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An integrated model for supplier location-selection and order allocation under capacity constraints in an uncertain environment

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Abstract. Facility/supplier location-allocation and supplier selection-order allocation are two of the most important decisions for both designing and operation supply chains. Conventionally, these two issues will be discussed separately. Due to similarity and relationship between these issues, in this paper, we investigate an integrated model for supplier location-selection and order allocation problems in Supply Chain Management (SCM). The objective function is set in such a way that the establishment costs, inventory-related costs, and transportation costs as quantitative criteria have been minimized. As regards, the costs are uncertainty; therefore, we have considered them stochastic. This paper develops a bi-objective model for optimization of the mean and variance of costs. Also, the capacities of supplier are limited. This mixed-integer nonlinear program is solved with two meta-heuristic methods: genetic algorithm and simulated annealing. Finally, these two methods are compared in terms of both solution quality and computational time. To obtain a high degree of validity and reliability, the results of GAMS software and meta-heuristic results are compared in small sizes.

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1. Introduction

The purpose of Facility Location-Allocation (FLA) problem is identifying the locations of some facilities to serve a set of distributed customers and allocation of each customer to the facilities such that the total transportation costs are minimized or other objectives are satisfied. Decision making about facility allocation plays a critical role in the strategic design of supply chain networks. The strategic level in SCM includes decisions related to the number, location, and capacities of the manufacturing plants, warehouses, and other facilities or the flow of materials in the logistics network. This statement establishes a clear relationship between allocation models and strategic SCM.

Many types of FLA models have been developed to find the optimal design with respect to different location objectives such as: time, costs, coverage, and access of others. The classical transportation problem satisfies demands of customers at minimum transportation cost. The incapacitated FLA problem model develops this by choosing among a number of potential sites for locating supply facilities so that the sum of transportation costs and the fixed costs of opening facilities are minimized. The incapacitated model assumes unlimited capacity for each facility, and as a result, if a facility supplies a customer, it will satisfy all the demands. Therefore, to serve a specific demand, only one facility is necessary. The capacitated facility

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allocation problem operates under the given supply capacity constraints. There are many extensions to this basic modeling framework that include multi-objective formulations, dynamic situations, etc.

Inventory management and determined inventory policy are other important issues in the SCM. Effective inventory management can play a vital role in decreasing inventory holding costs and boosting profit across different layers of the supply chain. Economic Order Quantity (EOQ) is one of the classical inventory models. EOQ determines the order quantity that minimizes total inventory holding and ordering costs. Given different conditions such as shortage allowed, discount, etc., EOQ model can be developed.

The two crucial decisions, namely facility allocation and inventory policy, are mutually dependent. For example, the transportation cost is one of the key cost components for the facility allocation problem, which depends on the frequency of inventory replenishment at facilities. This replenishment frequency is dependent on the inventory policy. The relevance between the facility allocation and inventory policy problems develops an integrated model with the FLA for which inventory problem is needed to solve network design problems.

Suppliers are a core component of supply chain because of the substantial role of their performance in quality, cost, delivery, service, etc. In achieving the objectives of a supply chain, supplier selection is one of the most critical activities of purchasing management in an SCM. The cost of raw materials and components in manufacturing industries involves a significant part of the cost of final product, sometimes up to 70% of product cost.

Supplier selection decisions are complicated by the fact that various criteria must be considered in decision making process. Some of the most important criteria include price, quality, delivery, performance history, warranties and claim policy, production facility and capacity, geographical location, and so on. These criteria are divided into qualitative and quantitative, generally. There are various methods to choose supplier based on the specified criteria such as MCDM techniques, Mathematical Programming (MP) techniques (LP, GP), Artificial Intelligence (AI) techniques, and integrated approaches (AHP, ANP, DEA).

In this study, we consider supplier as facility and develop a located-allocated model along with selected-order allocated supplier(s) with capacity constraint, simultaneously. Specifically, we consider a firm which operates several geographically dispersed plants/stores that face specific deterministic, stationary demand and stochastic costs. The supplier location-selection-order allocation decisions for each plant are conducted at the firm level, considering a collection of sites and suppliers that meet initial criteria. We analyze the case where each plant/store operates under the assumptions of EOQ model with backordering allowed.

We consider stochastic transportation (distance-based transportation cost), establishment fix, purchasing, inventory replenishment, holding, and shortage costs as quantitative criteria for the located and selected supplier(s); allocate customers to supplier(s); and determine order quantity for each customer. Transportation, establishment fix costs, and capacity of supplier(s) are dependent on the location of supplier establish but purchasing costs are independent.

We use MODM and Goal Attainment methods to solve this model along with Lp-metric for integrated objective functions. In small size, we use GAMS software; but in medium and large sizes, we used Genetic Algorithm and Simulated Annealing to solve this mixed-integer nonlinear model. The remainder of this paper is organized as follows: section 2 reviews the literature on the topics used in this research. Section 3 presents all the details about the model we have discussed. In Section 4, we have described MODM techniques and meta-heuristic algorithms used to solve the model. In the next section, numerical examples and results are presented. Finally, section 6 gives conclusions and suggestions for future works.

2. Literature review

Location theory has been considered in different studies. Here, some previous studies are briefly presented. Fontan (1826) was the first researcher who raised location theory in agricultural activities [1]. But, formulation of it took place by Alfred Weber in 1909 [2]. Weber located a single warehouse by minimizing the total travel distance between the warehouse and a set of distributed customers. This problem was extended from single warehouse (facility) to multiple supply points (facility) by another research in 1963 which was a p-median location allocation problem [3]. Then, according to distribution network and the objective function (maximum/minimum), the optimal number and location of facilities were determined. In some of the past studies, facilities and demands were used through nodes or continuous space through synthetic data. In facility location problem, a network of discrete nodes was used for facilities and demands, which were solved by Hosage and Goodchild [4]. Discrete nodes for facility or demand are also used by Medaglia et al. [5], Uno et al. [6], and Yang et al. [7]. In 1982, Murtagh and Niwattisyawong [8] proposed the capacitated Facility Location-Allocation (FLA). Their model is considered to be one of the most important FLA studies focusing on capacity of facility. Another important extension regards the inclusion of stochastic components such as future customer demands and costs in facility location models [9-12]. Owen and Daskin [13] provided an overview of research on facility location through the consideration of time and uncertainty.

Nowadays, FLA problems in combination with supply chain approach have been considered by researchers. Among the studies done based on solution approach, Ho et al. (2008) optimized the FLA problem in a customer-driven supply chain [14]. They considered both quantitative and qualitative criteria and used the Goal Programming (GP) and Analytic Hierarchy Process (AHP) in order to maximize. Then, Melo et al. presented a comprehensive review of Facility Location and SCM [15]. In 2011, Wang et al. [16] presented Location-Allocation (LA) decisions in the two-echelon supply chain with both profit and cost objectives. Ahmadi Javid and Nader Azad proposed a novel model to simultaneously optimize location, allocation, capacity, inventory, and routing decisions in a stochastic supply chain system [17]. Yu-Chung Tsao et al. applied an integrated facility location and inventory allocation problem for designing a distribution network with multiple distribution centers and retailers [18]. Amin and Zhang [19] used a multi-objective facility location model for closed-loop supply chain network under uncertain demand and return.

Weber and Current [20] represented the relationship between the facility location and supplier selection decisions. Research on supplier evaluation and selection in the context of purchasing strategy can go back to the early 1960s. There is a lot of research in this area, including conceptual and empirical studies. Weber et al. [21] provided a review of 74 articles related to supplier selection since 1966. This research categorized the models with respect to the solution methodologies used/developed. Degraeve et al. [22] examined some existing supplier selection models with respect to their efficiency. Minner [23] reviewed multi-supplier inventory models, which focused on the specification of the inventory policy of each store under the assumption of multi-sourcing. Aissaoui et al. [24] provided an extensive review focusing on supplier selection and order lot size modeling. Burcu et al. [25] Proposed an integration of strategic and tactical decisions for vendor selection under capacity constraints, (They developed an integrated location-inventory model with distance-based transportation costs and capacity constraints.) In their research, they noted that relatively little research had been devoted to developing mathematical programming models to address the supplier selection problem [26-28]. The research on the theory of integrated location-inventory problems is relatively new. The theory aims at investigating the interaction between the strategic facility location and tactical inventory decisions. Some research emphasizes the inclusion of inventory costs in network design problems, e.g. [29,30].

For solving FLA in SCM, numerous algorithms have been designed, involving branch-and-bound algorithms [31], branch-and-cut [32,33], Lagrangian relaxation [34,35], decomposition techniques [36,37], tabu search [38,39], genetic algorithms [40,41], simulated annealing [42,43], and scatter search [44,45]. In some cases, the development of a heuristic procedure combines different techniques. This is the case, for example, for Jang et al. [46] who use Lagrangian relaxation and a genetic algorithm.

The structure of the paper is as follows. Problem assumptions are discussed in the 'Problem description' section. In the 'Methods' section, the mathematical model is described; it is tested in a real case in the 'Results and discussion' section. Concluding remarks are in the 'Conclusions' section.

3. Problem description and the proposed model

In this paper, a two-echelon supply chain consisting of supplier as facility and plants/stores of a firm is represented. Capacity of supplier is limited. Also, in the context of capacitated supplier location-allocation, we consider transportation cost (fixed and variable) and establishment cost and in the context of supplier selection and order allocation, we consider the overall logistical costs including not only the purchasing costs considered in traditional models, but also the transportation (fixed and variable), inventory replenishment, holding, and [25] shortage costs.

This paper develops a bi-objective supplier location-selection-order allocation that determines inventory policy of each plant/store (when and how much to order at each plant/store) to minimize total variance and mean of the mentioned costs.

This proposed mixed-integer nonlinear programming model is solved by the following important decisions:

1. How many and which suppliers should be selected to meet the demand?
2. Which site(s) should be allocated to this (these) supplier(s)?
3. Which plants/stores should be allocated to this (these) supplier(s)?
4. How much should each plant/store order from this (these) supplier(s)?

3.1. Assumptions

To develop a mathematical model, we first present the assumptions and notations, respectively. The main assumptions considered in the problem formulation are as follows:

- All demands of plants/stores are satisfied by the supplier(s);

- All candidate suppliers and sites meet initial criteria;
- Each plant/store operates under the assumptions of the EOQ Model with backordering allowed;
- Repletion of each plant/store is done by a single supplier and holds inventory to meet the deterministic stationary demand;
- Capacity of supplier is limited and dependent on establishment site and ability of supplier;
- Fixed and variable transportation costs are dependent on establishment site and supplier;
- Except for fixed dispatch (transportation) cost, all costs are stochastic.

3.2. The notations of the model

Sets:

I : Set of plants/stores $i \in I = \{1, ..., m\}$

J : Set of candidate suppliers $j \in J = \{1, ..., n\}$

K : Set of candidate sites $k \in K = \{1, ..., l\}$

Parameters:

D_i : Annual demand of plant/store i

b_i : Amount of backordering allowed for each plant/store i

di_{ik} : Distance between plant/store i and site k

P_{jk} : Capacity of supplier j at site k

h_i : Inventory holding cost rate for each unit of inventory at plant/store i

k_i : Fixed ordering (inventory replenishment) cost of plant/store i

s_i : Shortage cost rate for each unit of commodity at plant/store i

c_j : Per-unit (purchasing, handling, etc.) cost offered by supplier j

f_{jk} : Fixed cost of establishment supplier j at site k

r_{ijk} : Per-mile (distance-based transportation) cost to plant/store i from supplier j is established at site k.

t_{ijk} : Fixed dispatch (transportation) cost to plant/store i from supplier j establish at site k.

$^*\mu$: The prefix indicates the mean of costs.

μh_i : Mean of inventory holding cost rate for each unit of inventory at plant/store i.

$^*\sigma$: The prefix indicates the standard deviation of costs, such as

σh_i : standard deviation of inventory holding cost rate for each unit of inventory at plant/store i.

Decision variables:

$$x_{jk} = \begin{cases} 1 & \text{if supplier } j \text{ is established at site } k \\ 0 & \text{otherwise} \end{cases}$$

$$y_{jk} = \begin{cases} 1 & \text{if supplier } j \text{ is established at site } k \\ & \text{is allocated to plant/store } i, \\ 0 & \text{otherwise} \end{cases}$$

$Q_i =$ order quantity of plant/store i

$T_i =$ D_i/Q_i, Order interval.

3.3. Model

$$\text{Min } Z1 = \sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{k=1}^{l}\Bigg(\mu c_j.D_i + \left(\frac{t_{ijk} + \mu_{ijk}.di_{ik}}{Q_i}D_i\right)\Bigg)y_{ijk} + \sum_{i=1}^{m}\left(\frac{\mu k_i.D_i}{Q_i} + \mu s_i\frac{b_i}{2Q_i} + \mu h_i\left(\frac{(Q_i - b_i)^2}{2Q_i}\right)\right) + \sum_{j=1}^{n}\sum_{k=1}^{l}\mu f_{jk}.x_{jk}, \tag{1}$$

$$\text{Min } Z2 = \sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{k=1}^{l}\Bigg((\sigma c_j.D_i.y_{ijk})^2 + \left(\left(\frac{\sigma r_{ijk}.di_{ik}}{Q_i}\right)D_i.y_{ijk}\right)^2\Bigg) + \sum_{i=1}^{m}\Bigg(\left(\frac{\sigma k_i.D_i}{Q_i}\right)^2 + (\sigma s_i\frac{b_i}{2Q_i})^2 + \left(\sigma h_i\left(\frac{(Q_i - b_i)^2}{2Q_i}\right)\right)^2\Bigg) + \sum_{j=1}^{n}\sum_{k=1}^{l}(\sigma f_{jk}.x_{jk})^2, \tag{2}$$

s.t. :

$$\sum_{j=1}^{n} x_{jk} \le 1 \quad \forall k \in K, \tag{3}$$

$$\sum_{k=1}^{l} x_{jk} \le 1 \quad \forall j \in J, \tag{4}$$

$$\sum_{k=1}^{l}\sum_{j=1}^{n} y_{ijk} = 1 \quad \forall i \in I, \tag{5}$$

$$y_{ijk} \leq x_{jk} \quad \forall i \in I,\ \forall j \in J,\ \forall k \in K, \tag{6}$$

$$\sum_{i=1}^{m} D_i y_{ijk} \leq p_{jk} x_{jk} \quad \forall j \in J,\ k \in K, \tag{7}$$

$$x_{jk} \in \{0,1\} \quad \forall j \in J,\ k \in K, \tag{8}$$

$$y_{ijk} \in \{0.1\} \quad \forall i \in I,\ \forall j \in J,\ \forall k \in K, \tag{9}$$

$$Q_i \in R^+ \quad \forall i \in I. \tag{10}$$

The first objective function is aimed at minimizing the mean of annual total cost, which includes (i) purchasing costs, (ii) fixed dispatch and distance-based transportation costs from the selected site to the plant/store, (iii) inventory replenishment, shortage, and holding costs of the plants/stores, and (iv) fixed cost of establishment supplier j at site k. The second objective function is aimed at minimizing the variance of annual mention costs (except fixed dispatch transportation cost).

Constraint (3) ensures that each site is assigned to, at maximum, one supplier. Constraint (4) ensures that each supplier is assigned to, at maximum, one site. Constraint (5) dictates that the demand of each plant/store must be satisfied. In other words, this constraint ensures that each plant/store is assigned to a supplier (repletion of each plant/store by a single supplier). Constraint (6) ensures that each plant/store is assigned to the located-selected supplier. Constraint (7) represents the throughput capacities of the suppliers. In other words, Constraint (7) relates to inflow and outflow with respect to the production capacities of the suppliers. Finally, Constraints (8) and (9) ensure integrality, whereas Constraint (10) ensures non-negativity.

4. The proposed solution method

The model developed in Section 3.3 is a constrained multiple-objective problem. Multiple-objective problems are concerned with the optimization of multiple (vector of objectives $F(x)$), conflicting, and non-commensurable objective functions subject to constraints representing the availability of multiple objective problems.

A multi-objective optimization problem can be formulated as:

$$\text{Min}\ \{F_1(x), F_2(x), ..., F_q(x)\}$$

$$X \in R^n$$

$$\text{s.t.}$$

$$X \in x,$$

where the integer $p \geq 2$ is the number of objectives and the set x is the feasible set of decision vectors. In multi-objective optimization, there does not usually exist a feasible solution that minimizes all objective functions simultaneously. Therefore, attention is paid to the Pareto-optimal solutions that cannot be improved in any of the objectives without degrading at least one of the other objectives. There are different ways for solving MOPS such as MODM techniques, NSGA-II, MOPSO, SPEA-2, etc.

In this research, MODM techniques are used to convert the original problem with multiple objectives into a single-objective optimization problem.

4.1. MODM techniques

Various methods that are available to solve multi-objective programming models are classified in four categories. The methods in the first category do not have to get primitive information from decision makers and consist of individual optimization, the Lp-metrics/global criteria, the Maxi-Min, and the filtering/displaced ideal solution (DIS). The methods in the second category consist of the goal programming, the lexicography/preemptive optimization, converting of objectives into constraints, the goal attainment, and the utility function that require primitive information from the decision maker. The methods of the third category include Geoffrion method, satisfactory goals method, and the STEM method and require reflection on the act with decision makers. The methods of the fourth category need information from the decision maker at the end of solution. The multi-criteria simplex method, the minimum deviation method, and the De Novo programming are placed in this category [25]. The selected MODM methods to solve the model include the Goal Attainment and Lp-metric.

4.1.1. Goal attainment method

The method described here is the Goal Attainment method of Gembicki [47]. It involves expressing a set of design goals, $\mathbf{F}^* = \{\mathbf{F}_1^*, \mathbf{F}_2^*, ..., \mathbf{F}_q^*\}$, which are associated with a set of objectives, $F(x) = \{F_1(x), F_2(x), ..., F_q(x)\}$. The problem formulation allows the objectives to be under- or over-achieved, enabling the designer to be relatively imprecise about initial design goals. A vector of weighting coefficients $w = \{w_1, w_2, ..., w_q\}$ controls the relative degree of under- or over-achievement of the goals. It is expressed as a standard optimization problem using the following formulation:

$$\text{Minimize}\ Z$$

$$\text{s.t.}$$

$$F_i(x) - w_i z \leq F_i^* \quad i = 1, 2, ..., q,$$

where Z is a scalar variable unrestricted in sign, and the weights $w = \{w_1, w_2, ..., w_q\}$ are normalized so that $\sum_{i=1}^{q} w_i = 1$.

4.1.2. Lp-metrics method

The idea behind this method is to find the closest feasible solution to an ideal point. Some authors, such as Zeleny 1982 [48], Duckstein & Opricovic 1980 [49], and Szidarovszky et al. 1986 [50], call this method compromise programming. The most common metrics to measure the distance between the reference point and the feasible region are those derived from the Lp-metric, which is defined by:

$$\text{Minimize } Z = \left(\sum_{i=1}^{q} \left| \frac{F_i(x) - F_i^*}{F_i^*} \right|^p \right)^{1/p}$$

s.t.

$$X \in x,$$

for $1 \leq p \leq \infty$. The value of p indicates the type of metric. For $p = 1$, we obtain the Manhattan metric, while for $p = \infty$, we obtain the so called Tchebycheff metric.

In this research, we used Lp-metric with $p = 1$.

4.2. Meta-heuristic algorithms

After using MODM techniques, the model is solved by GAMS software to solve smaller sizes. Since GAMS software cannot be used in larger sizes, Genetic algorithm and simulated annealing are used to solve the obtained model.

4.2.1. Genetic algorithm

Genetic Algorithms (GAs) are adaptive heuristic search algorithms based on the evolutionary ideas of natural selection and genetics by Fraser 1957 [51], Bremermann 1958 [52], and Holland 1975 [53]. They are search techniques used in computing to find true or approximate solutions to optimization and search problems. GAs use techniques inspired by evolutionary biology, such as inheritance, mutation, selection, and crossover (also called recombination). The flowchart of the proposed GA is shown in Figure 1.

Chromosomes. One of the major components of the GA is the selection of chromosomes. In the proposed GA, we tried to select the best chromosomes that would give us good results and require low run-times. The binary y_{ijk} and continuous Q_i variables were considered to design two-layer chromosomes. The first layer represents variable y_{ijk} and is three-dimensional, including dimensions i, j, and k. For each i (plant/store) at j (supplier), and k (site)surfaces, there is only one cell with number 1, and the other cells are zero. This indicates that each plant/store is allocated to only one located supplier. Different cells, containing (1), have exactly the same j and k indices or both indices are different. This guarantees satisfaction Constraints (3) and (4). Figure 2 shows an example of chromosomes.

x_{jk} is computed from y_{ijk} variables. For Constraint (7), we consider penalty function for violation of the constraints.

Initial population. A certain number of chromosomes were randomly created.

Genetic operations. The following describes the main operations of the GA, which are crossover, mutation, and selection.

- *Crossover.* To perform the crossover, two chromosomes (parents) must be merged. First, the parents to be combined should be identified. For this reason, we used Roulette Wheel Selection (RWS). After selection of parents, we used single-point crossover on the dimension i for the first layer, see Figure 3.

  For the second layer, we used the following crossover:

  $$\text{Parent1} = (Q_1^{P1}, Q_2^{P1}, ..., Q_m^{P1}) \xrightarrow{\propto = (\propto_1, \propto_2, ..., \propto_m)}$$

  $$\text{Child1} = (Q_1^{C1}, Q_2^{C1}, ..., Q_m^{C1})$$

  $$\text{Parent2} = (Q_1^{P2}, Q_2^{P2}, ..., Q_m^{P2}) \ 0 \leq \propto \leq 1$$

  $$\text{Child2} = (Q_1^{C2}, Q_2^{C2}, ..., Q_m^{C2})$$

  $$Q_i^{C1} = \propto_i Q_i^{P1} + (1 - \propto_i) Q_i^{P2}$$

  $$Q_i^{C2} = (1 - \propto_i) Q_i^{P1} + \propto_i Q_i^{P2}$$

  After applying crossover, the first layers of children were repaired. For repair child 1, first i layer after cut point parent 2 if have exactly the same j and k indices for (1) cell or both indices vary with j and k indices for (1) cell of i layers before cut point parent 1, this layer replace else don't replace, in order to end.

- *Mutation.* The mutation probability refers to the probability of change in any gene. Chromosomes were randomly selected for mutation. In this study, we defined two types of mutation for the first layer of chromosomes, which are illustrated in Figure 4. Mutation type was selected randomly. We used the following mutation for the second layer:

  $$\text{Parent} = (Q_1, Q_2, ..., Q_m) \quad \xrightarrow{Q_i^{\text{new}} = Q_i + \sigma N(0,1)}$$

  $$\text{Child} = (Q_1, Q_2, ..., Q_i^{\text{new}}, ..., Q_m).$$

- *Selection.* Different strategies can be applied to

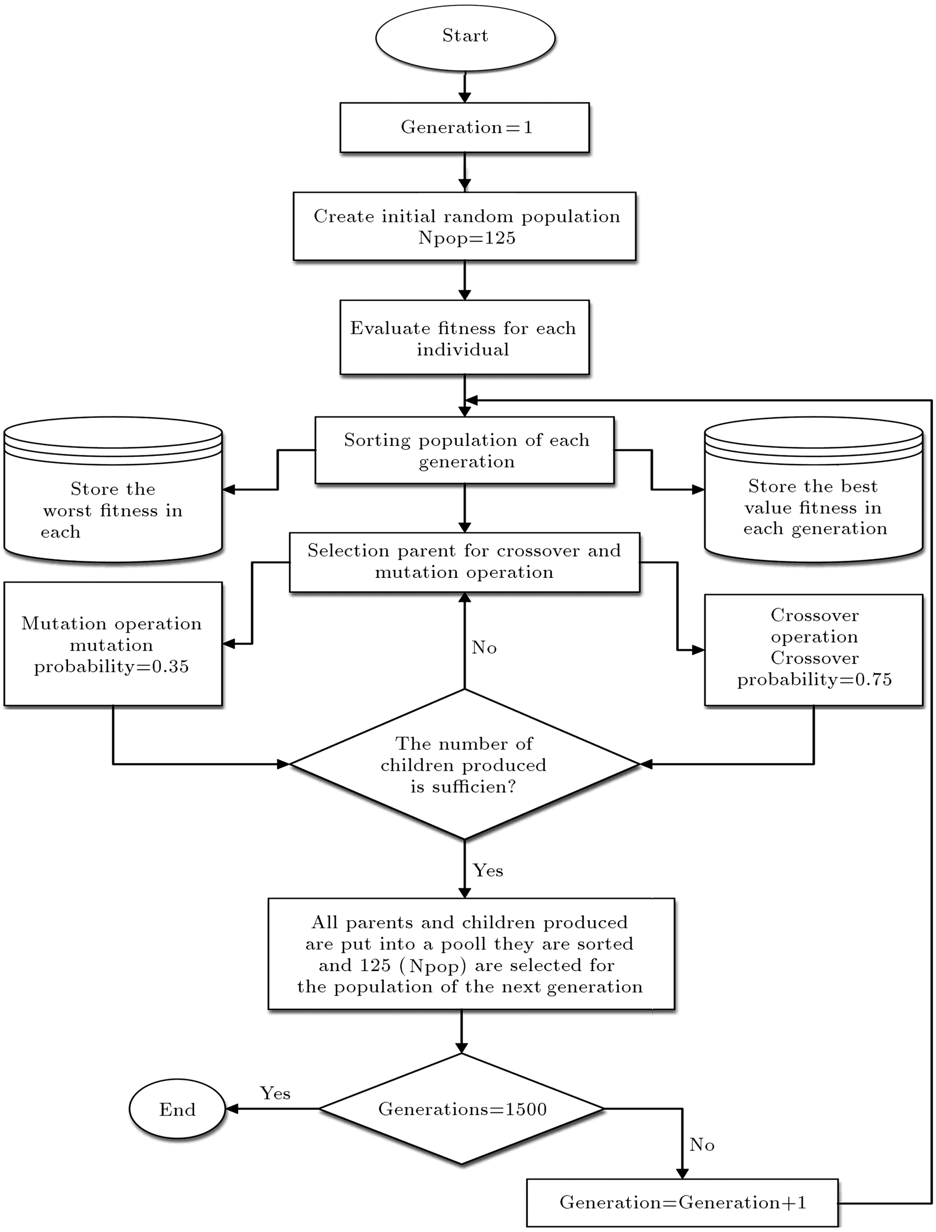

Figure 1. The flowchart of the proposed genetic algorithm.

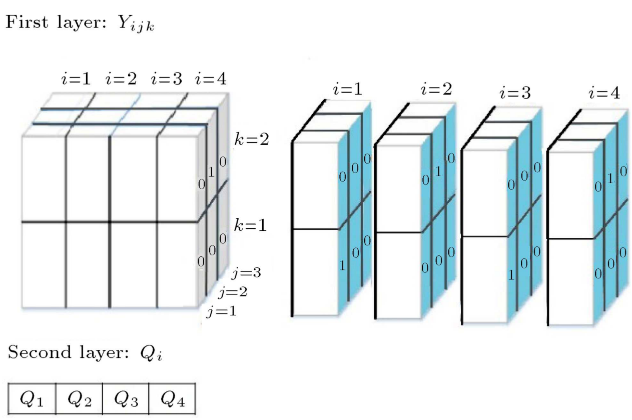

Figure 2. Two layers of chromosomes: $i = 4$, $j = 3$, and $k = 2$.

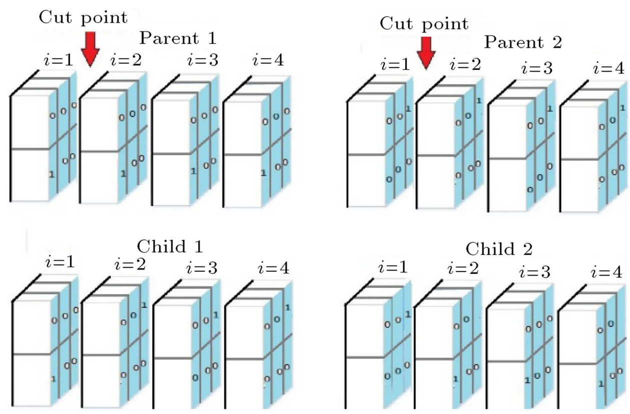

Figure 3. Crossover of the first layer (crossover was performed simultaneously in two layers).

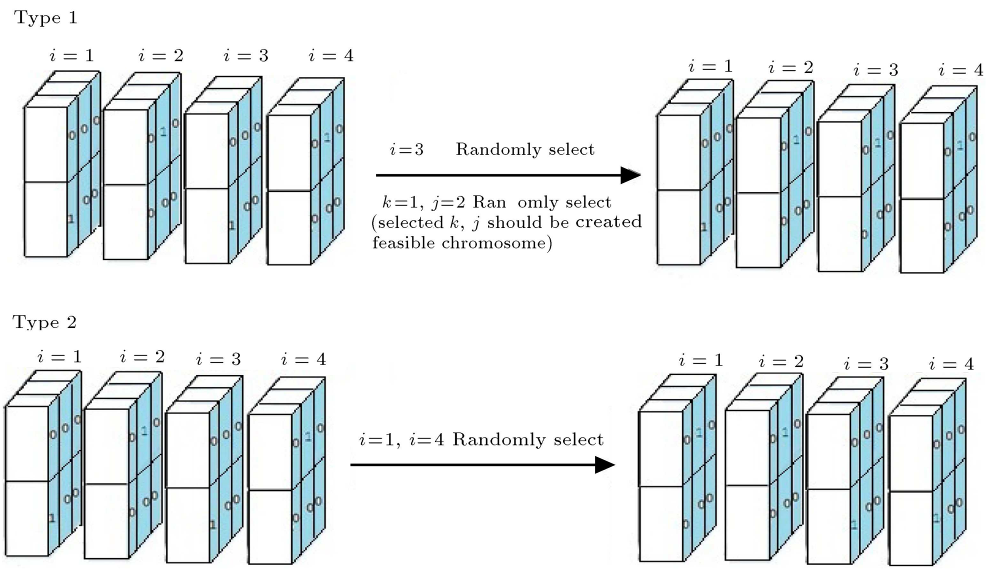

Figure 4. Mutation in the first layer (mutation was performed simultaneously in two layers).

perform the selection function, and the elite strategy was chosen in this study. First, the parents and the produced children were merged. Then, values of children's objective functions were calculated. Finally, these chromosomes were sorted according to the objective value and the best chromosomes were selected according to the population size of the next generation.

4.2.2. Simulated annealing

In the early 1980s, Kirkpatric Ketal (1983) [54] and, dependently, Cemy (1985) [55] introduced the concept of annealing in combinatorial optimization. Simulated Annealing (SA) is a random-search technique, which exploits an analogy between the annealing process (a process in which a metal cools and freezes into a minimum energy crystalline structure) and the search for a minimum in a more general system. The algorithm is as follows:

1. Generate an initial solution randomly and initialize the temperature parameter ($T_0 = 35$);
2. Evaluate fitness of the initial solution (z);
3. Move the initial solution randomly to a neighboring solution;
4. Evaluate fitness of the new solutions (z');
5. Accept the new solution if (i) $z' \leq z$; (ii)$z' \geq z$ with acceptance probability $p = exp(-\frac{\Delta z}{T})$;
6. Decrease temperature with $\alpha = 0.49$ rate.

In this algorithm, there are two loops: internal loop (sub-iteration = 15) for search neighbors of a solution in the same temperature (form stage 3 to 5), and external loop (iteration = 1500) for decreasing temperature. Also, to create neighbor, the mutation operation in GA is used.

5. Results and discussion

Parameter values were used for solving the model listed in Table 1. As shown in Table 2, the sample problems with different dimensions were used to solve the model with GAMS software (win 32, 24.1.2). For each size, three examples with different parameters

Table 1. Parameters and values.

Parameters	Values
D_i	Uniform (350-1400)
b_i	Uniform (50-100)
di_{ik}	Uniform (1-150)
P_{jk}	Uniform (35000-70000)
μh_i	Uniform (5-10)
μk_i	Uniform (75-300)
μs_i	Uniform (15-20)
μc_j	Uniform (0.05-0.3)
μf_{jk}	Uniform (50000-100000)
μr_{ijk}	Uniform (0.75-3)
t_{ijk}	Uniform (425-1700)
$\sigma^2 h_i$	Uniform (1-9)
$\sigma^2 k_i$	Uniform (25-225)
$\sigma^2 s_i$	Uniform (1-16)
$\sigma^2 c_j$	Uniform (0.0001-0.01)
$\sigma^2 f_{jk}$	Uniform (100000-400000)
$\sigma^2 r_{ijk}$	Uniform (0.01-025)

Table 2. Sample problems with different dimensions.

Sample problem	i	j	k	Sample problem	i	j	k
1	1	2	3	8	2	3	5
2	1	2	4	9	2	4	5
3	1	2	5	10	2	2	5
4	1	3	5	11	3	4	5
5	1	4	5	12	4	2	2
6	2	2	4	13	4	3	2
7	2	3	4	14	4	4	5

Table 3. Results of sample problems solved with the GAMS.

Sample problem	Z1		Z2		CPU time	
	Lp-metric	Goal attainment	Lp-metric	Goal attainment	Lp-metric	Goal attainment
1	78369.20	78697.18	201432.54	201070.76	12.00	0.56
	75381.67	73559.14	212578.88	224323.98	22.54	0.55
	77078.28	75448.41	176402.33	187258.95	3.68	0.55
2	62573.05	102072.43	263699.00	222953.83	8.38	0.64
	56810.29	84869.33	307955.43	246879.21	14.35	0.50
	66110.07	65413.24	211089.47	217681.99	12.25	0.23
3	76223.75	74808.98	248822.61	256845.31	6.07	0.48
	93058.09	89989.59	217589.47	238783.99	5.40	0.76
	73882.59	72144.21	129470.59	146029.27	8.27	1.00
4	61897.98	81583.77	355635.65	295536.59	5.04	1.40
	55727.25	56358.74	229099.54	227986.23	2.67	0.27
	84378.08	82747.18	210698.08	234744.31	10.62	1.64
5	65822.17	67678.35	221625.42	218704.99	12.71	2.29
	57347.17	76940.28	157334.02	151992.61	8.99	3.29
	74451.73	73146.80	227127.30	235993.92	13.81	2.51
6	80884.53	99706.93	464885.53	421627.99	9.88	3.01
	88378.05	86944.41	426118.90	438370.60	19.25	2.62
	77983.60	77252.66	338361.24	343318.83	7.92	7.27
7	88554.12	88442.90	382064.04	382590.13	14.60	3.34
	71868.39	85190.35	321585.63	311754.30	7.21	6.19
	67813.34	67276.63	339081.46	342627.05	14.06	3.11
8	74795.94	78480.46	323345.46	311931.54	7.38	2.72
	83458.47	97864.26	414081.58	355688.73	8.36	5.20
	62580.79	70956.41	339957.21	326584.42	10.78	4.51
9	65279.95	78734.37	402703.93	341300.62	15.40	9.28
	64500.04	92920.73	64500.04	271530.03	14.96	7.99
	84421.85	83068.17	260279.55	280344.47	14.60	6.15
10	91241.51	88457.49	253907.17	276414.50	17.75	2.92
	86501.53	101732.42	386941.23	331216.12	9.44	2.34
	80932.70	79857.07	247525.84	262327.25	1.89	0.50
11	81553.46	81948.93	401917.11	399674.35	29.47	18.33
	81952.34	112951.85	482179.51	425345.19	32.46	22.54
	88288.06	86744.63	402062.76	414572.92	35.12	19.64
12	103905.62	102545.93	467408.13	477137.12	12.78	0.52
	75428.12	76452.68	483032.76	476819.06	14.85	6.07
13*	78413.44	119397.58	563847.56	513860.43	29.94	84.07
	77655.55	78885.29	552931.62	544183.62	26.57	5.57
14*	86073.84	120078.02	602041.31	539802.79	26.16	6.47
	85007.38	84693.62	442757.04	445505.45	9.63	5.51

* GAMS software could not solve the sample problems by changing the parameters; for this reason, only two examples were solved.

were solved. Table 3 shows the results of the first and the second objective functions and CPU times in two Goal Attainment and Lp-metric techniques. The Goal Attainment and Lp-metric techniques are compared with using $Z1$, $Z2$, and CPU time criteria to find which technique is better. For this purpose, SAW and TOPSIS methods are used.

One of the best models of MADM (Multiple-Attribute Decision Making) is TOPSIS (Technique for Order-Preference by Similarity to Ideal Solution)

Table 4. Decision matrix.

	$Z1$	$Z2$	CPU time
Lp-metric	76579.08	326514.79	13.82
Goal attainment	84513.88	321572.14	6.80

Table 5. Results of SAW and TOPSIS methods.

	Lp-metric		Goal attainment
SAW	0.82	$\leq$	0.96
TOPSIS	0.13	$\leq$	0.24

method. In this method, I alternatives are evaluated by J criteria. TOPSIS technique is based on the concept that the selected alternative should have the farthest distance from ideal negative solution (worst possible manner) and nearest distance from ideal positive solution (best possible manner). SAW is a simple scoring method, which is another method of MADM. The SAW method is based on the weighted average.

Table 4 shows decision matrix. Weights of the three criteria were assumed to be equal. After calculation, the results of the SAW and TOPSIS show that goal attainment is better than in Lp-metric technique, see Table 5.

By increasing the size of the problems, GAMS software is not able to solve them. For this reason, we used genetic algorithm and simulated annealing (explained above) and solved them with Matlab software (R2013a).

For validation of genetic algorithm and simulated annealing, several sample problems with small sizes were solved by GAMS software, GA, and SA. Then, the results were compared, as shown in Tables 6 and 7. The results show that the solution for the first and second objective functions ($Z1$ and $Z2$) in three techniques (individual optimization, Lp-metric, goal attainment) is very small. Thus, the designed algorithms are valid.

Table 8 shows 30 problems with different dimensions used to solve the model with meta-heuristics and Matlab. Each problem was solved three times and mean of values was considered. Table 9 shows the results of $Z1$, $Z2$, and CPU time for solving the problems with genetic algorithm and simulated annealing for two Lp-metric and goal attainment MCDM techniques.

As an illustrative example, the results for the twenty-fifth sample problem are presented. In this sample problem, fifteen plants/stores, eight potential suppliers, and seven potential locations have been considered. After solving the model with genetic algorithm and goal attainment approach, these results were obtained. The third supplier is established in the seventh location and all of the plants/stores are

Table 6. Results of the first objective function ($Z1$) in GA and SA validations.

S.P	Individual				
	GAMS	GA	SA	GA % gap	SA % gap
6	65303.6	65303.6	65305.6	0	0
	63073.9	63073.8	63074.6	0	0
7	59256.1	59258.6	59258	0	0
	63802.6	63802.8	63805.1	0	0
8	58890	58890.5	58890	0	0
	60622.6	60622.6	60624.2	0	0
9	57116.5	57116.5	57120	0	0.01
	56909.4	56909.4	56910.2	0	0
10	69805.2	69805.2	69806.3	0	0
	63802.6	63802.8	59152.9	0	-7.29
S.P.	**Lp-metric**				
	GAMS	GA	SA	GA % gap	SA % gap
6	72524.9	72479.4	72722.8	-0.06	0.27
	90108.6	90113.1	90585.5	0	0.53
7	82903.4	82646.9	76326.4	-0.31	-7.93
	65147.3	77360.2	65985.4	18.75	1.29
8	63766.2	64612.7	64476.2	1.33	1.11
	64253.1	64261.3	64171.4	0.01	-0.13
9	62323.9	62452.1	62645.3	0.21	0.52
	70137.9	70978.9	70781.7	1.2	0.92
10	75131.4	75236.6	75107	0.14	-0.03
	64711.8	64727.7	64136.3	0.02	-0.89
S.P.	**Goal attainment**				
	GAMS	GA	SA	GA % gap	SA % gap
6	72025.1	72090.8	73022.9	0.09	1.39
	87224.5	87522.8	87792.9	0.34	0.65
7	80829.8	81056.3	81335.1	0.28	0.63
	70719.2	66368.9	74478.3	-6.15	5.32
8	80719.8	80523.2	80073.9	-0.24	-0.8
	82604.3	82960.5	83097.7	0.43	0.6
9	61732.8	61982.2	62044.9	0.4	0.51
	69860	71672.6	70817.3	2.59	1.37
10	101450.4	101456.3	101830.4	0.01	0.37
	77990.4	78001.9	78138.5	0.01	0.19

Table 7. Results of the second objective function ($Z2$) in GA and SA validations.

S.P	Individual				
	GAMS	GA	SA	GA % gap	SA % gap
6	263996.4	263652.2	263883.5	-0.13	-0.04
	224859.7	224775	225201	-0.04	0.15
7	297429.9	297366.6	297652.5	-0.02	0.07
	250284.3	250692.8	251099.2	0.16	0.33
8	375924.6	374022	378263.2	-0.51	0.62
	244031.5	243705.7	244122.4	-0.13	0.04
9	192738.5	191735.7	192122.5	-0.52	-0.32
	294152.2	288300.9	288496.8	-1.99	-1.92
10	265346.8	265662.1	266534.9	0.12	0.45
	390185.8	390599	391055.8	0.11	0.22
S.P.	Lp-metric				
	GAMS	GA	SA	GA % gap	SA % gap
6	268208.6	268706.7	266947.4	0.19	-0.47
	232161.4	232144.4	230662.9	-0.01	-0.65
7	333543.1	306190.8	336889.7	-8.2	1
	252914.4	252505.1	249254.4	-0.16	-1.45
8	396800.8	440861.6	442117.9	11.1	11.42
	322545.6	322526.5	324197.7	-0.01	0.51
9	194277.8	193389.3	193100.9	-0.46	-0.61
	305486.2	299680.7	301334	-1.9	-1.36
10	344171.4	343998.1	344860.2	-0.05	0.2
	487072.6	487307.5	493349.3	0.05	1.29
S.P.	Goal attainment				
	GAMS	GA	SA	GA % gap	SA % gap
6	270717.9	270457.8	270406.1	-0.1	-0.12
	249010.3	249298.6	248662.1	0.12	-0.14
7	317176.9	317351.5	315807.4	0.06	-0.43
	256162.4	250260	253857.7	-2.3	-0.9
8	406367	395797.6	402874.6	-2.6	-0.86
	266013.2	266044.5	263722	0.01	-0.86
9	197354.8	196602.2	195913.7	-0.38	-0.73
	307102.8	303035.4	300350.7	-1.32	-2.2
10	296992	297293.6	292078.6	0.1	-1.65
	409024.6	409319.6	409411.3	0.07	0.09

Table 8. Sample problems with different dimensions.

Sample problem	i	j	k	Sample problem	i	j	k
1	6	3	2	16	12	6	6
2	6	4	4	17	13	5	4
3	7	4	3	18	13	6	5
4	7	5	5	19	13	7	7
5	8	5	4	20	14	4	3
6	8	6	6	21	14	7	6
7	9	4	3	22	14	8	8
8	9	6	5	23	15	3	2
9	9	7	7	24	15	5	4
10	10	5	4	25	15	8	7
11	10	7	6	26	15	9	9
12	10	8	8	27	16	3	2
13	11	4	3	28	16	4	3
14	11	5	5	29	17	4	3
15	12	5	4	30	18	5	4

allocated to this supplier. Capacity of supplier 3 at site 7 (P3,7) is equal to 48259 and order quantity for each supplier is, respectively, Q1 = 132, Q2 = 207, Q3 = 81, Q4 = 284, Q5 = 142, Q6 = 165, Q7 = 52, Q8 = 229, Q9 = 344, Q10 = 303, Q11 = 44, Q12 = 154, Q13 = 254, Q14 = 252, Q15 = 154. Mean of costs (the first objective function) is $Z1 = 221739.5$, variance of costs (the second objective function) is $Z2 = 1605303$, and CPU time is 1133 sec.

To compare the performance of two algorithms, we used $Z1$, $Z2$, and CPU time criteria (Lp-metric and goal attainment techniques were compared separately). We used TOPSIS and SAW methods and statistical comparison in this section.

Tables 10 and 11 show decision matrices for the two techniques. Weights of the three criteria were assumed to be equal. The results show that in both techniques, simulated annealing is better than genetic algorithm, see Tables 12 and 13. We used T-test with P-value = 0.05 for statistical comparisons and the calculations were performed with the SPSS20 software. The results showed that the means of $Z1$ and $Z2$ at two meta-heuristics did not have significant difference (sing = 0.503, 0.783 for Lp-metric and sing = 0.834, 0.983 for goal attainment), but the means of CPU time had a significant difference (sing = 0 for both Lp-metric and Goal attainment), see Tables 14 and 15.

The amount of CPU time in simulated annealing is less than that in genetic algorithm and this criterion plays a very important role in excellence of simulated annealing in the genetic algorithm. The comparisons between $Z1$, $Z2$, and CPU time for SA and GA in each technique are presented in Figure 5.

Table 9. Results of sample problems solved with the meta-heuristic and Matlab software.

	Lp- Metric						Goal attainment					
	Genetic algorithm			Simulated annealing			Genetic algorithm			Simulated annealing		
S.P.	*Z*1	*Z*2	CPU time	*Z*1	*Z*2	CPU time	*Z*1	*Z*2	CPU time	*Z*1	*Z*2	CPU time
1	111316	666199.8	352	111601.8	686948.6	43	116802.8	658919.4	296	120452.3	659677.7	47
2	85350.56	815663.2	357	85241.09	831163.7	44	116988.3	667219.8	412	123321.7	672362.9	41
3	120121.6	1004373	258	120173.4	1031606	41	151668.2	841390.2	380	156832.3	829730.9	44
4	92161.37	1089152	296	99823.35	1075225	49	147713.6	950962.6	300	149192	951025.2	48
5	107088.2	1103056	310	107348.7	1143167	52	121556.3	1017019	323	126216.9	1011673	49
6	106881.2	981270.3	345	108471.7	980949.9	56	148380.6	871596.6	365	146533.9	868391.6	58
7	114236.5	1148340	533	113707.3	1190270	97	120401.9	1147627	522	122358.1	1146639	98
8	106972.3	1086426	438	112783.6	1110021	57	149785.3	973248.6	365	158741.8	980148.3	60
9	105602.1	952799.2	450	105997.5	979744.5	75	165677.7	898789.3	437	159552.6	899634	62
10	120436.4	1591069	640	125246	1539498	111	157882.1	1324413	669	158641.8	1321445	115
11	120959.8	1555807	465	123646.3	1568916	64	151849.7	1342203	519	163703	1395016	65
12	106176	990601	507	106720.9	1009228	76	172929.5	977184	501	134594.9	948246.5	71
13	128468	1034148	342	129079	1062740	52	139982	997897.7	337	144747.6	998636.1	53
14	132887.4	1479758	630	143940.5	1414000	63	158692.3	1337603	787	179592.6	1375389	116
15	131788	1409446	695	133146.8	1446710	127	144858.2	1401054	803	140849.5	1404656	93
16	128415.1	1678481	850	136381.9	1611856	66	231897.9	1414346	727	182154.1	1361938	67
17	144393.1	1218640	697	148052.4	1238450	71	161078.4	1116197	773	172749	1131822	79
18	140820.8	1391234	439	156850.2	1300088	68	175483.8	1122810	439	184015.9	1106218	68
19	128462.3	1739833	965	124071.1	1879146	147	227399.8	1601900	834	205244.4	1559139	118
20	122735.6	1437541	800	126707.7	1432979	126	138735.1	1265117	811	154096.3	1296829	127
21	136942	1832377	935	155138.6	1761580	160	160503	1634610	1059	169965.7	1626426	152
22	133153.8	1569222	1165	128853.1	1755144	188	210568.5	1503785	1189	181660.6	1466525	188
23	154889.6	1897515	680	159258.7	1892494	64	221593.9	1612890	676	235486.3	1623305	60
24	149931.6	1967127	572	157951.2	1942434	87	209214.1	1583165	570	205501.8	1589100	73
25	155216.7	1854720	1105	154433.1	2083120	181	221739.5	1605303	1133	217777.6	1632670	140
26	143791.5	1735830	1138	151822.5	1711112	113	207597.3	1432004	1192	212644.5	1467300	168
27	156875.5	1845484	509	161153.3	1928905	101	181292.2	1667965	441	191627.5	1691505	106
28	146780.6	1975734	744	162321.9	1873334	98	261372.9	1794488	860	188109.8	1722377	74
29	163226.5	2075764	650	163767	2322417	71	206382.2	1817243	700	217816	1848579	79
30	172097.1	2120824	1089	170051.9	2365483	143	199939.1	1941822	767	217709.9	1998395	152

Table 10. Lp-metric decision matrix.

	*Z*1	*Z*2	CPU time
Genetic algorithm	128939.24	1441614.55	631.82
Simulated annealing	132791.41	1472291.00	89.76

Table 11. Goal attainment decision matrix.

	*Z*1	*Z*2	CPU time
Genetic algorithm	172665.54	1284025.74	639.52
Simulated annealing	170729.67	1286159.96	89.08

Table 12. Results of SAW and TOPSIS methods for Lp-metric technique.

	Genetic algorithm		Simulated annealing
SAW	0.71	$\leq$	0.97
TOPSIS	0.03	$\leq$	0.97

Table 13. Results of SAW and TOPSIS methods for Goal attainment technique.

	Genetic algorithm		Simulated annealing
SAW	0.70	$\leq$	0.99
TOPSIS	0.001	$\leq$	0.998

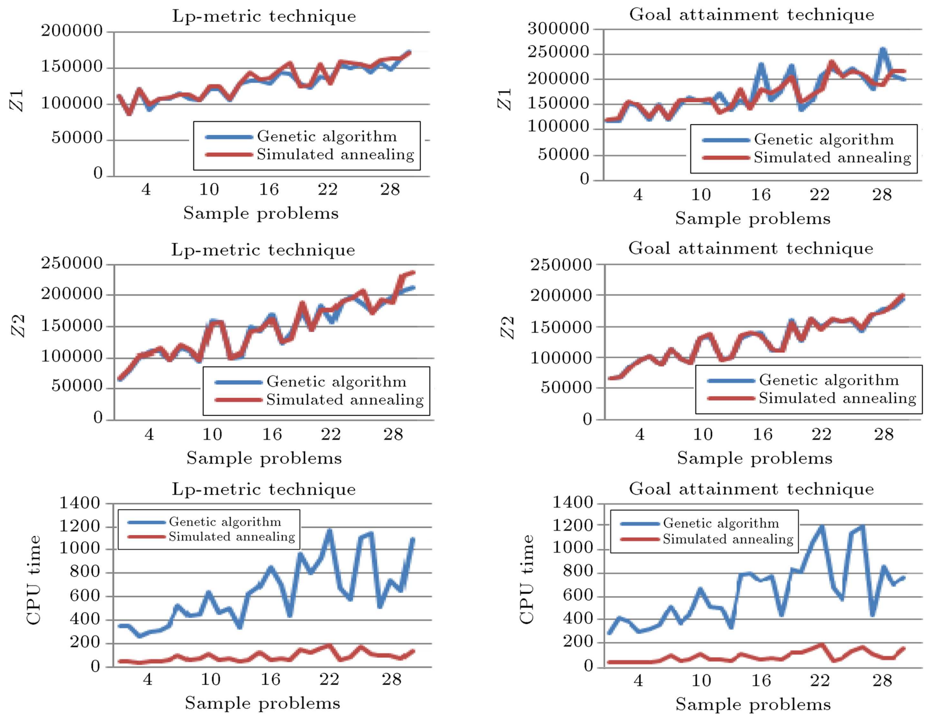

Figure 5. Comparison between the values of $Z1$, $Z2$, and CPU time for genetic algorithm and simulated annealing.

Table 14. Results of T-test for comparison genetic algorithm and simulated annealing (Lp-metric technique).

		Levene's test for equality of variances		T-test for equality of means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean difference	Std. error difference	95% confidence interval of the difference: Lower	Upper
$Z1$	Equal variances assumed	0.682	0.412	-0.673	58	0.503	-3852.16727	5720.10198	-15302.1954	7597.86088
	Equal variances not assumed			-0.673	57.69	0.503	-3852.16727	5720.10198	-15303.5065	7599.17198
$Z2$	Equal variances assumed	0.155	0.696	-0.277	58	0.783	-30676.45294	110629.6652	-252125.788	190772.882
	Equal variances not assumed			-0.277	57.656	0.783	-30676.45294	110629.6652	-252153.904	190800.998
CPU time	Equal variances assumed	43.69	0	10.83	58	0	542.05471	50.06625	441.83621	642.2732
	Equal variances not assumed			10.83	30.369	0	542.05471	50.06625	439.85781	644.2516

Table 15. Results of T-test for comparison genetic algorithm and simulated annealing (goal attainment technique).

		Levene's test for equality of variances		T-test for equality of means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean difference	Std. error difference	95% confidence interval of the difference: Lower	Upper
$Z1$	Equal variances assumed	1.226	0.273	0.211	58	0.834	1935.86234	9174.76957	-16429.4343	20301.159
	Equal variances not assumed			0.211	56.267	0.834	1935.86234	9174.76957	-16441.4861	20313.2108
$Z2$	Equal variances assumed	0.004	0.948	-0.023	58	0.981	-2134.22001	91146.88006	-184584.523	180316.083
	Equal variances not assumed			-0.023	57.992	0.981	-2134.22001	91146.88006	-184585.041	180316.601
CPU time	Equal variances assumed	54.37	0	11.06	58	0	550.43964	49.75211	450.84997	650.02932
	Equal variances not assumed			11.06	30.298	0	550.43964	49.75211	448.87421	652.00508

6. Conclusions and suggestions

In this paper, a novel model for integrating the facility (supplier) location-allocation problem and supplier selection-order allocation for a two-echelon supply chain (supplier(s) and plant(s)/store(s)) was proposed. This model also determined the inventory policy for each plant/store (when and how much to order at each plant/store). Therefore, the proposed bi-objective mixed-integer nonlinear programming was solved using two MODM methods by GAMS software for small-size and meta-heuristic algorithms (genetic algorithm and simulated annealing) by Matlab software for medium and large sizes. Numerical examples with different sizes were provided to demonstrate the application and to compare the performances of the investigated solution methods in terms of mean and variance of the overall supply chain costs and required CPU time. The results showed that goal attainment had better performance than Lp-metric technique for small sizes. For large sizes, the comparisons showed that the means of objective functions ($Z1$ and $Z2$) obtained from GA and SA did not have significant differences, but the mean of SA-CPU time was significantly less than that of the GA-CPU time. Thus, the simulated annealing had better performance than the genetic algorithm.

Design of a Model with fuzzy or stochastic demand or use of De Novo programming to determine the capacity of the supplier are suggested for future research. Moreover, NSGA-II, NRGA, and MOPSO algorithms can be used to solve the model.

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