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Research Article

Two-Layer Location-Routing Problem Based on Heuristic Hybrid Algorithm

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Location-routing problem (LRP) thoroughly considers location allocation problem (LAP) and vehicle routing problem (VRP) which has been an integral part applied in modern logistics. A number of researchers at home and aboard have put forward their views by establishing fine models. On the basis of studying the previous research results by classification, summary, and comparative analysis, this study hence proposes a new solution-fuzzy clustering model and algorithm to resolve two-layer location-routing problem based on a heuristic hybrid algorithm: Designing a hybrid genetic and simulated annealing algorithm (GASA) to optimize the initial value of the fuzzy C-means clustering algorithm (FCM); considering the roving visit characteristics of vehicles to design the path by employing a special VRP problem—the multiple traveling salesman problem (MTSP). Theoretical analysis and experimental results show that the algorithm used in this study has the advantages of fast convergence speed and less iterations, which significantly improve the quality of the initial solution of FCM in LAP, shorten the vehicle patrol cycle in VRP to a great extent, improve the vehicle utilization, and save the vehicle patrol costs. A specific example is programmed by MATLAB to verify the feasibility of this method.

1. Introduction

Location allocation problem (LAP) and vehicle routing problem (VRP) are two essential parts in logistics which are widely used in life and engineering. On the one hand, LAP strategically considers the location of the distribution center, but it fails to include the characteristics of vehicle tours from a tactical aspect, which may easily lead to a larger actual distribution distance. On the other hand, VRP takes the characteristics of vehicle tours into account; however, it does not consider whether the location of the distribution center is reasonable from a strategic view, which will easily result in a high total cost of the entire logistics system [1]. To address both disadvantages arising from LAP and VRP, some scholars have put forward the location-routing solution from the strategic and tactical aspects which comprehensively considers problems of the site selection of distribution center, coverage of distribution services, and vehicle routing optimization, aiming to seek the optimal solution of the entire logistics system by integrating both merits of LAP and VRP. The LRP is an NP-complete problem, and a series of related approximation algorithms have emerged in recent years, so we hope to obtain a satisfactory solution (may not be the optimal solution) with high quality through the approximation algorithm.

In practice, the site selection of the distribution center and the path design of the distribution service are two vital aspects. The site selection is related to the strategic decision made by the logistics enterprises, while the path design concerns their tactical decision. In order to better serve the needs of economic and societal developments, a number of experts and scholars at home and abroad have actively explored the field of LRP and achieved enormous results.

A large number of studies have shown that the overall optimization of positioning, allocation, and path holds the key to solving LRP. Previously, scholars were limited to the study of a single distribution center, employing the total cost function to describe the path cost [2]. By comparing the total cost function and the potential location path cost, Webb pointed out that the path cost cannot be represented by the approximate total cost function at a certain moment [3]. Wang dan et al. also made similar findings in their research [4]. Later on, scholars realized the importance of site decision-making and path coordination. Therefore, many scholars have renewed their research on this matter: Cooper believes that the appropriate location of the distribution center directly affects future transportation costs, so the site selection and the path problem should be integrated for study [5]. Bookbinder seeks to solve LRP by building a nonlinear mixed integer programming model [6]. There are also extensive research studies on LRP in China. Some scholars have established a two-stage planning model to determine the site selection plan [7], customer division, and logistics distribution in terms of recycling and transportation path design [8]; studied multiobjective random LRP in the context of considering a variety of uncertainties [9]; established a three-layer LRP model on the basis of introducing the important parameter of storage cost to the traditional two-layer LRP model; and applied the genetic algorithm to seek a solution [10, 11].

In addition, the study by Tang et al. is noteworthy, who solved the TSP with the asymptotic formulation. The result was approximately equal to the path length in the distribution system, while the time cost was much shorter [12, 13].

For LRP research, there are various common solutions:

The traditional fuzzy C-means clustering algorithm (FCM) is essentially a local optimization algorithm, which is very sensitive to the selection of the initial value and is easy to converge to the local extreme point.

The present single heuristic algorithm also has its shortcomings. For example, genetic algorithms are susceptible to fall into local optimum; simulated annealing algorithm is lacking incomprehensive search ability, etc [14].

The tour feature of vehicles has not been fully utilized.

With regard to the shortcomings of previous studies in these aspects, this study proposes a new solution, namely, the fuzzy clustering model and algorithm to resolve a two-layer location-routing problem based on heuristic hybrid algorithm:

In the first-layer mathematical model (LAP model), the initial value of FCM is optimized by using the genetic simulated annealing algorithm (GASA) [15].

In the second-layer mathematical model (VRP model), the genetic algorithm is used to solve a special VRP problem—the multiple traveling salesman (MTSP) problem [16].

Therefore, this study aims to solve the LRP more effectively by using the above methods.

2. Problem Statement and Model Building

LRP can be defined as follows: a distribution network plans to set up m distribution centers, with available vehicles and n customers. The set of the distribution center is defined as $M = \{M|M = 1, 2, \ldots, m\}$. The set of the available vehicles is defined as $S = \{S|S = 1, 2, \ldots, s\}$. The set of the customers is defined as $N = \{N|N = 1, 2, \ldots, n\}$.

The set of points composed by the distribution center and customers is defined as $V = M \cup N = \{V|V = 1, 2, \ldots, m + n\}$.

The set of edges is defined as $E = \{(m, n)|m, n \in V\}$. Let the distance (Euclidean distance) corresponding to each edge be D_{mn}, and let the distribution cost be C_{mn}. There is no capacity limitation for vehicles and distribution centers.

Each vehicle has only one service path, and the start and end points must be at the same distribution center. Each distribution center can have multiple vehicles to provide service for multiple customers while each customer can only be served once by one vehicle at the same distribution center. The decision variable x_{mns} represents whether the vehicle S accesses the edge (m, n) (yes = 1, no = 0). The decision variable y_{mn} represents whether customer N is within the service range of distribution center M (yes = 1, no = 0).

Fuzzy C-Means (FCM) can be defined as follows: selecting $m\,(2 \leq m \leq n)$ locations for a distribution center and let n data samples be $X = \{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_N\}$. The set of served customers is defined as $\{P_1, P_2, \ldots, P_m\}$. The location of the distribution center is $\{P_1, P_2, \ldots, P_m\}$ Let the similarity classification matrix be U, and let the degree of membership of the n customer to the m distribution center be μ_{mn}.

The dissimilarity between $\mathbf{x}_i$ and e_j is defined as $d(\mathbf{x}_i, e_j)$. Let the characteristic of the sample be p.

Since this paper focuses on shortening the solution time on the basis of optimizing the solution method, only the situation where distance cost is the core factor of site selection will be considered.

2.1. The First Layer of the Mathematical Model. Let the objective function be $J_q(U, e)$, and the maximum value of U is as follows:

$$\min \quad J_q(U, e) = \sum_{i=1}^{m} \sum_{j=1}^{n} \left(\mu_{ij}\right)^q \left(D_{ij}\right)^2. \tag{1}$$

To divide X into m clusters, the following three conditions should be satisfied:

$$\begin{gathered} \mu_{mn}\colon X \longrightarrow [0, 1], \forall m \in M, \forall n \in N, \\ \sum_{i=1}^{m} \sum_{j=1}^{n} \mu_{mn}(\mathbf{x}_k) = 1, k = 1, 2, \ldots N, \\ 0 < \sum_{k=1}^{N} \mu_{mn}(\mathbf{x}_k) < N, \forall m \in M, \forall n \in N. \end{gathered} \tag{2}$$

The minimized constraints of $J(U, e)$ is (4). This leads to the following Lagrange function:

$$J(U, e) = \sum_{i=1}^{m} \sum_{j=1}^{N} \left(\mu_{ij}\right)^q \left(D_{ij}\right)^2 - \sum_{j=1}^{N} \lambda_j \left(\mu_{ij} - 1\right). \tag{3}$$

The membership μ_{mn} is calculated as follows:

$$\mu_{mn} = \frac{1}{\sum_{i=1}^{m} \left(D_{ji} / D_{li} \right)^{2/q-1}}. \tag{4}$$

The center (distribution center) $\{e_i\}$ of each cluster can be written as follows:

$$e_{ij} = \frac{\sum_{i=1}^{m} \left(\mu_{ij} \right)^{q} \mathbf{x}_{ij}}{\sum_{i=1}^{m} \left(\mu_{ij} \right)^{q}}. \tag{5}$$

These functions are called membership functions. The fuzzy membership function value has the mathematical characteristics of a set. In other words, each vector $\mathbf{x}$ belongs to multiple clusters at the same time but with a different degree of membership. The corresponding value μ_{mn} in the interval $[0, 1]$ quantifies the degree of membership. A value close to 1 indicates a high degree of membership to the cluster while a value close to 0 indicates a low degree of membership to the cluster.

2.2. The Second Layer of the Mathematical Model. The objective function can be written as follows:

$$\min \quad G_d = \sum_{m \in M} \sum_{n \in N} \sum_{s \in S} C_{mn} * x_{mns}, \tag{6}$$

C_{mn} depends on the distance from the distribution center m to the customer n:

$$C_{ij} = K * D_{ij} = K * D\left(\mathbf{x}_i - e_j\right) = K * \sqrt{\sum_{j=1}^{p} \left(\mathbf{x}_{ij} - e_{ij}\right)^2}, \tag{7}$$

here K represents the freight cost per unit, namely the freight rate.

A customer can only be served by one car:

$$\sum_{m \in V} \sum_{s \in S} x_{mns} = 1, \forall n \in N. \tag{8}$$

A customer can only be served by one distribution center:

$$\sum_{m \in M} y_{mn} = 1, \forall n \in N. \tag{9}$$

Each vehicle can be dispatched to finish the delivery tasks only on one route:

$$\sum_{m \in M} \sum_{n \in N} x_{mns} \leq 1, \forall s \in S. \tag{10}$$

Neither the customer nor the distribution center is allowed to ship to itself, which means there is no route between them:

$$x_{mms} = 0, \forall m \in V, \forall s \in K. \tag{11}$$

Distribution centers are not allowed to ship between each other:

$$\sum_{m \in M} \sum_{n \in M} x_{mns} = 0, \forall s \in S. \tag{12}$$

The number of vehicles departing to and returning from the customers should be equal:

$$\sum_{m \in V} x_{mns} - \sum_{m \in V} x_{nms} = 0, \forall n \in V, \forall s \in S. \tag{13}$$

The total number of vehicles in the entire distribution system should not exceed the total number of existing vehicles S:

$$\sum_{m \in M} \sum_{n \in N} \sum_{s \in S} x_{mns} \leq s. \tag{14}$$

Suppose each distribution center has the same number of vehicles mean_V:

$$\begin{aligned} \text{mean\_}V &= \frac{S}{cn}, \\ \text{mean\_}V &= 1, 2, \ldots. \end{aligned} \tag{15}$$

In addition, x_{mns} and y_{mn} are 0–1 decision variables, the properties of which are as follows:

$$\begin{aligned} x_{mns} &\in \{0, 1\}, \forall m, n \in V, \forall s \in S, \\ y_{mn} &\in \{0, 1\}, \forall m \in M, \forall n \in N. \end{aligned} \tag{16}$$

3. Algorithm Design

3.1. Implementation of the Fuzzy C-Means Clustering Algorithm. In the fuzzy C-means clustering method, each data point belongs to a certain cluster center according to a certain fuzzy membership degree [17]. Jim Bezdek proposed the clustering technology as an improvement to the traditional clustering technology in 1981 [18]. Firstly, a number of cluster centers are randomly selected, and all data points are given a certain fuzzy membership degree to the cluster center [19]. Then, the iterative method is used to continuously modify the cluster center, and the iterative process minimizes the distance from all data points to each cluster center as well as the weighting and optimization objectives of the membership value [20]. The output of fuzzy C-means clustering is a list of cluster centers and the membership value of each data point for each cluster center [21].

3.2. Genetic Algorithm. The genetic algorithm (GA) is a probabilistic optimization algorithm that is based on natural selection and genetic theory and uses the combination of evolutionary survival of the fittest and the random exchange of chromosome information in a population to search for global solutions. It was first put forward by Professor J. Holland of the University of Michigan in 1975 [22].

The genetic algorithm is composed of three modules: encoding and decoding, individual fitness evaluation, and genetic operation. In the genetic algorithm, we define a population or group as the set of encoded chromosomes, and each individual is the phenotype of its corresponding chromosome [23].

3.2.1. Encoding and Decoding. The encoding and decoding of genetic algorithms correspond to the genotype and phenotype of organism at the macro level and correspond to the transcription and translation of DNA at the micro level [24]. The operation object of the genetic algorithm is a point set (string), the mapping from the solution space of the problem to the genetic algorithm space is called encoding, and the mapping from the genetic algorithm space to the solution space of the problem is called decoding [25].

Binary coding is adopted for the two-layer model in this study. In the first layer of the model, each chromosome is composed of m cluster centers. For the p-dimension sample vector, the number of variables to be optimized is $m^* p^*$. If each variable uses k-bit binary coding, the length of the chromosome is a binary code string of $\mathrm{m}^* p^* k$. In the second layer of the model, each chromosome is composed of n nodes (including customers and distribution centers). For the q-dimension sample vector, the number of variables to be optimized is $n^* q$. If each variable uses l-bit binary coding, the length of the chromosome is a binary code string of $n^* q^* l$.

3.2.2. Individual Fitness Evaluation. The fitness function is a measure of individual fitness. In this study, the first layer of the model takes (1) as the objective function and its reciprocal $1/J_q$ as the fitness function, the value of J_q is smaller, the value of its reciprocal $1/J_q$ is higher, the individual fitness value is higher, and it can satisfy two conditions that is the customer is more intensive, the establishment of distribution center is more economical and the fitness is higher. The chance of genetic inheritance to progeny individuals is higher. Similarly, the second layer of the model takes Equation [26]. (6) as the objective function and its reciprocal $1/G_d$ as the fitness function. The value of $1/G_d$ is smaller, the value of reciprocal $1/G_d$ is higher, the individual fitness value is higher, and it can satisfy two conditions: the total distance of distribution is shorter, the cost is lower, and the probability of the gene with the highest fitness being passed on to the progeny individuals is higher [27].

3.2.3. Genetic Operation. Selection Operator: In this study, the individual fitness of the parent population is evaluated and sorted according to the size of the fitness value, and then a random traversal sampling strategy is used to generate the progeny population.

Crossover Operator: Considering that the number of effective genes on each chromosome may not be the same, the single point crossover operator is used in this study.

Mutation Operator: The mutation operator refers to the generation of mutation genes with a certain probability and the selection of mutation genes by a random method. In this study, two individuals are randomly selected, and then two genes of the selected individuals are randomly exchanged to achieve mutation operation [28].

3.3. Simulated Annealing Algorithm. Although the parallel search pattern of the genetic algorithm has a strong search capability in the whole solution space, it has a slow convergence and poor local search capability. The probabilistic abrupt jump nature of the simulated annealing algorithm is an effective way to find the optimal solution to the problem in the search space. However, the serial search approach of the simulated annealing algorithm leads to less than comprehensive results for the search space and does not facilitate running the search process in the most promising search regions [29]. Thus making itself inefficient in terms of operations. Therefore, we combine the advantages of the genetic algorithm and simulated annealing algorithm to optimize the initial clustering centers of the fuzzy C-mean clustering algorithm.

Lombard et al. mentioned in their paper that the simulated annealing algorithm originated from the findings of statistical mechanics of materials and was originally proposed by Metropolis et al. In 1983, Kivkpatrick et al. proposed to apply the simulated annealing algorithm to solve combinatorial optimization problems, and their starting point was based on the similarity between the annealing process of physical solids and combinatorial optimization problems in general [30].

The simulated annealing algorithm is a kind of stochastic search algorithm. Theoretically, it is a globally optimal algorithm. Its core is composed of "Three Functions" and "Two Criteria." The former refers to the state generation function, state acceptance function, and temperature update function, and the latter refers to the sampling stability criterion (inner loop termination criterion) and the annealing termination criterion (outer loop termination criterion) [10].

3.3.1. State Generation and Acceptance Functions. The state generation function, also known as the neighborhood function, is a function that ensures that the generated candidate solutions are spread throughout the solution space as much as possible. In this study, the genetic algorithm is embedded in the simulated annealing algorithm as its inner loop structure. In other words, the state generation function corresponds to the genetic operator in the genetic algorithm, and the state acceptance function in the simulated annealing algorithm corresponds to the population iteration operation in the genetic algorithm [10].

3.3.2. Temperature Update Function. The temperature update function can have various forms. In this study, it is given as follows [29]:

$$T_{i+1} = T_i * k_q \quad i = 0, 1, 2, \ldots, \tag{17}$$

here k_q is the cooling coefficient, and its value determines how fast the temperature drops.

3.3.3. Sampling Stability Criterion. The Metropolis sampling stability criterion, also known as the inner loop termination criterion, is used to reach thermal equilibrium at any constant temperature. Its role in the algorithm is to define

Table 1: Client coordinates.

Nos.	Coordinates
1	(0.2266, 0.0658)
2	(0.9020, 0.6752)
3	(0.6990, 0.6662)
4	(0.8107, 0.7774)
5	(0.3453, 0.3365)
6	(0.2889, 0.2624)
7	(0.5827, 0.3995)
8	(0.5572, 0.7973)
9	(0.1611, 0.1290)
10	(0.0525, 0.3003)
11	(0.1226, 0.0865)
12	(0.6464, 0.4419)
13	(0.3726, 0.4734)
14	(0.8218, 0.6348)
15	(0.5215, 0.2849)
16	(0.5307, 0.2081)
17	(0.5215, 0.7569)
18	(0.6243, 0.3511)
19	(0.7841, 0.6275)
20	(0.8483, 0.0178)
21	(0.0616, 0.3822)
22	(0.1692, 0.8558)
23	(0.3142, 0.3240)
24	(0.3095, 0.6284)
25	(0.5163, 0.1034)
26	(0.3364, 0.9960)
27	(0.9675, 0.4120)
28	(0.0251, 0.6994)
29	(0.5178, 0.8281)
30	(0.2201, 0.9690)
31	(0.5455, 0.7088)
32	(0.9107, 0.0855)
33	(0.5668, 0.7064)
34	(0.0494, 0.7305)
35	(0.4789, 0.7273)
36	(0.2233, 0.5032)
37	(0.8480, 0.2040)
38	(0.4529, 0.9115)
39	(0.4823, 0.3539)
40	(0.6527, 0.9238)
41	(0.9248, 0.3725)
42	(0.5147, 0.0494)
43	(0.0617, 0.3826)
44	(0.7940, 0.2926)
45	(0.7414, 0.5063)
46	(0.5395, 0.1430)
47	(0.8302, 0.7108)
48	(0.1240, 0.2596)
49	(0.5330, 0.2463)
50	(0.3668, 0.1719)
51	(0.0403, 0.0030)
52	(0.1390, 0.8815)
53	(0.1311, 0.9338)
54	(0.1679, 0.9176)
55	(0.8107, 0.2406)
56	(0.8808, 0.2671)
57	(0.1797, 0.3355)
58	(0.3126, 0.0158)
59	(0.3268, 0.5915)
60	(0.1077, 0.9922)

Table 1: Continued.

Nos.	Coordinates
61	(0.0449, 0.8286)
62	(0.5965, 0.2003)
63	(0.1101, 0.9886)
64	(0.2517, 0.1577)
65	(0.3456, 0.6481)
66	(0.5236, 0.5425)
67	(0.1704, 0.6832)
68	(0.9218, 0.4146)
69	(0.0745, 0.3948)
70	(0.4568, 0.6939)
71	(0.9960, 0.1876)
72	(0.7049, 0.8491)
73	(0.2948, 0.0159)
74	(0.6819, 0.7943)
75	(0.4643, 0.4818)
76	(0.1130, 0.8745)
77	(0.7603, 0.5215)
78	(0.7316, 0.1828)
79	(0.2154, 0.2482)
80	(0.6186, 0.6382)

the acceptance probability in terms of the difference between the objective function of the new solution and the current solution, i.e.,

$$P = \begin{cases} 1, & \text{if } E(x_{\text{new}}) < E(x_{\text{old}}), \\ \exp\left(\dfrac{E(x_{\text{new}}) - E(x_{\text{old}})}{K * T}\right), & \text{if } E(x_{\text{new}}) \geq E(x_{\text{old}}), \end{cases} \quad (18)$$

here K is the Boltzmann constant.

In order to better integrate the genetic algorithm and simulated annealing algorithm, the genetic generation in the genetic algorithm is set to the length of the Markov chain in the simulated annealing algorithm as the inner loop termination criterion in this study [16].

3.3.4. Annealing Termination Criterion. The annealing termination criterion, also known as the outer loop termination criterion, is used in this study to determine whether the program is terminated or not. If it holds, the program terminates; otherwise, the program proceeds to the next iteration.

4. Algorithm and Its Example Verification

4.1. Algorithm Flow of the First Layer Mathematical Model

(1) Initializing control parameters: simulate initial annealing temperature T_0, cooling coefficient k_q, end temperature T_{end}, individual size of population sizepop, maximum generation MAXGEN, crossover probability p_c , and mutation probability P_m, etc.

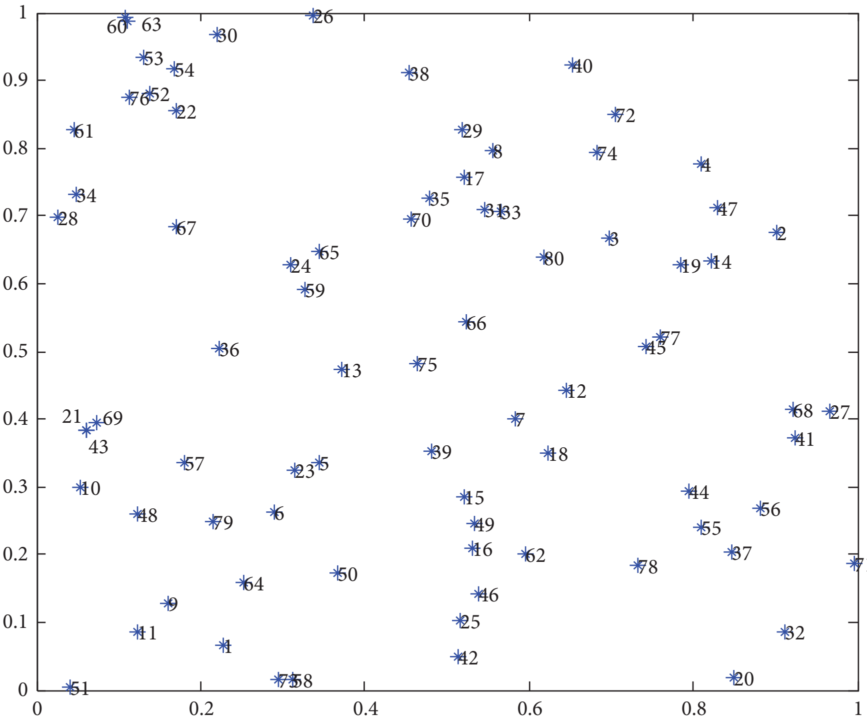

Figure 1: Client distribution map of the distribution network.

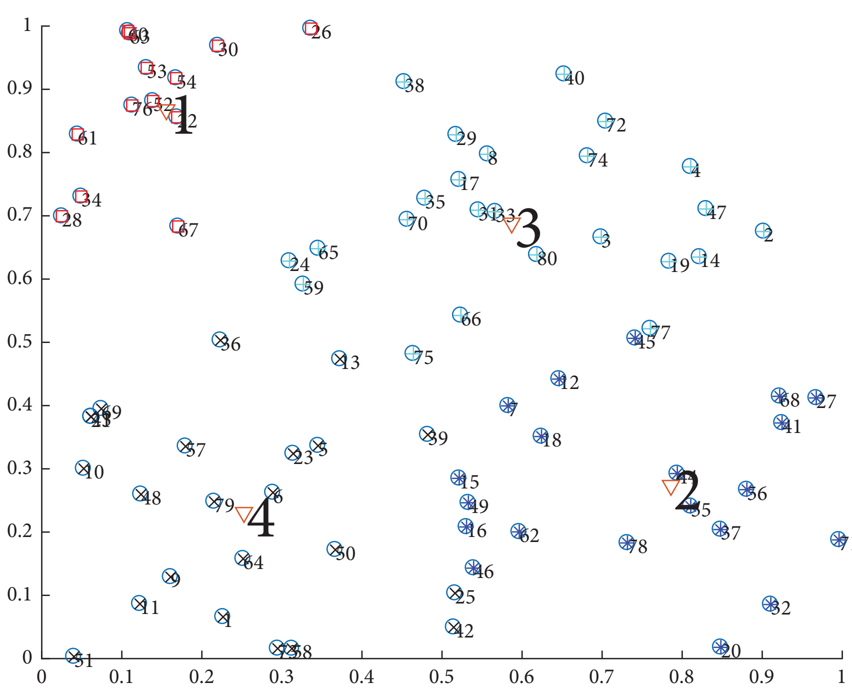

Figure 2: Location-distribution map.

(2) Randomly initializing *cn* cluster center generates the initial population *Chrom*. Then, formula (4) is used to calculate degree of membership μ_{mn} of each node to the cluster center, and formula (1) is used to calculate the fitness value of each individual f_i, $i = 1, 2, \ldots, \text{sizepop}$.

(3) Setting iteration counter gen←0.

(4) The selection operator, crossover operator, mutation operator, and other genetic operations of population Chrom are performed to generate the progeny population. For the individuals in the progeny population, the formula (4) is used to calculate the

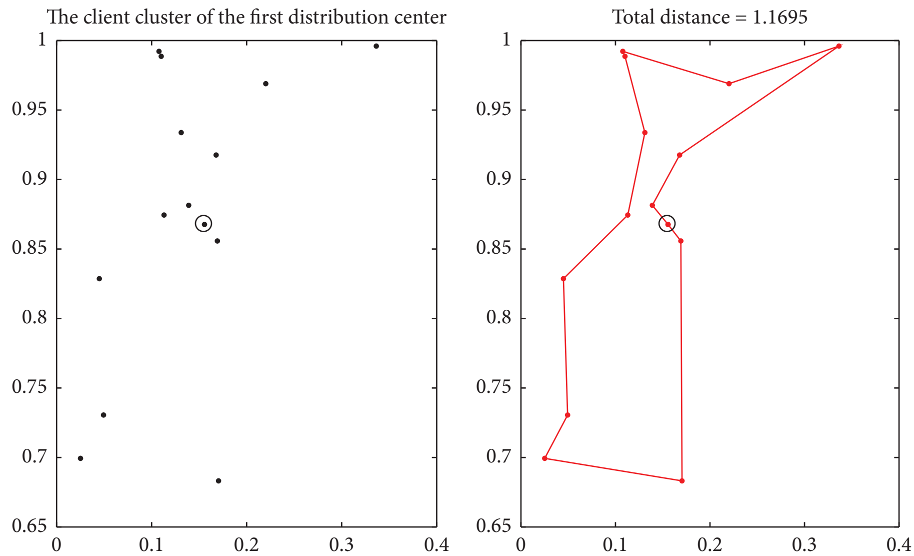

Figure 3: The client cluster and the distribution route of the first distribution center.

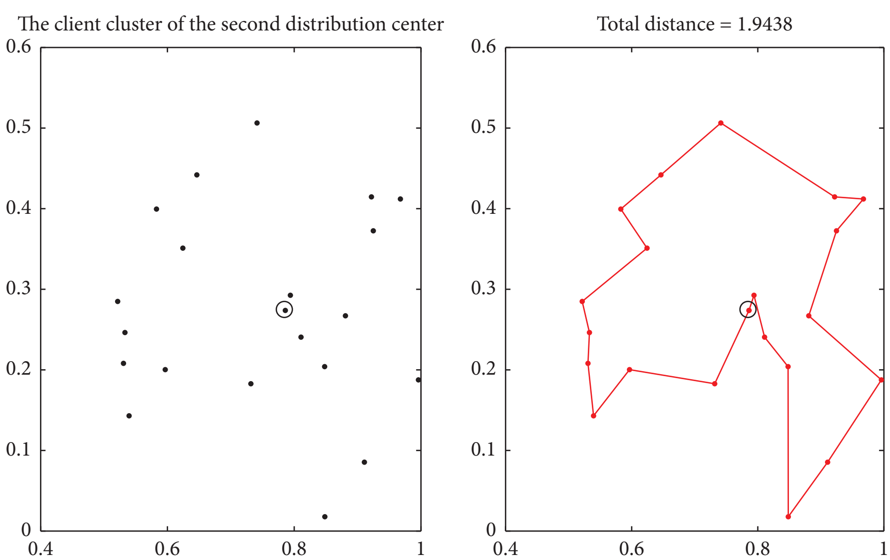

Figure 4: The client cluster and the distribution route of the second distribution center.

degree of membership of each node to cn cluster center, and the formula (1) is used to calculate the fitness value of each progeny individual. The metropolis algorithm is used to determine whether or not to accept the progeny individuals. If $f_i' > f_i$, then the progeny individuals replace the parent individuals; otherwise, the progeny individual is $P = \exp(f_i - f_i'/T)$.

(5) Determining whether or not out of the inner loop. If gen < MAXGEN, then gen ⟵ gen + 1, turn to Step4; otherwise, go to Step6.

(6) Determining whether or not out of the outer loop. If $T_i < T_{\text{end}}$, then producing the cluster result, the first layer model program ends, and the second layer model program starts.

4.2. Algorithm Flow of the Second Layer Mathematical Model

(1) Initializing control parameters: population size pop_size, maximum number of iterations MAX_num_iter, coordinate matrix xy of each node, distance matrix $dmat$ of each node, maximum number of vehicles MAX_V that can be dispatched by each distribution center, etc.

(2) Importing the location distribution results of the first layer model. If $fenzu$ ⟵ 1, then $fenzu = 1, 2, \ldots, cn$.

(3) Initializing the population generates the initial population tmp_pop_rte and formula (6) is used to calculate the fitness value of each individual, $i = 1, 2, \ldots,$ pop_size.

(4) Setting iteration counter num_iter ⟵ 0.

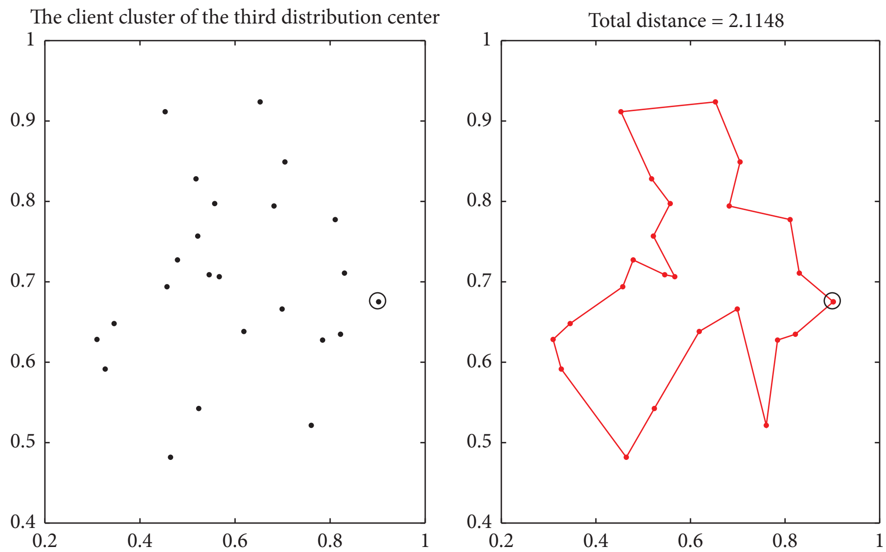

Figure 5: The client cluster and the distribution route of the third distribution center.

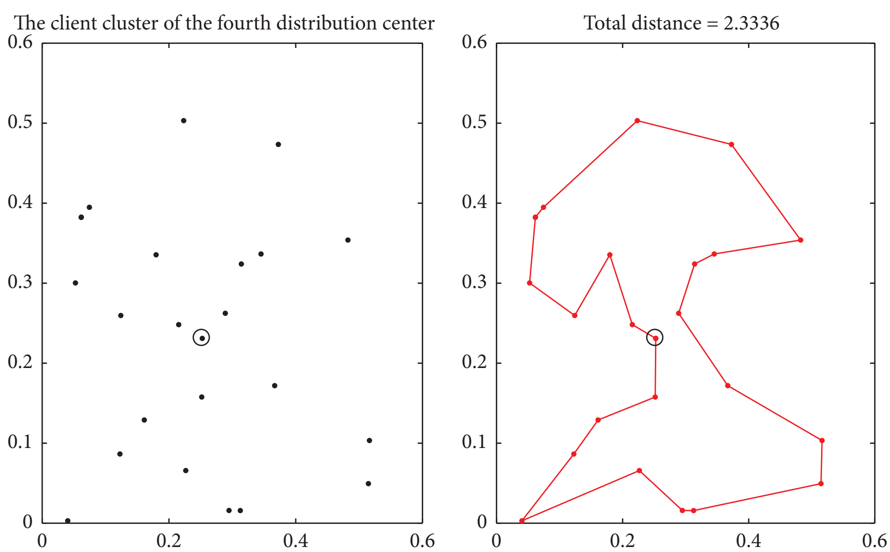

Figure 6: The client cluster and the distribution route of the fourth distribution center.

Table 2: The client distribution served by each distribution center (mean_$V = 1$).

Distribution center Nos.	The number of the clients	Client numbers
1	13	22, 26, 28, 30, 34, 52, 53, 54, 60, 61, 63, 67, 76.
2	20	7, 12, 15, 16, 18, 20, 27, 32, 37, 41, 44, 45, 46, 49, 55, 56, 62, 68, 71, 78.
3	24	2, 3, 4, 8, 14, 17, 19, 24, 29, 31, 33, 35, 38, 40, 47, 59, 65, 66, 70, 72, 74, 75, 77, 80.
4	23	0.1, 5, 6, 9, 10, 11, 13, 21, 23, 25, 36, 39, 42, 43, 48, 50, 51, 57, 58, 64, 69, 73, 79.

(5) According to the genetic operation, three operations of selection, crossover, and mutation are used to make the population *tmp_pop_rte* generate progeny population *new_pop_rte*. For the individuals in the progeny population, formula (7) is used to calculate the cost of the cluster center to each node, and formula (6) is used to calculate the fitness value of the progeny individual to judge whether or not to accept the progeny individuals $\text{fitness}'_i$. If $\text{fitness}'_i > \text{fitness}_i$, the progeny individuals replace the parent and copy

it to the next generation; otherwise, the progeny individuals are not accepted and the parent individuals are copied to the next generation.

(6) Determining whether or not out of the iteration loop. If num_iter < MAX_num_iter, then num_iter ⟵ num_iter + 1 go to Step4; otherwise, go to Step7.

(7) Producing the distribution routes from each distribution center to the customer groups, and the second layer model program ends.

5. Verification of the Algorithm Case and Result Analysis

Assuming that 4 distribution centers which can form a distribution network are going to be built, all 4 available dispatching vehicles will be sent for 80 clients. Client coordinates are shown in Table 1.

According to the designed algorithm, in the first-layer model settings, we set the initial temperature as $T_0 = 100$, the cooling coefficient as $k_q = 0.8$, the final temperature as $T_{\text{end}} = 64$, the population size as sizepop = 20, the genetic maximum as MAXGEN = 30, the crossover probability as $P_c = 0.8$, mutation probability as $P_m = 0.05$. In the second-layer model settings, we set the the population size as $pop\_size = 20$, the genetic maximum as MAX_num_iter = 2000, and the number of the vehicles available in each distribution center as mean_V = 4. MATLAB R2012a is used to write the program for calculation in the experiment, and the program runs on the PC (CPU: Pentium dual-core 1.5 G·Hz; memory: 4 G; operating system: window7 64 bit). By running the program, the client distribution map of the distribution network and the location-distribution map can be obtained, as shown in Figures 1 and 2, respectively:

Every vehicle route map corresponding to each distribution center is shown in Figures 3 to 6, respectively.

The client distribution served by each distribution center is shown in Table 2.

The study shows that the designed two-layer location selection and route model based on the hybrid heuristic algorithm is of high computational efficiency and can deliver a satisfactory solution in a short time.

6. Conclusion

This study has analyzed the advantages and disadvantages of the c-means clustering algorithm, genetic algorithm, and simulated annealing algorithm. The innovations are as follows:

The classical algorithm in the fuzzy c-means clustering algorithm, the original production method of initial value, is improved.

(1) This study has improved the original way of generating initial values based on the synthesis of previous scholars' research. Stimulating the probabilistic jump of the simulated annealing algorithm can make the algorithm jump out of the local minimum and find the optimal solution in a large search space, which effectively makes up for the lack of search ability of the genetic algorithm in the local solution space and can effectively converge to the global optimal solution.

(2) The parallel search ability of genetic algorithm can quickly carry out global search. Making use of the advantages of genetic simulated annealing, a hybrid heuristic algorithm with global search and parallel search is designed to optimize the initial value and improve the convergence speed of the algorithm. This avoids the drawbacks arising from a single algorithm, and at the same time creates the "one plus one greater than two" effect.

The traditional LRP model has also been improved as follows:

(1) Making full use of the tour visit characteristics of vehicles, the multitraveling salesman problem (MTSP) is introduced into the LRP model, which shortens the tour cycle of vehicles, improves the utilization rate of vehicles, and saves the tour cost of vehicles. At the same time, it saves the vehicle's cruising cost and verifies the feasibility of the method in this study by implementing a specific arithmetic example through MATLAB programming.

(2) The complex mathematical model is replaced by a simple mathematical model. Although there is a sacrifice in the accuracy of the model, the solution time of the problem is greatly shortened and the timeliness of the distribution system is ensured with simple solution method. Compared with other methods for LRP solution, the method in this study has a stronger overall solution effect.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request. The questionnaire data was acquired mainly through e-mail and paper filling out.

Conflicts of Interest

The authors declare that there no conflicts of interest.

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