Heuristic Methods for the Capacitated Location-Allocation Problem with Stochastic Demand

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Abstract**—**The proper number and appropriate locations of service centers can save cost, raise revenue and gain more satisfaction from customers. Establishing service centers is high-cost and difficult to relocate. In long-term planning periods, several factors may affect the service. One of the most critical factors is uncertain demand of customers. The opened service centers need to be capable of serving customers and making a profit although the demand in each period is changed. In this work, the capacitated location-allocation problem with stochastic demand is considered. A mathematical model is formulated to determine suitable locations of service centers and their allocation to maximize total profit for multiple planning periods. Two heuristic methods, a local search and genetic algorithm, are used to solve this problem. For the local search, five different chances to choose each type of moves are applied. For the genetic algorithm, three different replacement strategies are considered. The results of applying each method to solve numerical examples are compared. Both methods reach to the same best found solution in most examples but the genetic algorithm provides better solutions in some cases.

Keywords**—**Location-allocation problem, stochastic demand, local search, genetic algorithm.

I. Introduction

THE classical location-allocation problem combines two well-known problems: the facility location problem and the allocation problem. Both locations of facilities and their allocation are considered simultaneously. This problem was introduced by Cooper in 1963 [1]. In his work, the number of sources and the location and capacity of each source were determined from the given sets of destination locations, requirements and shipping costs. The goal was to obtain the minimum total cost of operating sources and supplying destinations. After that there have been various aspects, assumptions, restrictions and applications considered in the location-allocation problem.

For the potential locations or candidates of facilities, they can be classified as: discrete locations and continuous locations. The discrete locations mean that the potential locations are already fixed. On the other hand, the continuous locations are considered as Cartesian coordinates. Therefore, the potential locations can be anywhere in the xy-plane. Many studies, including this work, deal with the fixed potential locations. Nevertheless, Goodchild [2] studied retail site selection on a continuous space. He took customer behaviors, competitive locations and cost-effectiveness into consideration. Gokbayrak and Kocaman [3] also focused on continuous locations with limited distance. Brimberg and Salhi [4] also considered the continuous locations but they used dependent fixed cost. Mousavi and Niaki [5] applied stochastic locations and fuzzy demand to their location-allocation problem.

The studies related to the location-allocation problem can be classified according to the number of layers or levels of the networks. Each layer represents each supply chain actor in the network such as plants, distribution centers, collection centers and customers. In general, networks contain only two layers: supplier's facilities and customers' locations [1]-[5]. Therefore, resource allocation is decided between facilities and customers. However, the supply chain networks may be complicated in real-life problems. They may consist of more than two layers. Fard and Hajaghaei-Keshteli [6] studied a tri-level location-allocation problem for a forward/reverse supply chain. In their problem, products were passed through manufacturers, distribution centers, customer zones and recovery centers.

Besides single-period planning, which the locations and allocation of facilities are decided once for the whole plan, multi-period planning is also applied in the location-allocation problem. Khodaparasti et al. [7] considered locating facilities and assigning customers in multiple periods. Moreover, the opened facilities and assigned customers can be changed in each period to deal with uncertain demand. Similarly, multi-period planning was considered by Ghasemi et al. [8]. They proposed the mixed-integer programming for a multi-echelon relief logistic supply chain. Their model was used for setting temporary centers and allocating available resources after disaster which was flexible and suitable to the real situations in each period.

Some studies on the location-allocation problem take more than one objective functions into consideration. Instead of minimizing only the total cost, Ghasemi et al. [8] minimized both the total cost for establishing relief facilities and the amount of shortage relief supplies. Baharmand et al. [9] proposed the model with two objective functions minimizing total logistics costs and response time for the immediate aftermath of sudden-onset disasters. The model presented by Jenkins et al. [10] contained three objective functions, including maximizing total expected covered demand, minimizing the number of located facilities and minimizing the number of facility relocations.

One of the most important factors to make a decision for the location-allocation problem is demand. If the amount of demand of each customer is constant or known in advance, the plans for opening facilities and their allocation can be simply

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made even in the long term. If the demand is known, it is called deterministic demand. In reality, the amount of demand is not deterministic. The amount of demand of each customer is usually not constant. It may be changed over time or affected by several factors such as product price, income, customer preference and satisfaction and expectation of changes of product price in the future. However, the factors that influence demand may vary with different types of products and services. Welble et al. [11] studied the factors affecting school milk demand in primary schools in Germany. Benjamin and Lin [12] investigated the factors that affected electricity demand in the nonmetallic mineral product industry of China. Inganga et al. [13] examined the factors affecting customer demand of financial services offered by commercial banks in Nairobi.

It is a challenge to estimate or predict customer demand accurately. Some studies estimated the demand by applying forecasting methods. Cano-Belmán and Meyr [14] applied forecasted demand to their multi-period allocation models for multi-stage customer hierarchies. New approaches based on machine learning [15] and data mining [16] were also used to predict customer demand. The location-allocation problems with fuzzy demand were studied by Mousavi and Naiki [5] and Ghodratnama et al [17]. A number of studies on the location-allocation problem considered stochastic demand. In these cases, the demand was uncertain but its distribution was known. Yan et al. [18] determined the sizes of rental bike locations based on stochastic demand. Different distributions of demand were considered in the location-allocation problem. Wang et al. [19] studied a two-echelon supply chain and used lognormal distributed demand. Alzadeh et al. [20] applied the demand with Bernoulli distribution. The distribution of user demand arrival and general service time of immobile servers studied by Vidyarthi and Jayaswal were Poisson [21].

The location-allocation problem has been applied to various real-life problems. Setting different types of facilities contains different restrictions. Özceylan et al. [22] determined the new locations of pharmacy warehouses and their coverage area. Kaveh and Mesgari [23] applied the location-allocation problem to set urban emergency centers. Sarker et al. [24] found the optimal number and locations of storage hubs for biogas production. The location-allocation problem was applied to end-of-life vehicle recovery in a reverse supply chain by Lin et al. [25]. Recently, the location-allocation problem is widely applied to humanitarian supply chain management. It helps to obtain suitable plans, including setting temporary facilities and allocating resources, in emergency situations in a short time. The evacuation planning for disasters such as earthquake in different countries were considered [8]-[10]. Barzinpour and Esmaeilli [26] were interested in setting relief locations for urban disaster management and considered multiple objectives. Sharma et al. [27] studied the dynamic temporary blood facility location-allocation during post-disaster period.

Applying the location-allocation problem to a real problem makes it complicated and difficult to obtain the optimal solution in reasonable time. Therefore, a novel method called a heuristic method was proposed to find a near-optimal solution in a short time. Various heuristic methods were developed and applied to solve the location-allocation problems. Ghasemi et al. [8] modified the genetic algorithm and particle swarm optimization for solving the multi-objective problem. Wang et al. [19] applied the genetic algorithm to their two-echelon location-allocation problem. Kaveh and Mesgari [23] proposed a new heuristic method and compared its performance with other heuristic methods, including biogeography-based optimization, genetic algorithm and particle swarm optimization. Their method provided better results to determine the locations that maximized population coverage. Lin et al. [25] improved an artificial bee colony optimization to find the solutions of their location-allocation problem for end-of-life vehicle recovery network. Their method was compared with other heuristic methods by solving the real problem.

The remainder of this paper is organized as follows. Section II describes the characteristics and assumptions of this problem. Section III presents a mathematical model for the capacitated location-allocation problem with stochastic demand. Section IV explains the heuristic methods used in the work. Section V shows results of applying the heuristic methods to numerical examples. Finally, Section VI provides the conclusion and suggestion of this work.

II. Problem Statement

This work considers a single echelon supply chain network in multiple planning periods. There are potential locations of service centers and customers. The locations of customers and potential locations are known. An example of the network of the location-allocation problem considered in this work is given in Fig. 1. Fig. 1 (a) shows the locations of potential service centers and customers in the network before choosing the suitable service centers. The demand of each customer in each period is stochastic. Each potential location of service center has limited capacity. The opened service centers are selected from set of potential locations as demonstrated in Fig. 1 (b). Each customer is served by only one opened service center as can be seen in Fig. 1 (c).

This location-allocation problem contains locating service centers and assigning customers to each opened service center to maximize the total profit of the provider. Note that each service center cannot be relocated. When it is opened, it has to serve customers for the whole planning period. Moreover, shortage is allowed and there is no backorder. The demand of some customers may not be fulfilled in some periods if the maximum capacities of the service centers are already reached. These customers will be served only some of their demand and the provider needs to pay the penalty cost for the amount of unsatisfied demand. The amount of unsatisfied demand of customers is considered as lost sales. It cannot be served in the succeeding periods. Moreover, the number of opened service center is fixed. The optimal number of opened service centers can be found by varying this number.

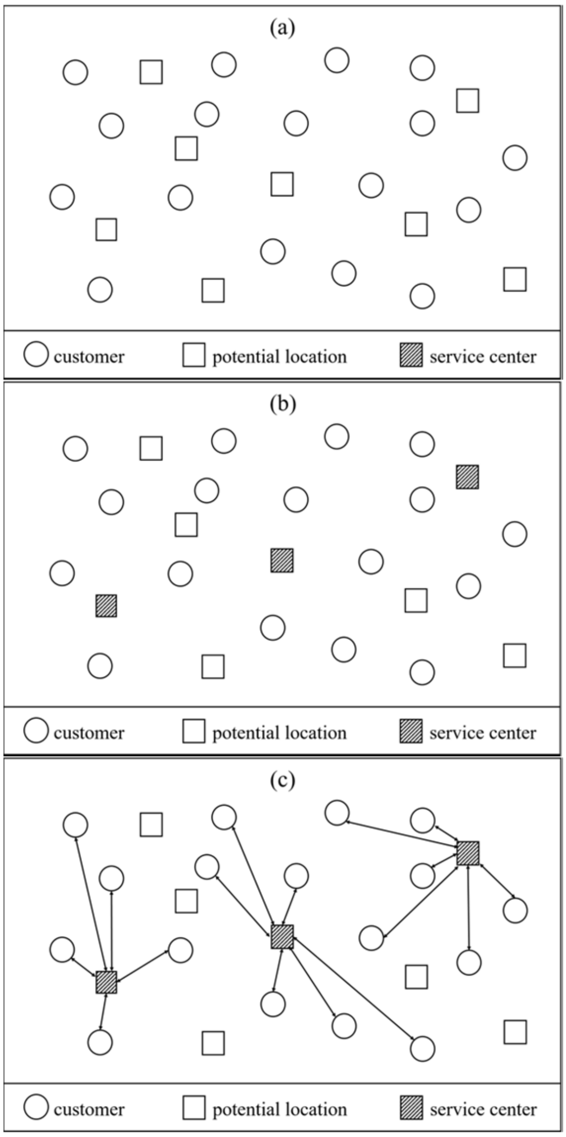

Fig. 1 An example of the location-allocation problem

III. Mathematical Formulation

According to the characteristics and assumptions of the location-allocation problem given in Section II, a mathematical model can be formulated by using the following notations.

A. Set and Indices

- I: set of potential locations of service centers indexed by i,
- J: set of customers indexed by j,
- T: set of planning periods indexed by t.

B. Parameters

- N: the number of opened service centers,
- Q_i: the maximum capacity of potential location i,
- D_{jt}: demand of customer j during planning period t,
- C_{ij}: transportation cost for traveling between potential location i and customer j,
- F_i: fixed cost for opening service center i,
- R: revenue of covered demand (per unit),
- P: penalty cost of uncovered demand (per unit).

C. Decision Variables

$$y_i = \begin{cases} 1, \text{ if potential location } i \text{ is opened,} \\ 0, \text{ otherwise,} \end{cases}$$

$$x_{ij} = \begin{cases} 1, \text{ if service center } i \text{ serves customer } j, \\ 0, \text{ otherwise.} \end{cases}$$

D. Mathematical Model

Maximize

$$R\sum_{t\in T}\sum_{i\in I}\min\left\{\sum_{j\in J}E\left[D_{jt}\right]x_{ji}, Q_i\right\} - P\sum_{t\in T}\sum_{i\in I}\max\left\{\left(\sum_{j\in J}E\left[D_{jt}\right]x_{ji}\right) - Q_i, 0\right\} - \sum_{i\in I}F_i y_i - T\sum_{i\in I}\sum_{j\in J}C_{ij}x_{ij} \quad (1)$$

subject to

$$\sum_{i\in I} y_i = N \quad (2)$$

$$\sum_{i\in I} x_{ij} = 1 \qquad \forall j \in J \quad (3)$$

$$x_{ji} \le y_i \qquad \forall i \in I, \forall j \in J \quad (4)$$

$$y_i \in \{0,1\} \qquad \forall i \in I \quad (5)$$

$$x_{ij} \in \{0,1\} \qquad \forall i \in I, \forall j \in J \quad (6)$$

The objective function (1) is to maximize the total profit during the whole planning periods. It is computed from the revenue obtaining from serving customers' demand subtracting by the penalty cost of uncovered demand, fixed opening cost and transportation cost between customer and service center. The term $E\left[D_{jt}\right]$ represents the expectation of demand of customer j in period t. The number of opened service centers is limited as shown in Constraint (2). Each customer is served by only one service center as written in Constraint (3). Constraint (4) guarantees that each customer can be served by the service center that is opened. The possible values of decision variables are given in Constraint (5) and Constraint (6).

IV. Heuristic Methods

According to the complexity of optimization problems, the exact method may not be capable of finding the optimal solution in polynomial time. Consequently, heuristic methods were developed. Starting with an initial feasible solution, we find a new feasible solution by using any methods. If the new one is better than the current one, we keep it as the current solution. Then we continue to search for a new solution until reaching stopping criterion. Although the heuristic method cannot guarantee the optimality, they are widely used to find reasonable solution within a short time. This work applies two well-known heuristic methods, the local search and the genetic algorithm, to solve the location-allocation problem.

A. Local Search (LS)

LS is a single-solution based heuristic method. Each time only one solution is considered. It searches for a new solution within a neighborhood of the current solution. Since the location-allocation problem contains two parts, including determining the locations of service centers and allocation, two types of moves related to each part are applied to obtain new solutions. They are called Relocation and Reallocation. The detail of each type is given as follows:

- *Type 1: Relocation:* An opened service center is randomly selected to be closed and a potential location is randomly selected to be opened as a service center.
- *Type 2: Reallocation:* A customer is randomly selected and then randomly assigned to another opened service center.

The procedures of LS used in this work are:

Step1. Generate an initial feasible solution of the problem and compute its total profit.
Step2. Choose type of move. Given a probability to choose Type 1 is α. (Then the probability to choose Type 2 is 1-α.)
Step3. Find a new candidate of solution by applying the selected type of move and compute its total profit.
Step4. If the candidate gives more total profit, keep it as the current solution.
Step5. Check the stopping criterion. If it is met, terminate the algorithm. Otherwise, repeat Step 2.

B. Genetic Algorithm (GA)

GA is a population-based heuristic method. Each time a set of solutions called population is considered. Based on concepts of evolution theory, the GA was first introduced by Halland [28]. The GA consists of six steps, including initialization, fitness evaluation, parent selection, crossover, mutation and replacement as shown in Fig. 2.

The GA begins with initialization. First, a set of initial feasible solutions is generated. The population size is denoted by NP. Each solution or individual of the population is evaluated for its fitness. The fitness value is used to determine how good or fit of each individual to the circumstance. The more fitness value, the more chance is to reproduce offspring or to survive in the next generation. In this work, the fitness value was computed from the objective function (total profit) of the location-allocation problem. Then, two individuals are selected to be parents and reproduce offspring. This work used tournament selection. Given tournament size k, then, k individuals are randomly chosen from the current population. The best two individuals are selected from the tournament.

A pair of selected parents provides a pair of offspring by reproduction or crossover. The characteristics or information of parents are passed through their offspring. This work applied uniform crossover because each characteristic will pass through each offspring according to a chance. An example of applying uniform crossover is demonstrated in Fig. 3. By setting the crossover probability CR ($0 < CR < 1$), the characteristic of Parent 1 will transfer to Offspring 1 if a random chance is less than or equal to CR.

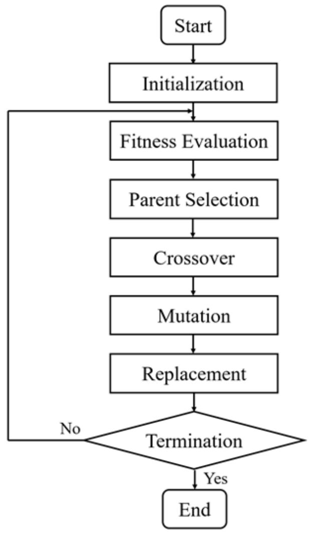

Fig. 2 The flowchart of the GA

Later, the offspring obtained from crossover may be changed some of their characteristics. This is called mutation. Given the mutation probability, MU ($0 < MU < 1$). Each characteristic will be changed if a random chance is less than or equal to MU. After mutation, all offspring and parents are pooled together to choose NP individuals that will survive and act as parents in the next generation. The current population will be replaced with these chosen individuals. The algorithm will be repeated as the flowchart in Fig. 2 until it reaches the stopping criterion.

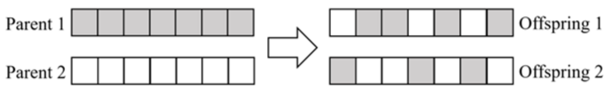

Fig. 3 An example of applying uniform crossover

There are many strategies for the replacement procedure. This work considered three types of replacement strategies as follows:

- Strategy 1: *Remove Oldest:* The oldest individual is removed from the pool.
- Strategy 2: *Remove Randomly:* A half of individuals in the pool are removed by random.
- Strategy 3: *Conservative:* The 2-tournament selection is applied to remove individuals from the pool.

V. Numerical Examples

The proposed mathematical model for the capacitated location-allocation problem in Section III was solved by using the heuristic methods presented in Section IV. The numerical examples used in this work were adapted from the instances of Prodhon [29]. Five scenarios with different sizes of problem were considered. The numbers and locations (xy-coordinates) of customers and potential locations of service centers, the maximum capacities in each period and fixed costs of service centers were used from the instances. Twelve planning periods were considered in each example. The demand of each customer in each period, D_{jt}, was assumed to be normal distribution. The demand data applied in the examples were generated from $D_{jt} \sim N(15, 2.5)$. The number of opened service centers were varied from 1 to $|J|-1$, where $|J|$ is the total number of potential locations of service centers. The numbers of customers and potential locations of each scenario are shown in Table I. The maximum capacity of fixed opening cost of service centers for each scenario in Table I is given as intervals if they are not identical.

TABLE I
PROBLEM SIZES AND PARAMETER VALUES OF NUMERICAL EXAMPLES

Scenario	No. of customers	No. of potential locations	Capacity of service centers	Opening cost of service centers
1	20	5	140	[6091, 11961]
2	50	5	[350, 420]	[5029, 13647]
3	100	5	[700, 770]	[41688, 52810]
4	100	10	[420, 560]	[47865, 59082]
5	200	10	[910, 1190]	[71504, 124443]

Both the LS and the GA were implemented by coding in C. All numerical examples were run on a 2.5 GHz Intel Core i5-7200U CPU with 4 GB of RAM and Window 10 Pro. For the LS, the probability that choosing the Relocation move was varied as 0.2, 0.4, 0.6, 0.8 and 1.0. The stopping criteria were set as 200 thousand iterations. For the GA, the population size was 100. The crossover probability was used as 0.9 and the mutation probability was 0.2. The stopping criteria were set as 200 generations or 200 thousand times of function evaluation.

The results of each example were obtained from 50 replications. Table II shows the total profit of the best found solution obtained from the LS and GA in Scenario 1. The names S1, S2 and S3 refer to the replacement strategies, Strategy 1, Strategy 2 and Strategy 3 described in Section VI, respectively. The best value of the total profit obtained from each heuristic method in each case is written in bold. The better value of the total profit compared between the LS and the GA is shown in highlight.

In Scenario 1, the LS and the GA provide the same best found solution in most cases. However, the GA reaches a better solution when opening three service centers as grey highlighted in Table II. Comparing among different parameter values of the LS, using α as 0.6 gives the best result. For different replacement strategies of the GA, S3 or Conservative Strategy provide the best results among other replacement strategies and the LS.

The results of solving the numerical examples in Scenario 2 by the LS and the GA are displayed in Table III. They are similar to the results of Scenario 1 given in Table II in the sense that the GA reaches the better best found solution. Furthermore, the best found solution also obtained from the replacement strategy S3. This is because the Conservative Strategy chose the new parents by applying the tournament selection. It leads to the diversity of the population. Then new characteristics that may be fit to the better solutions can be found by using this strategy.

TABLE II
COMPARISON OF BEST FOUND SOLUTION BETWEEN LS AND GA IN SCENARIO 1

N	**LS**					**GA**		
	α = 0.2	α = 0.4	α = 0.6	α = 0.8	α = 1.0	S1	S2	S3
1	**66,742**	**66,742**	**66,742**	**66,742**	**66,742**	**66,742**	**66,742**	**66,742**
2	**252,876**	**252,876**	**252,876**	**252,876**	**252,876**	**252,876**	**252,876**	**252,876**
3	271,070	271,070	**272,653**	271,936	268,664	269,187	268,664	**274,865**
4	**268,886**	**268,886**	**268,886**	**268,886**	**268,886**	**268,886**	**268,886**	**268,886**

TABLE III
COMPARISON OF BEST FOUND SOLUTION BETWEEN LS AND GA IN SCENARIO 2

N	**LS**					**GA**		
	α = 0.2	α = 0.4	α = 0.6	α = 0.8	α = 1.0	S1	S2	S3
1	**209,481**	**209,481**	**209,481**	**209,481**	**209,481**	**209,481**	**209,481**	**209,481**
2	**672,696**	669,135	669,574	667,007	658,191	658,191	658,191	**673,164**
3	**688,203**	**688,203**	**688,203**	**688,203**	**688,203**	**688,203**	**688,203**	**688,203**
4	**689,417**	**689,417**	**689,417**	**689,417**	**689,417**	**689,417**	**689,417**	**689,417**

The results of Scenario 3 are similar to those of Scenario 1 and Scenario 2. For Scenario 4 and Scenario 5, every replacement strategy of the GA reaches the same best found solution in every example. The LS also gives these best found solutions by some values of α. However, it cannot be concluded the most suitable value of α from these numerical examples.

The LS is easy to implement and takes less running time than the GA. Nevertheless, it may not reach as a good solution as the GA because it may be stuck in a local optimum. Even though the GA is more complicated and takes longer time to find a solution, it can escape from the local optimum.

VI. CONCLUSION

The location-allocation problem aims to find the suitable locations of facilities and their service areas in order to cover the customer demand. It is considered as a NP-hard problem. Even when the demand is deterministic, it is difficult to obtain the optimal solutions, especially for large-scaled problems. This work considered the capacitated location-allocation problem with stochastic demand in multiple planning periods. The goal of locating the facilities called service centers was to obtain the maximum profit during the whole planning periods although the demand is uncertain.

The mathematical model was formulated for the single-echelon multi-period location-allocation problem. The heuristic methods, LS and GA, were applied to solve numerical examples of this problem. Different values of parameters were considered in utilizing the LS. The chance to select each move had an impact on the best found solution. However, there was no remarkable value of chance found in solving these numerical examples. On the other hand, the Conservative replacement strategy applied in GA provided outstanding results compared with other replacement strategies considered in this work.

Comparing two heuristic methods, LS and GA, GA spent longer running time but provided better results. Its best found solutions had higher total profit than those obtained from LS. This derived from the fact that the GA contained some procedures that helped escaping the local optimum. For further work, other heuristic methods may be developed to solve this problem, and also, compare their performance in solving other instances. Moreover, the capacitated location-allocation problem can be applied to several real-life problems and case studies.

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