lead to a greater investment cost.

4. Mathematical model

Indices:

i	locations of the established 3PLs local stores, each of which can be used as a collection site. $i = 0, 1, \ldots, I$
j	locations of the established 3PL's warehouses, which can be treated as potential locations for installing repair and inventory facilities. $j = 0, 1, \ldots, J$
h	locations of the plants of the manufacturer. $h = 0, 1, \ldots, H$
k	products of the manufacturer. $k = 0, 1, \ldots, K$
n	number of capacity units (level of capacity). $n = 0, 1, \ldots, N$

Parameters:

a_{ik}	the number of returned products k received at collection site i
t_k	the average equipment working-hours required for repairing a piece of returned product k
A	$\sum_{i=1}^{I}\sum_{k=1}^{K} a_{ik}t_k$ is the total required capacity for all returned products
b	capacity unit, which is the minimal level of the facility capacity option. The capacity level options at a location can be $0, b, 2b, \ldots$ or Nb

N	total required number of repair capacity units to be installed; $N = \lceil \frac{A}{b} \rceil$
t_{ij}	the round trip transportation time between collection site i and repair facility j
t_e	expected cycle time by customers
c_{ij}	variable round trip transportation cost for a unit of product between collection site i and repair facility j
c_{jh}	variable round trip transportation cost for a spare part or a replaced part between repair facility j and plant h
ρ	the average number of parts which need to be replaced from a returned product
f_{jn}	the fixed cost of installing a repair facility with capacity level of nb at location j. $n = 0, 1, \ldots, N$
α	the exponent which measures the ratio of the incremental to the costs of a unit of capacity ($0 < \alpha < 1$). The parameter represents the economies of scale for installing a facility

Decision variables:

$$X_{jn} \quad \begin{cases} 1 & \text{if } n \text{ repair capacity units are installed at location } j; \\ 0 & otherwise \end{cases}$$

Y_{ijk}	the percentage of returned products k that is collected at collection site i and is assigned to repair facility j
W_{jhk}	the percentage of spare parts for products k that is supplied by plant h

According to Manne [27], since the fixed cost of installing a facility with one capacity unit b is $f_{j1} = \kappa b^{\alpha}$, the fixed cost of installing a repair facility with n capacity units is $f_{jn} = \kappa(nb)^{\alpha} = n^{\alpha}kb^{\alpha} = n^{\alpha} f_{j1}$. Then, the fixed cost of installing a facility at a location j is

$$f_{jn} = f_{j1}X_{j1} + f_{j1}2^{\alpha}X_{j2} + \cdots + f_{j1}n^{\alpha}X_{jn} + \cdots + f_{j1}N^{\alpha}X_{jN} = \sum_{n=1}^{N} n^{\alpha} f_{j1} X_{jn},$$

as long as the X_{jn} are restricted by $\sum_{n=1}^{N} X_{jn} \leqslant 1$.

The first objective function consists of the fixed cost of installing repair facilities and the transportation costs:

$$Z_1 = \sum_{j=1}^{J}\sum_{n=1}^{N} n^{\alpha} f_{j1} X_{jn} + \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K} c_{ij} a_{ik} Y_{ijk} + \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{h=1}^{H}\sum_{k=1}^{K} c_{jk} a_{ik} \rho W_{jhk}.$$

The second objective function is represented by the total tardiness:

$$Z_2 = \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K} \mathrm{Max}[(t_k + t_{ij} - t_e), 0] a_{ik} Y_{ijk}.$$

Model formulation:

$$\begin{aligned} &\text{minimize} \quad \{Z_1, Z_2\} \\ &\text{subject to} && (1) \\ &\sum_{n=1}^{N} X_{jn} \leqslant = 1 \quad \forall j, && (2) \\ &\sum_{n=1}^{N} nbX_{jn} \geqslant \sum_{i=1}^{I}\sum_{k=1}^{K} a_{ik} t_k Y_{ijk} \quad \forall j, && (3) \\ &\sum_{j=1}^{J} Y_{ijk} = 1 \quad \forall i, \forall k, && (4) \\ &\sum_{h=1}^{H} W_{jhk} = 1 \quad \forall j, \forall k, && (5) \\ &X_{jn} \in \{0, 1\}, \quad Y_{ijk} \geqslant 0, \quad W_{jhk} \geqslant 0 \quad \forall i, \forall j, \forall h, \forall k, \forall n. && (6) \end{aligned}$$

Constraints (2) ensure that only one option of repair capacity arrangement is chosen at location j. Constraints (3) ensure that the installed repair capacity at location j must be enough to process returned products transported to the location j. Constraints (4) ensure that all the returned products are sent to repair facilities. Constraints (5) ensure that all the replaced parts are supplied by the plants of the manufacturer.

This is a bi-objective mixed integer linear programming problem with two sets of decision variables, binary variables X_{jn}, which determine the facility capacity arrangement at each potential location, and continuous variables Y_{ijk} and W_{jhk}, which determine the network flow assignment.

5. Solution approach

The solution procedure has two purposes: one is to find optimal solutions for the optimization models associated with each of the two objective models, respectively; the other is to obtain a set of non-dominated solutions with respect to the two competing objectives.

The solution procedure consists of a combination of three algorithms: SS, the dual simplex method and the constraint method. Specifically, a SS algorithm is used to deal with the binary decision variables. Then, based upon a set of determined binary variables, the dual simplex method is applied to find optimal solutions with respect to the continuous variables in terms of the two objective functions, respectively. Furthermore, the constraint method is applied to yield a set of non-dominated solutions. Through the iteration of the SS procedure, finally, best solutions in terms of the two objectives, respectively, will be obtained. In the meantime, by eliminating the dominated solutions, a set of non-dominated solutions is also obtained.

5.1. A solution procedure involving scatter search

SS is an evolutionary algorithm. SS is chosen as a solution algorithm for this research because of its success in dealing with a wide range of discrete optimization problems [28]. The template for implementing SS consists of five component methods [29]:

(1) A diversification generation method to generate $P(P\text{Size})$ diverse trial solutions. In most SS applications, P is set to a value of 100 or approximately 10 times the cardinality of the reference set.
(2) An improvement method to transform each trial solution into one or more enhanced trial solutions.
(3) A reference set update method to build and maintain a reference set consisting of both quality solutions and diverse solutions.
(4) A subset generation method to operate on the reference set, to produce a subset of its solutions as a basis for creating combined solutions.
(5) A solution combination method to transform a given subset of solutions into one or more combined solutions.

The basic SS scheme is illustrated in Fig. 1.

The SS methodology is very flexible, since each of its components can be implemented in a variety of ways with various degrees of sophistication according to a specific problem [28,29]. The detailed SS scheme applied to this research is illustrated as follows:

(1) *The diversification generation method*: A diversification generation method is designed with two steps to generate a number of $P1$ diverse trial solutions with respect to the binary variables.

Step one: Use discrete uniform random number $r_1 \sim \mathrm{DU}(0\text{–}1)$ to randomly decide if a facility is installed at location j or not, that is: if $r_1 = 1$, a facility is installed at j; otherwise, no facility is installed at j.

Step two: Randomly decide how many units to install at j by using a discrete uniform distribution $r_2 \sim \mathrm{DU}(0\text{–}N)$. For example, if $r_2 = 3$, that means a number of 3 capacity units is installed at location j, then, the binary variable $X_{j3} = 1$, and other binary variables $X_{jn|n \neq 3} = 0$.

The diversification generation method focuses on diversification and not on the quality of the resulting solutions. Moreover, some of diverse solutions obtained from the above two steps may be insufficient in the total assigned capacity; some of the other diverse solutions may have redundant capacity. Thus, the next step is the use of an improvement

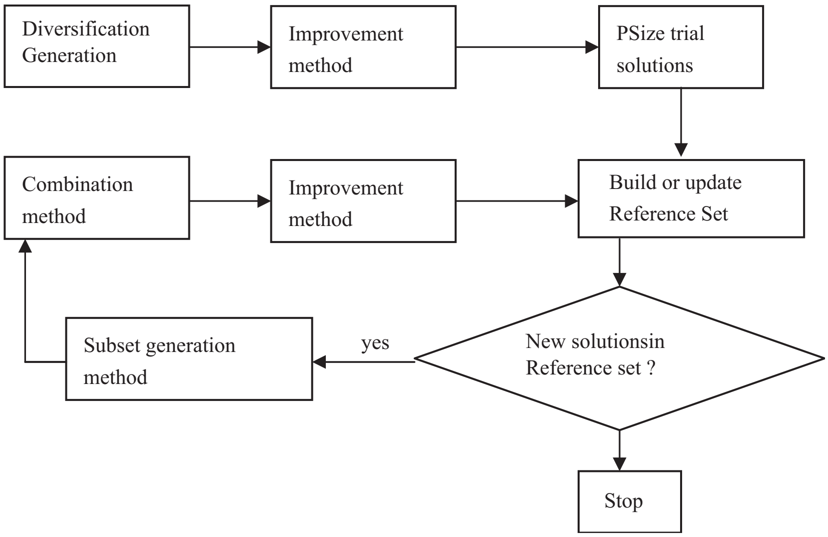

Fig. 1. The basic scatter search scheme.

method to obtain improved trial solutions by improving the diverse solutions generated by the diversification generation method.

(2) *The improvement method*: This improvement procedure also consists of two steps: step one improves the binary decision variable solutions ($P1$) obtained by the diversification method. The major purpose of step one is to make sure that the total assigned capacity is exactly equal to the required capacity. Step two further obtains a set of the optimal values with respect to the continuous decision variables based on the improved binary variable solutions.

This particular problem features two competing objectives. When designing a scheme to generate the improved solutions and further introduce quality solutions to the reference set, these two competing objectives need to be considered at this stage of the algorithm. Therefore, the improvement method is designed to generate two sets of improved solutions: one set, denoted as $P2$, favors the first objective; the other set, denoted as $P3$, favors the second objective.

Considering these two objectives may imply different tendencies with respect to the configuration of the reverse logistic networks. For example, the first objective has a tendency towards centralization in terms of the capacity arrangement; in other words, all of the required capacity is located at a very small number of potential locations in order to achieve economies of scale. On the other hand, the second objective has a tendency towards decentralization in terms of the capacity arrangement in order to fulfill the service within the expected cycle time for the customers.

Step one for the improvement method is as follows:

(a) Generation of the improved solution set $P2$ with respect to binary variables from diverse solution set $P1$:

Randomly select a location to place the required additional capacity if the total assigned capacity is insufficient; or take some or all the capacity from this location if there is redundant capacity.

(b) Generation of the improved solution set $P3$ with respect to binary variables from diverse solution set $P1$:

When additional required capacity is needed, randomly select a location to add a single unit of capacity. Repeat this procedure until the required capacity is reached. When there is redundant capacity, randomly select a location to reduce a single unit of capacity away from it. Repeat this procedure until there is no redundant capacity.

Once step one of the improvement method is complete, all of the binary variables are fixed. The MIP problems are reduced to LP problems.

Step two of the improvement method is to obtain optimal solutions with respect to the continuous variables for these two sets of improved solutions $P2$ and $P3$. A dual simplex method is applied to these sets of LP problems.

Through this improvement method, two sets of improved trial solutions with respect to both the binary and continuous decision variables are attained. By now, the total size of the generated trial solution set is $P = P1 + P2 + P3$. In this research $P1$ is set as 50.

(3) *Create the reference set (RefSet)*: The reference set is a collection of both the high quality solutions and the diverse solutions that are used to further generate new solutions by way of applying the combination method. The reference set in this research is created in the following way and consists of three subsets: two subsets of quality solutions and one subset of diverse solutions.

(a) Choose a number of $R1$ best improved solutions in terms of the first objective from the improved solution set $P2$ as the first quality subset for RefSet. The first solution in this subset is the best solution found so far in terms of the first objective.
(b) Choose a number of $R2$ best improved solutions in terms of the second objective from the improved solution set $P3$ as the second subset for RefSet. The first solution in this subset is the best solution found so far for the second objective.
(c) Choose a number of $R3$ diverse solutions from the rest of the trial solutions in PSize according to the following diversity method.

First, define the distance between two solutions, which is the sum of the absolute difference between their corresponding variable values. For example, the distance between solutions A and B is $d(A, B) = \sum_i abs(a_i - b_i)$, where a_i and b_i represent the binary variables for the solutions A and B, respectively. For each solution in PSize, the minimum distance to the solutions in RefSet is computed. Then, the solution with the maximum of these minimum distances in PSize is selected to add to RefSet. This procedure is continued until a number of $R3$ diverse solutions are selected for the reference set.

Finally, the reference set (RefSet) with a number of $R1$ quality solutions in terms of the first objective, a number of $R2$ quality solutions in terms of the second objective and a number of $R3$ diverse solutions are built. The total size of RefSet is $R = R1 + R2 + R3$. In this research, $R1 = 4$; $R2 = 4$; and $R3 = 3$.

(4) *Generation of new trial solutions by the combination method*: The combination method combines the elements in a subset of the reference set with the purpose of creating new trial solutions with respect to the binary decision variables. A combination method is typically a problem-specific procedure [28]. The implementation depends on the solution representation, which in this research involves a string of binary variables. The size of the subsets is determined to be two. With a number of R ($R = R1 + R2 + R3$) solutions in the reference set, there are up to $(\frac{1}{2}) * R * (R - 1)$ possible combined solutions with respect to the binary variables generated by this combination method.

First, a score for each binary variable is calculated based on the binary portion of the objective values, which results from the fixed installation costs, of the two reference solutions being combined. For example, the score for a binary variable X_{jn} of a new trial solution C that corresponds to the combination of reference solutions A and B, is calculated with the following formula:

$$Score(X_{jn}^C) = \frac{BinaObjVal(A) * X_{jn}^A + BinaObjVal(B) * X_{jn}^B}{BinaObjVal(A) + BinaObjVal(B)},$$

where *BinaObjVal*(A) and *BinaObjVal*(B) represent the portions of the fixed costs in the objective values of solutions A and B, respectively.

Secondly, the new trial solution with respect to binary variables is constructed by using the score as the probability for setting each variable to one. This can be implemented as follows: $X_{jn}^C = 1$, if $r \leqslant score(X_{jn}^C)$; $X_{jn}^C = 0$, otherwise, where $r \sim \mathrm{U}(0, 1)$.

For example, assume that there are three potential facility locations; a number of four units of capacity are needed; and *BinaObjVal*$(A) = 500$ and *BinaObjVal*$(B) = 600$. Table 1 shows how to use solutions A and B to generate a new solution C.

Some of combined solutions may have capacity redundancy, such as solution C generated above; some of the others may have insufficient capacity. Therefore, the improvement method must be used again to apply to these combined solutions to obtain a new set of trial solutions with respect to all of the decision variables.

(5) *Update reference set*: Among the newly generated solutions, if there are better solutions than the best solution obtained before in terms of the first objective in the quality solution subset $R1$, update the subset $R1$ by replacing some solutions in $R1$ with these newly generated better solutions; and if there are better solutions than the best solution obtained before in terms of the second objective in the quality solution subset $R2$, update the subset $R2$ by replacing

Table 1
Illustration of combination of two solutions

Variables (X_{jn})	X_{01}	X_{02}	X_{03}	X_{04}	X_{11}	X_{12}	X_{13}	X_{14}	X_{21}	X_{22}	X_{23}	X_{24}
Solution *A*	0	1	0	0	1	0	0	0	1	0	0	0
Solution *B*	0	0	0	0	1	0	0	0	0	0	1	0
Score (X^C_{jn})	0	0.45	0	0	1	0	0	0	0.45	0	0.55	0
r		0.32			0.76				0.82		0.44	
New solution *C* X^C_{jn}	0	1	0	0	1	0	0	0	0	0	1	0

Table 2
Payoff table

	$Z_1(X)$	$Z_2(X)$
X^1	$Z_1^*(X^1)$	$Z_2(X^1)$
X^2	$Z_1(X^2)$	$Z_2^*(X^2)$

some solutions in $R2$ with these newly generated better solutions. If either or both of the above situations happen, the diverse solution subset $R3$ needs to be rebuilt based on the maximum minimum distance rule.

With the above procedure, the reference set is updated. The combination method will be applied to the updated reference set again, and the reference set may be able to be further updated. The combination method and the update method are applied in an iterative fashion until no newly generated solution obtained is better than the best solutions obtained in the quality solution subsets $R1$ and/or $R2$ in the reference set.

5.2. A procedure for obtaining a set of non-dominated solutions

For a multi-objective problem, a solution that optimizes one objective will not, in general, optimize any of the other objectives [8]. A concept of non-dominance or efficiency is introduced to multi-objective programming, which draws researchers' attention to identifying a set of feasible alternative solutions called non-dominated solutions within the feasible region, instead of seeking a single optimal solution [7,30]. A solution is efficient if it is not possible to move feasibly from it to improve an objective function value without making worse at least one of the other objective values.

For this research, a set of non-dominated solutions can be obtained through the sequential application of the SS procedure and the constraint method.

The constraint method for a bi-objective model is described as follows: Given a minimization bi-objective problem:

$$\begin{aligned} \text{minimize} \quad & \{Z_1(X), Z_2(X)\} \\ \text{s.t.} \quad & X \in F_d, \end{aligned}$$

where F_d is feasible region in objective space.

Step 1. Construct a payoff table:

(a) Solve the optimization models for each of the two objective functions, respectively. Let X^1 denote an optimal solution for the first objective and X^2 denote an optimal solution for the second objective. Then, $Z_1^*(X^1)$ and $Z_2(X^1)$ denote the first objective function value and the second objective function value associated with the solution X^1, respectively; $Z_1(X^2)$ and $Z_2^*(X^2)$ denote the first objective function value and the second objective function value associated with the solution X^2, respectively.
(b) Construct a payoff table as in Table 2.

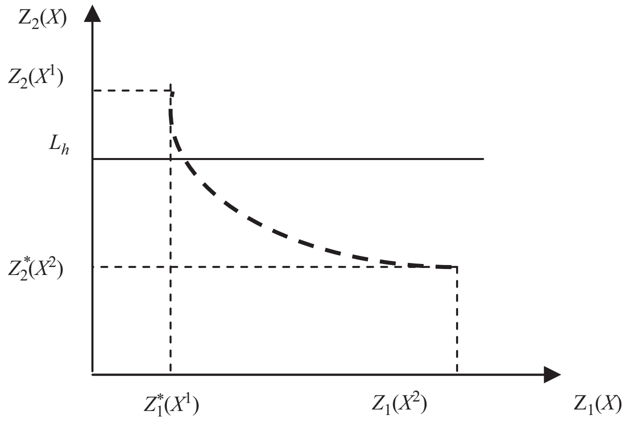

Fig. 2. An illustration for the constraint method.

The payoff table provides a systematic way of finding ranges for the objectives in the non-dominated set: $Z_1^*(X^1) \leqslant Z_1(X) \leqslant Z_1(X^2)$, $Z_2^*(X^2) \leqslant Z_2(X) \leqslant Z_2(X^1)$.

Step 2. Convert the bi-objective programming problem to its corresponding constrained problem. For example:

$$\begin{aligned} \text{minimize} \quad & \{Z_1(X)\} \\ \text{s.t.} \quad & X \in F_d, \\ & Z_2(X) \leqslant L_h. \end{aligned}$$

The first objective is chosen for minimization, and the second objective is modeled as a constraint. This formulation is a single objective problem with the feasible region further constrained. The range of the second objective $Z_2(X)$ will apply to L_h. In other words, the upper bound of L_h is $Z_2(X^1)$, and the lower bound of L_h is $Z_2^*(X^2)$. Fig. 2 provides an illustration for the constraint method.

Step 3. Arbitrarily choose a number γ, which is the number of different values of L_h that are used in the generation of candidate non-dominated solutions.

$$L_h = Z_2^*(X^2) + [h/(\gamma - 1)][Z_2(X^1) - Z_2^*(X^2)],$$

where $h = 0, 1, 2, \ldots, (\gamma - 1)$.

The larger the γ is, the more candidate solutions would be generated. In this research, γ is set as five.

Step 4. Solve the constrained single optimization problem with a number of γ of L_h values. As a result, a series of candidate solutions is generated. From these candidate solutions a set of the non-dominated solutions is selected. This approach guarantees feasibility and non-dominance of the constraint problem for two-objective problems [8].

First of all, through the solution search for the two objectives, the SS procedure generates many solutions with respect to the capacity arrangement (binary variables). For each specific settled capacity arrangement, two optimal solutions in terms of the two objectives can be obtained, respectively, by applying the dual simplex method, as $Z_1^*(X^1)$ and $Z_2^*(X^2)$ in Fig. 2. Secondly, these two optimal solutions attained for the two objectives based upon a specific settled capacity arrangement determine a payoff table. Then, by applying the constraint method and the dual simplex method, a set of non-dominated solutions can be generated, which represents a series of possible transportation arrangements exclusively based upon the settled capacity arrangement.

The curve in Fig. 2 can represent a capacity arrangement and a series of transportation arrangements based upon the capacity arrangement. Two extreme points of the curve represent two optimal solutions for the two objective functions, respectively, based on the capacity arrangement. Different transportation arrangements lead to changes in the two objective function values.

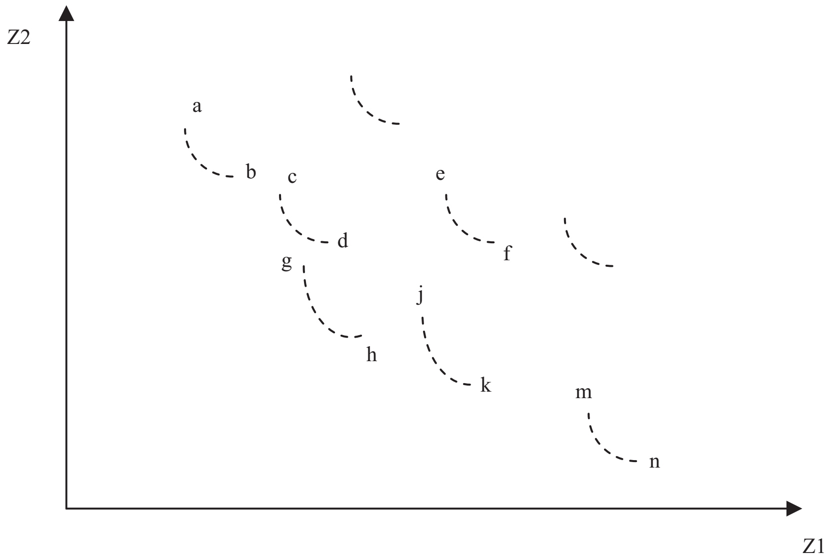

Fig. 3. A demonstration for obtaining non-dominated solutions.

Table 3
Trial examples

Trial example	Number of collection sites (I)	Number of potential facility locations (J)	Number of of plants (H)	Number of products (K)	Side of square
(1)	20	8	3	3	100
(2)	50	15	3	3	150
(3)	80	20	3	3	200

In a narrow sense, a curve represents the non-dominated solutions exclusively based upon a specific capacity arrangement. Regarding the entire solution space, in a broad sense, some or all of them may or may not be non-dominated solutions. Fig. 3 provides a simple demonstration for obtaining non-dominated solutions.

Some curves like a–b, g–h and m–n are entirely non-dominated; some curves like e–f are entirely dominated by other curves; and others like c–d and j–k are partly dominated, in the sense that only some portion of the curve represents non-dominated solutions. Therefore, before applying the constraint method, there is a screening process. For example, for a specific capacity arrangement solution, if both extreme points of the curve are dominated, this capacity arrangement solution should be eliminated; otherwise, the constraint method will be applied. Another screening process is also applied later on to eliminate dominated solutions.

6. Computational results

6.1. Data generation

Three trial examples are designed as follows for the computational study: a number of collection sites (customer zones), a number of manufacturing sites and a number of potential facility sites are generated from a uniform distribution over a square with a designated length of side. Table 3 presents the trial examples.

Other parameters are generated as follows:

(a) The amounts of returns at a collection site are drawn from a uniform distribution between 10 and 100.
(b) Capacity unit $b = 0.30*$ (total amount of collections/the total number of potential repair facility locations).

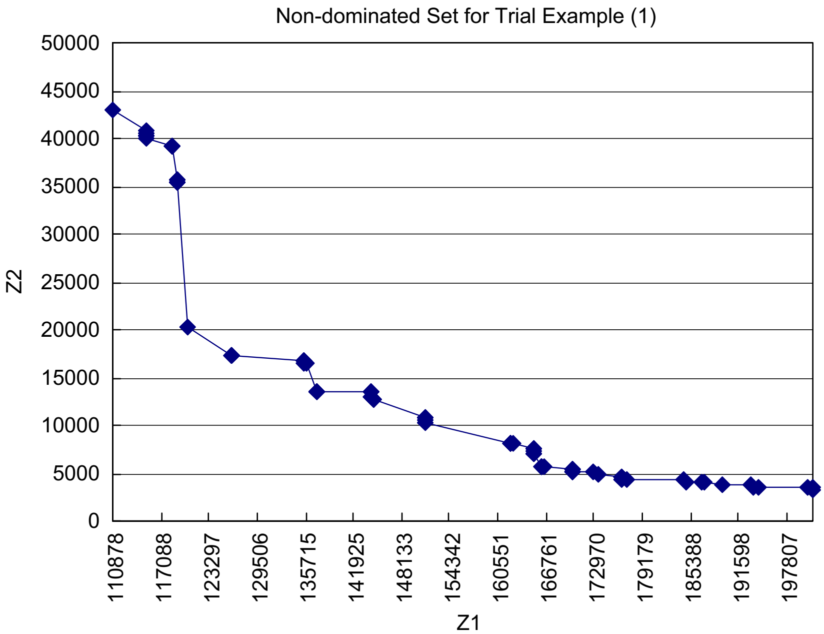

Fig. 4. The illustration of the non-dominated set for trial example (1).

(c) The average process (repair) time by plant k: $t_k = [8, 10, 12]$.
(d) The fixed cost for installing an equipment unit with one capacity unit b at location j is set as $f_{j1} = b * [5, 10]$. The parameter that represents the economies of scale is $\alpha = 0.8$.
(e) Transportation times and costs are computed as being proportional to the Euclidean distance among the locations of collection sites, repair facilities and manufacturer sites, respectively, as follows:
$t_{ij} = 0.6*$ Euclidean distance between collection site i and repair facility j.
$c_{ij} = 0.1*$ Euclidean distance between collection site i and repair facility j.
$c_{ih} = 0.05*$ Euclidean distance between repair facility j and plant h.
(f) Expected cycle time by customers $t_e = 30$.
(g) The average number of parts which need to be replaced from a returned product $\rho = 0.2$.

6.2. Numerical results

6.2.1. Trial example (1)

This trial example has 216 binary variables, 552 continuous variables and 100 constraints. Table 4 shows a replicate of the non-dominated solutions for trial example (1). The table presents the first objective values, the second objective values and the solutions to the capacity arrangement. The capacity arrangement is represented by (j, n), where j represents a facility location and n represents the number of capacity units installed at j. The first non-dominated solution gives the best value for objective one; and the last non- dominated solution gives the best value for objective two.

Fig. 4 illustrates this non-dominated set as a graph where the axes correspond to the objective function values, respectively.

Both Table 4 and Fig. 4 illustrate a trade-off between the total cost and the total tardiness. There is a trend that fewer potential locations chosen for installation of facilities lead to a lower total cost and a greater total tardiness; more potential locations chosen for installation of facilities lead to a higher total cost and a less total tardiness. Not only is the installation cost involved in the trade-off relationship with the total tardiness, the transportation cost is also involved in this trade-off relationship.

Table 4
The non-dominated solutions for trial example (1)

Non-dominated solution	The first objective value $Z1$	The second objective value $Z2$	Solutions to capacity arrangement
1	110 878	43 043	(3,27)
2	115 116	40 707	(3,26)(5,1)
3	115 117	40 540	(3,26)(5,1)
4	115 117	40 373	(3,26)(5,1)
5	115 118	40 205	(3,26)(5,1)
6	115 126	40 038	(3,26)(5,1)
7	118 686	39 214	(0,4)(3,23)
8	118 687	39 194	(0,4)(3,23)
9	118 687	39 174	(0,4)(3,23)
10	118 687	39 153	(0,4)(3,23)
11	118 692	39 133	(0,4)(3,23)
12	119 195	35 706	(3,24)(5,3)
13	119 195	35 600	(3,24)(5,3)
14	119 196	35 495	(3,24)(5,3)
15	119 223	35 389	(3,24)(5,3)
16	119 280	35 283	(3,24)(5,3)
17	120 416	20 281	(5,27)
18	126 324	17 293	(0,5)(5,22)
19	126 332	17 288	(0,5)(5,22)
20	126 342	17 282	(0,5)(5,22)
21	126 351	17 277	(0,5)(5,22)
22	126 361	17 272	(0,5)(5,22)
23	135 660	16 860	(3,18(4,9)
24	135 661	16 769	(3,18(4,9)
25	135 662	16 678	(3,18(4,9)
26	135 689	16 587	(3,18(4,9)
27	135 738	16 496	(3,18(4,9)
28	137 206	13 542	(4,5)(5,22)
29	137 206	13 541	(4,5)(5,22)
30	137 206	13 540	(4,5)(5,22)
31	137 206	13 539	(4,5)(5,22)
32	137 206	13 538	(2,8)(5,19)
33	144 191	13 507	(2,8)(5,19)
34	144 215	13 448	(4,9)(5,18)
35	144 239	13 389	(4,9)(5,18
36	144 349	12 936	(4,9)(5,18)
37	144 355	12 896	(4,9)(5,18)
38	144 363	12 856	(0,3)(4,5)(5,19)
39	144 371	12 816	(0,3)(4,5)(5,19)
40	144 378	12 777	(0,3)(4,5)(5,19)
41	151 168	10 861	(0,3)(4,5)(5,19)
42	151 178	10 678	(0,3)(4,5)(5,19)
43	151 189	10 495	(3,11)(4,5)(5,11)
44	151 210	10 312	(0,3)(4,5)(5,19)
45	162 330	8194	(2,8)(3,9)(5,10)
46	162 337	8174	(2,8)(3,9)(5,10)
47	162 343	8153	(2,8)(3,9)(5,10)
48	162 350	8132	(2,8)(3,9)(5,10)
49	162 358	8112	(2,8)(3,9)(5,10)
50	165 092	7634	(3,10)(4,5)(5,10)
51	165 098	7474	(3,10)(4,5)(5,10)
52	165110	7314	(3,10)(4,5)(5,10)
53	165 150	7154	(0,3)(2,4)(3,10)(4,9)(5,1)
54	165 295	6994	(0,3)(2,4)(3,10)(4,9)(5,1)
55	166 326	5685	(0,3)(2,4)(3,10)(4,9)(5,1)
56	166 329	5654	(0,3)(2,4)(3,10)(4,9)(5,1)
57	166 333	5622	(0,3)(2,4)(3,10)(4,9)(7,1)

Table 4 (*continued*)

Non-dominated solution	The first objective value $Z1$	The second objective value $Z2$	Solutions to capacity arrangement
58	166 344	5591	(0,3)(2,4)(3,10)(4,9)(5,1)
59	166 486	5559	(0,3)(2,4)(3,10)(4,9)(5,1)
60	170 141	5428	(0,3)(2,4)(3,10)(4,9)(5,1)
61	170 153	5339	(0,3)(2,4)(3,10)(4,9)(5,1)
62	170 174	5250	(0,5)(2,6)(3,6)(4,6)(5,4)
63	170 235	5161	(0,5)(2,6)(3,6)(4,6)(5,4)
64	172 784	5019	(0,5)(2,6)(3,6)(4,6)(5,4)
65	173 417	4849	(0,5)(2,3)(3,4)(4,3)(5,9)(7,3)
66	176 622	4666	(0,5)(2,3)(3,4)(4,3)(5,9)(7,3)
67	176 623	4574	(0,5)(2,3)(3,4)(4,3)(5,9)(7,3)
68	176 632	4482	(0,3)(1,2)(2,4)(3,8)(4,9)(5,1)
69	176 659	4390	(2,8)(3,9)(4,3)(6,3)(7,4)
70	177 163	4299	(1,5)(2,3)(3,5)(4,7)(5,7)
71	184 410	4198	(1,5)(2,3)(3,5)(4,7)(5,7)
72	184 683	3996	(1,5)(2,3)(3,5)(4,7)(5,7)
73	187 003	3992	(0,1)(1,3)(2,3)(3,4)(4,3)(5,10)(7,3)
74	187 261	3984	(0,1)(1,3)(2,3)(3,4)(4,3)(5,10)(7,3)
75	189 397	3886	(0,1)(1,3)(2,3)(3,4)(4,3)(5,10)(7,3)
76	193 265	3800	(0,4)(1,2)(2,5)(3,5)(4,2)(5,4)(6,1)(7,4)
77	193 597	3634	(0,3)(1,2)(2,8)(3,3)(4,3)(5,3)(6,1)(7,4)
78	194 239	3614	(0,1)(1,3)(2,7)(3,5)(4,4)(5,4)(6,2)(7,1)
79	200 464	3510	(0,1)(1,3)(2,6)(3,5)(4,4)(5,2)(6,1)(7,5)
80	201 037	3500	(0,2)(1,3)(2,4)(3,6)(4,2)(5,3)(6,5)(7,2)
81	201 176	3342	(0,2)(1,3)(2,4)(3,6)(4,2)(5,3)(6,5)(7,2)

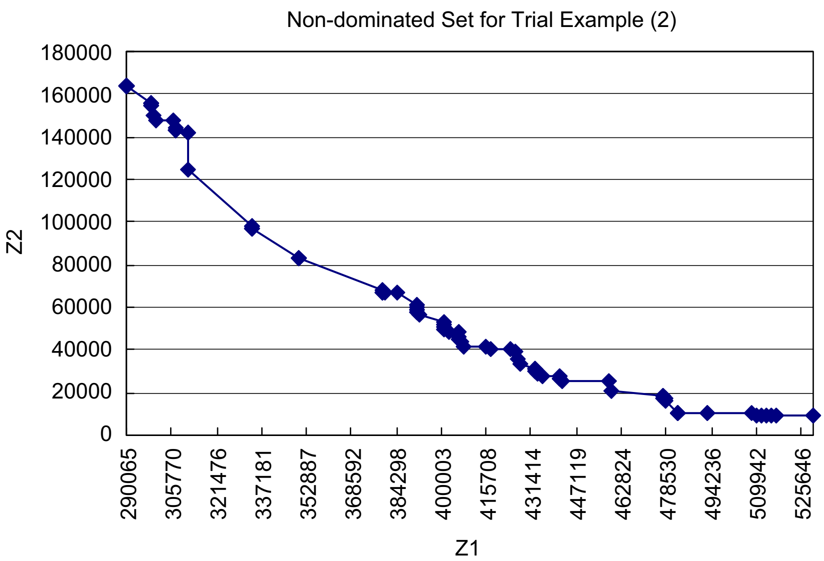

Fig. 5. The illustration of the non-dominated set for trial example (2).

As illustrated by the graph of Fig. 4 and Table 4, there are points in the non-dominated solution space where one can achieve a large improvement in one objective function value with only a slight degradation in the other; and there are also other points where one can achieve a slight improvement in one objective function value at the expense of a large increase in another objective function value.

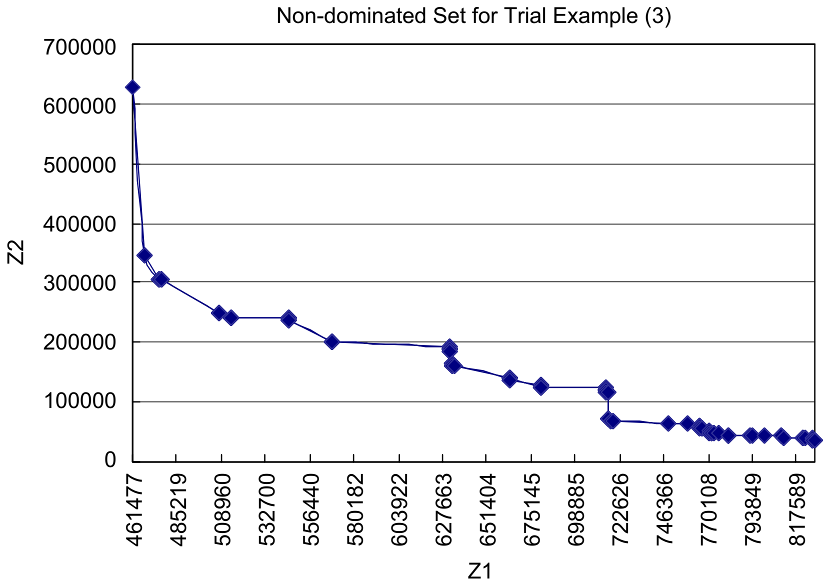

Fig. 6. The illustration of the non-dominated set for trial example (3).

Table 5
The best values obtained and the LP relaxation values of the two objective functions for trial examples

Trial example		The first objective	The second objective
(1)	The best value obtained by the solution approach	110 878	3342
	The value obtained by LP relaxation	108 756	3342
(2)	The best value obtained by the solution approach	290 065	8915
	The value obtained by LP relaxation	278 243	8905
(3)	The best value obtained by the solution approach	461 477	33 160
	The value obtained by LP relaxation	412 168	24 485

Table 6
Computational times for the three trial examples

Trial example	Computational time (s)
(1)	96
(2)	3310
(3)	18 179

6.2.2. *Trial examples (2) and (3)*

Trial example (2) has 765 binary variables, 2385 continuous variables and 210 constraints. Fig. 5 illustrates a replicate of the non-dominated set for trial example (2). Trial example (3) involves 1340 binary variables, 4980 continuous variables and 320 constraints. Fig. 6 illustrates a replicate of the non-dominated set for trial example (3).

6.2.3. *Performance of the solution approach*

Table 5 shows the set of best values for the two objective functions obtained by the designed solution approach and the two objective function values obtained by LP relaxation.

Table 6 shows the computational times for the three trial examples. When the problem size gets larger, there are more binary and continuous variables and a larger number of constraints. Thus, additional computational effort is required. For example, a larger trial example has a larger number of combinations for binary variables than a smaller

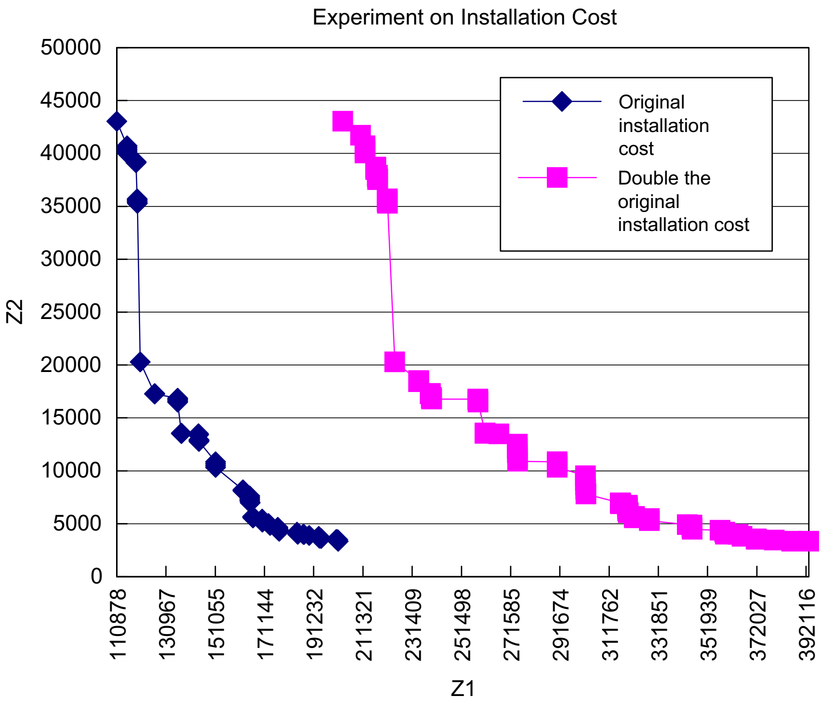

Fig. 7. The effect of the installation cost on the non-dominated set.

trial example. Therefore, the SS algorithm is required to search in a larger solution space. The dual simplex method also needs to solve more and larger linear optimization problems for a larger trial example.

6.2.4. Sensitivity analysis

Sensitivity experiments were conducted on investment costs, transportation costs, transportation times, customer expected cycle time and other parameters to see how these parameters affect the objective function values and the non-dominated solution set. The experiments show that the cost-related parameters mostly affect the first objective value and the time-related parameters mostly affect the second objective values. Both types of parameters affect the outcome of the non-dominated solution set.

Fig. 7 illustrates the effect of the change in facility installation cost on the non-dominated set, which is an example of the cost-rated parameters. Fig. 8 illustrates the effect of the change in transportation time on the non-dominated set, which is an example of the time-rated parameters. Fig. 9 illustrates the effect of the change in customer expected cycle time on the non-dominated set, which also is an example of the time-rated parameters.

7. Conclusions

This paper focuses on the design of a bi-objective reverse logistics network. A reverse logistics problem was proposed, in which a third-party logistics company provides logistics service for the post-sales service network. A bi-objective MIP optimization model for the reverse logistic network problem was developed, with one objective related to total cost and the other related to customer satisfaction. The purpose was to study the tradeoffs between two major objectives and provide decision makers with possible solutions. A solution approach was designed, which consists of a combination of three algorithms: scatter search, the constraint method and the dual simplex method. The scatter search algorithm is used to search the solutions with respect to binary decision variables; the dual simplex method is applied to deal with continuous variables; and the constraint method is used to attain a set of non-dominated solutions for the reverse logistic network. The numerical results demonstrate the trade-off relationship between the two competing objectives. Both installation costs and transportation cost in the first objective function involve in the trade-off relationship with the

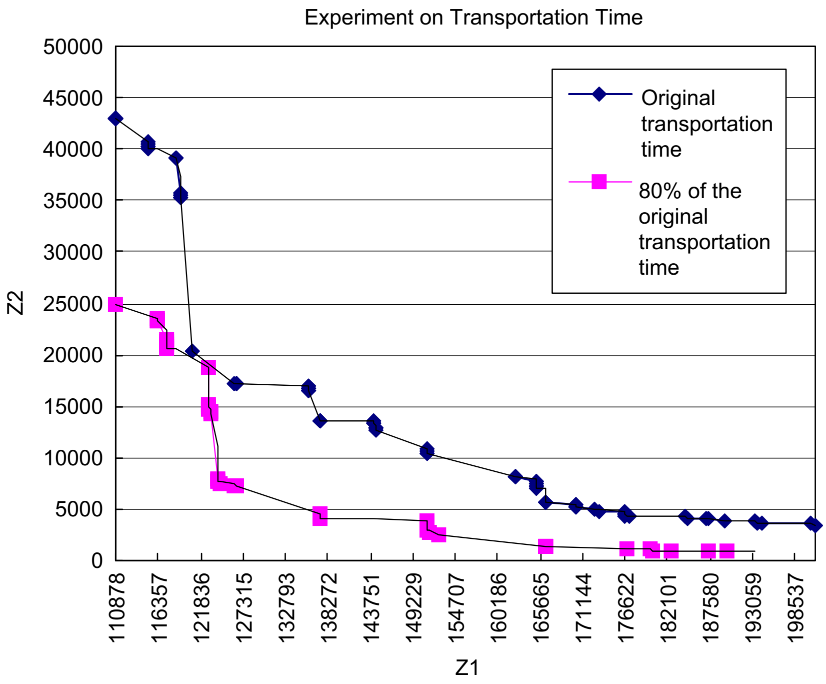

Fig. 8. The effect of the transportation time on the non-dominated set.

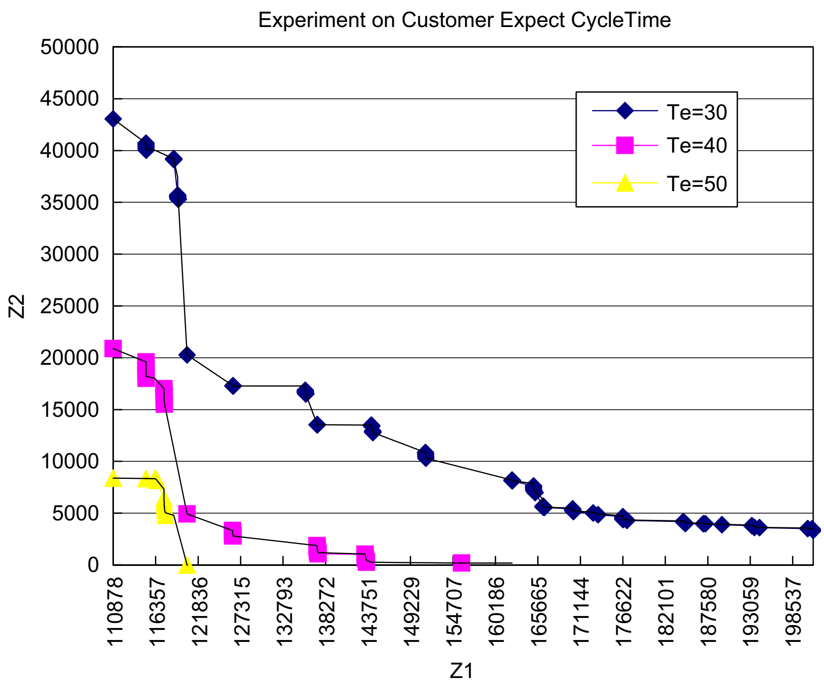

Fig. 9. The effect of customer expected cycle time on the non-dominated set.

second objective. The results also show that the optimization for the first objective function leads to a centralized network structure; the optimization for the second objective function results in a decentralized network structure. Finally, the paper studied the impacts of some factors. It is concluded that the cost related parameters, such as installation cost and transportation cost, mostly influence the outcomes of the first objective; and the time related parameters, such as transportation time and customer's expected cycle time heavily influence the outcome of the second objective.

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