Research Article

Multidistribution Center Location Based on Real-Parameter Quantum Evolutionary Clustering Algorithm

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To determine the multidistribution center location and the distribution scope of the distribution center with high efficiency, the real-parameter quantum-inspired evolutionary clustering algorithm (RQECA) is proposed. RQECA is applied to choose multidistribution center location on the basis of the conventional fuzzy C-means clustering algorithm (FCM). The combination of the real-parameter quantum-inspired evolutionary algorithm (RQIEA) and FCM can overcome the local search defect of FCM and make the optimization result independent of the choice of initial values. The comparison of FCM, clustering based on simulated annealing genetic algorithm (CSAGA), and RQECA indicates that RQECA has the same good convergence as CSAGA, but the search efficiency of RQECA is better than that of CSAGA. Therefore, RQECA is more efficient to solve the multidistribution center location problem.

1. Introduction

The logistics industry is developing rapidly with the development of economy [1]. The development of logistics industry has huge influence on the social production and management, life and employment of people, social system, and so on [2]. So the logistics industry is considered as the artery of economic development and basic industry [3]. In the operation of the logistics system, the task of the distribution center is to receive and deliver products according to the needs of customers in time, efficiently and economically. Distribution center is the key position between suppliers and customers. The distribution distance and distribution model are dependent on the location and distribution range of distribution center. So the distribution center affects the efficiency of the entire distribution system [4]. Logistics center location model is a NP-hard problem [5] which is nonconvex and nonsmooth nonlinear programming model with complex constraints.

FCM is utilized more among all kinds of clustering algorithms such as knowledge discovery [6], pattern recognition [7], and image processing [8]. FCM is the foundation of other fuzzy clustering analysis methods. However, because FCM is a local search algorithm and it is affected by the initial value, some methods are introduced to improve the performance of FCM to prevent the algorithm trapped into local minimum point. Zhang and Yu reviewed the fuzzy clustering algorithm based on partition, analyzed the advantages and disadvantages of the algorithm, pointed out that the standard FCM is robust for the different scaling of data, and proved the influence of parameters on the algorithm performance [9]. Rana and Jain proposed a dynamic recommender system based on evolutionary clustering algorithm which performs an optimization of conflicting parameters instead of using the traditional evolutionary algorithms. They also studied the evolutionary clustering algorithm based on time characteristics [10]. Kou et al. applied multiple criteria decision making method to evaluate economic risk based on clustering algorithm [11]. Maulik and Bandyopadhyay [12] proposed genetic algorithm-based clustering (GAC) technique and proved that the performance of GAC is better than k-means clustering algorithm. Xi et al. [13] introduced the idea of simulated annealing into genetic algorithm for document clustering. Though the accuracy of clustering algorithm can be improved through combination of several algorithms, the cost time is long which reduces the efficiency of the algorithm.

Quantum-inspired evolutionary algorithm (QIEA) is with good population diversity and can keep better balance between exploration and exploitation because of the introduction mechanism of uncertainty, coherence, interference, and parallelism [14]. Conventional QIEA is based on binary so conversion between decimalism and binary needs to be carried out. It is more suitable for combinatorial optimization problems. QIEA is slower to solve the numerical optimization problem. Therefore, the RQIEA is introduced to FCM to solve the problem of the multidistribution center location. Encoding according to the actual circumstances of the clustering problem in RQIEA makes the algorithm converge to the global optimal solution faster.

2. Multidistribution Center Location Model Based on Clustering Algorithm

It needs to determine the location of distribution center and the distribution range of each distribution center to solve the multidistribution center location problem. The most important object of the problem is to make the distribution distance shortest. Therefore, FCM model is suitable to address this issue.

2.1. Description of the Problem. The distribution center location model in this paper satisfies the following assumptions:

(1) the capacity of the distribution center can always meet the demand of all demand points;

(2) a demand point can only be supplied by a distribution center;

(3) complex situation such as river, road network, the customer request, and the transportation cost is not considered; the only measure is the distance between the distribution center and demand points.

Establish distribution center location model based on the above assumptions. This model is a location/distribution model in which n demand distribution centers and corresponding demand points need to be found out.

2.2. FCM Model for Multidistribution Center Location. C-means clustering is proposed in 1957 [15]; subsequently, many local classification algorithms based on gradient descent method are put forward. FCM utilizes the concept of geometric closeness degree of the determined data point in the Euclidean space to classify data and determine the distance of the clustering.

If there is a data sample $X = \{x_1, x_2, \ldots, x_n\}$ which needs to be divided into c $(2 \leq c \leq n)$ distribution areas $\{A_1, A_2, \ldots, A_c\}$, the similar classification matrix is U; the distribution centers of each distribution area are $\{v_1, v_2, \ldots, v_c\}$; the membership grade of the sample x_i belonging to A_k is $\mu_k(x_i)$ (μ_{ik} for short). The expression of the objective function J_b is

$$J_b(U, v) = \sum_{i=1}^{n} \sum_{k=1}^{c} (\mu_{ik})^b (d_{ik})^2, \tag{1}$$

where $d_{ik} = d(x_i - v_k) = \sqrt{\sum_{j=1}^{m}(x_{ij} - v_{kj})^2}$, d_{ik} is the Euclidean distance, which stands for the distance between the ith sample x_i and the kth distribution center, m is the characteristic number of sample, and b $(1 \leq b \leq \infty)$ is the weighted parameter. The object of FCM is to find the best classification to make the function value J_b minimum. The sum of all the membership degrees of each clustering is 1; that is, $\sum_{j=1}^{c} \mu_j(x_i) = 1$, $i = 1, 2, \ldots, n$.

The calculation formula of membership degree μ_{ik} is

$$\mu_{ik} = \frac{1}{\sum_{l=1}^{c} (d_{ik}/d_{lk})^{2/(b-1)}}$$

$$= \frac{1}{\sum_{l=1}^{c} \left(\sqrt{\sum_{j=1}^{m} (x_{ij} - v_{kj})^2} / \sqrt{\sum_{j=1}^{m} (x_{lj} - v_{kj})^2} \right)^{2/(b-1)}}. \tag{2}$$

The formula used to calculate c distribution centers $\{v_i\}$ is

$$v_{ij} = \frac{\sum_{k=1}^{n} (\mu_{ik})^b x_{kj}}{\sum_{k=1}^{n} (\mu_{ik})^b}. \tag{3}$$
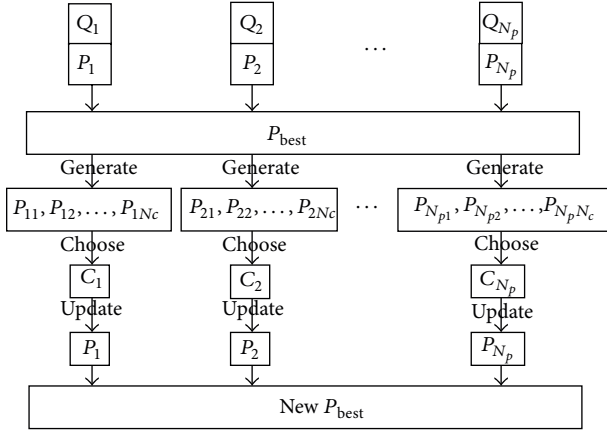
Set $I_k = \{i \mid 2 \leq c < n; \ d_{ik} = 0\}$, for all the class i, $i \in I_k$; $\mu_{ik} = 0$.

Apply formulas (2) and (3) to modify data clustering center, membership degree, and classification repeatedly. When the algorithm is convergent, the clustering center of all clusters and the membership degree of each sample belonging to each cluster are gotten. Though the search speed of FCM is fast, FCM is essentially a local search algorithm and is sensitive to the initial value of clustering center. If the selection of the initial value is undeserved, the algorithm will converge to a local minimal value.

3. Real-Parameter Quantum-Inspired Evolutionary Algorithm

Conventional QIEA is based on binary code; α and β are, respectively, the probability amplitude of 0 and 1. Conventional QIEA has a good performance in solving the optimization function with binary parameters or combinatorial problem. QIEA based on real parameters needs to be designed to make the optimization problem with real parameters better solved [16]. S.-Y. Li and P.-C. Li adopted real numbers to encode quantum bits to optimize the weights of neural network [17]. Chen et al. proposed real-coded chaotic quantum-inspired genetic algorithm (RCQGA) [18], which avoids the premature convergence of binary QGA. Sailesh Babu et al. proposed real-parameter quantum evolutionary algorithm and used it on economic load dispatch [16]. This algorithm is regarded as classical RQIEA. The new RQIEA is proposed based on the algorithm in literature [16].

The candidate solution string in RQIEA is generated as follows: a group of N_p quantum bit strings, Q_i^t, $(i = 1, 2, \ldots, N_p)$, is the ith qubit string in the tth iteration; correspondingly, the other group of N_p bit strings of N_g real

FIGURE 1: The flow chart of generation of P_{best}^t.

FIGURE 2: The flow chart of applying NO1 to calculate the kth element of the jth individual of the ith population in the tth generation.

numbers is P_i^t, $(i = 1, 2, \ldots, N_p)$; P_i^t is maintained. Each Q_i has N_g qubits, which stands for the probability amplitude of α_i. The probability of generating a real number on the higher (lower) side of present value is decided by $|\alpha_i|^2(|\beta_i|^2)$. Early in the search process, all the probabilities are equal; α_i and β_i of Q_i are all initialized with 0.707. Each element of P_i ($i = 1, 2, \ldots, N_p$) is initialized to a random number in the range between the minimum and maximum in the domain. Each pair of Q_i and P_i represents the ith family in the tth iteration. The N_c solution strings p_{ij}^t, $(j = 1, 2, \ldots, N_c)$, of the ith family are generated by Q_i^t, P_i^t, and P_{best}^t (the solution string with best fitness currently found). The fitness of p_{ij}^t is calculated after the constraint conditions are determined.

The flow chart of generation of P_{best}^t is shown in Figure 1.

3.1. Two Neighborhood Operators. Two neighborhood operators, neighborhood operator 1 (NO1) and neighborhood operator 2 (NO2), are used to generate N_c neighborhood solution strings. The best out of these C_i^t is determined for each family. If C_i^t is better than P_i^t, then C_i^t replaces P_i^t to be P_i^{t+1}. The best value of all P_i^{t+1} (if it is better than P_{best}^t) replaces P_{best}^t to be P_{best}^{t+1}.

In RQIEA, the evolution of the quantum bits represents the evolution of the coherence state of 0 and 1. The change of $|\alpha|^2$ and $|\beta|^2$ is translated to the real-valued parameters in the problem space by two neighborhood operators, NO1 and NO2.

NO1. In the tth generation, N_p quantum bits Q_i, there are N_g elements in each Q_i. NO1 is used to generate solution strings p_{ij}^t, $(j = 1, 2, \ldots, N_c)$, each of which has N_g elements.

The array R_{ij} with N_g elements is generated, whose elements are $+1$ or -1, randomly. ρ_{ijk} is the kth element of R_{ij}; then

$$\theta_{ijk}^t = \theta_{ijk}^{t-1} + \rho_{ijk}\delta', \qquad (4)$$

where δ' is the alteration of angle, θ_{ijk}^t is the rotation angle, and $\theta_{ijk}^t = \arctan(\beta_{ijk}/\alpha_{ijk})$. If $\rho_{ijk} = -1$, δ' is a random
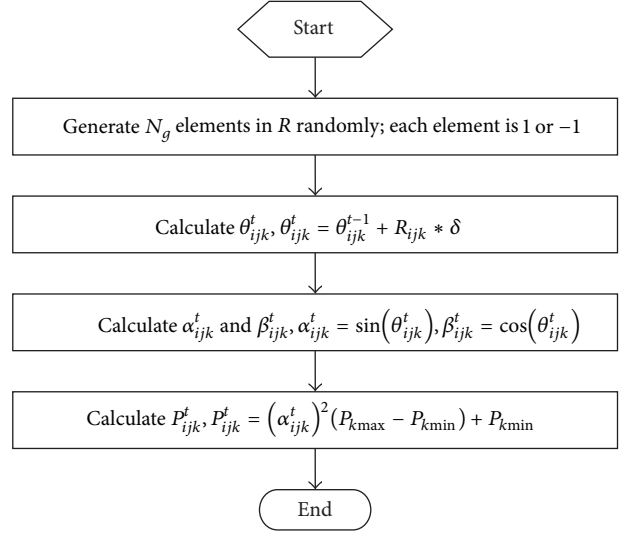
number in the range $[0, \pi/2 + \theta_{ijk}^{t-1}]$; if $\rho_{ijk} = +1$, δ' is a random number in the range $[0, \pi/2 - \theta_{ijk}^{t-1}]$ (Figure 2).

The formula of calculating the probability amplitude is

$$\begin{bmatrix} \alpha_{ijk}^t \\ \beta_{ijk}^t \end{bmatrix} = \begin{bmatrix} \cos\delta & \sin\delta \\ -\sin\delta & \cos\delta \end{bmatrix} \begin{bmatrix} \alpha_{ijk}^{t-1} \\ \beta_{ijk}^{t-1} \end{bmatrix}. \qquad (5)$$

Then, the formula to calculate the individual elements is

$$P_{ijk}^t = \left(\alpha_{ijk}^t\right)^2 \left(P_{k\max} - P_{k\min}\right) + P_{k\min}, \qquad (6)$$

where $P_{k\max}$ and $P_{k\min}$ are the maximum and minimum values in the allowable range.

NO2. Most mechanisms of NO2 are the same with NO1, except for the fact that the value point generated by NO2 is between P_b and P_{best}. NO2 utilizes formula (6) to determine P_{ijk}^t, where, $P_{k\max} = \max(P_{\text{best}ik}, C_i^t)$, $P_{k\min} = \min(P_{\text{best}ik}, C_i^t)$, and C_i^t is the best individual of the ith population in the tth generation.

NO1 is better in exploration and NO2 is better in exploitation. Due to the different characteristics of NO1 and NO2, NO1 and NO2 are used in different frequencies during the different process of the algorithm. The frequencies are decided by formula (7). Consider

$$\begin{aligned} F_{\text{NO1}} &= 90 - \frac{80t}{T}, \\ F_{\text{NO2}} &= 10 + \frac{80t}{T}, \end{aligned} \qquad (7)$$

where t is the present evolution generation and T is the total evolution generation.

The basic principle of the two neighborhood operators is as follows: NO1 is better in exploration performance, for

TABLE 1: Determine method of $\Delta\theta$ in tth iteration.

Fitness	Element value	$\Delta\theta$
X	$C_{ij} = P_{\mathrm{BEST}\,j}$	0
$F(P) > F(P_{\mathrm{BEST}})$	$C_{ij} > P_{\mathrm{BEST}\,j}$	θ_t
	$C_{ij} < P_{\mathrm{BEST}\,j}$	$-\theta_t$
$F(P) < F(P_{\mathrm{BEST}})$	$C_{ij} > P_{\mathrm{BEST}\,j}$	$-\theta_t$
	$C_{ij} < P_{\mathrm{BEST}\,j}$	θ_t
$F(P) = F(P_{\mathrm{BEST}})$	$C_{ij} > P_{\mathrm{BEST}\,j}$	0
	$C_{ij} < P_{\mathrm{BEST}\,j}$	0

the solutions generated by given strings are different with the given strings in a great tendency; NO2 is better in exploitation performance, for P_j will converge to $P_{\mathrm{best}\,j}$ with the process of the algorithm. This algorithm avoids the shortcoming of binary representation and keeps a good balance between exploration and exploitation.

3.2. Update Quantum Bit Sting. All the individual states of quantum bit in Q are changed in the process of updating, so that the probability of generating the solution which is similar to the current optimal solution increases in each of the subsequent iterations. The change of the probability is determined by the learning rate $\Delta\theta$. The value of $\Delta\theta$ under different conditions of objective function values and kth element of P_i and P_{best} in the tth iteration is shown in Table 1.

$\Delta\theta$ determines the rate of qubits from 0.707 to the final value 0 or 1. The value of $\Delta\theta$ is very important for exploration in the early evolution and exploitation in the late evolution.

Where θ_t is the size of rotation angle in tth iteration, $\theta_t = \theta_{\max} - ((\theta_{\max} - \theta_{\min})/T) \times t$, $\theta_{\max}$ is the maximal rotation angle, $\theta_{\min}$ is the minimal rotation angle, t is the present evolution generation, and T is the total evolution generation. This determined method of $\Delta\theta$ is helpful for exploration in the early evolution and exploitation in the late evolution.

3.3. The Migration. Global migration and local migration take effect in common. Random selected P^t is used to update some Q_i^t in the local migration; P_{best} is used to update Q_i^t in the global migration.

The flow chart of RQIEA is shown in Figure 3.

4. Clustering Algorithm Based on RQIEA

The essence of local optimization of clustering algorithm greatly limits the quality of distribution center location. There is no coding and decoding process in RQIEA, and the precision of solution is not affected by coding bits so RQIEA can quickly converge to the global optimal solution. RQIEA uses the probability characteristics of qubit to realize evolution to guarantee the directionality of the evolution and the diversity of population. Combination of RQIEA and FCM can effectively overcome the shortcoming of local optimum of FCM; thereby the quality of distribution center location can be improved [11].
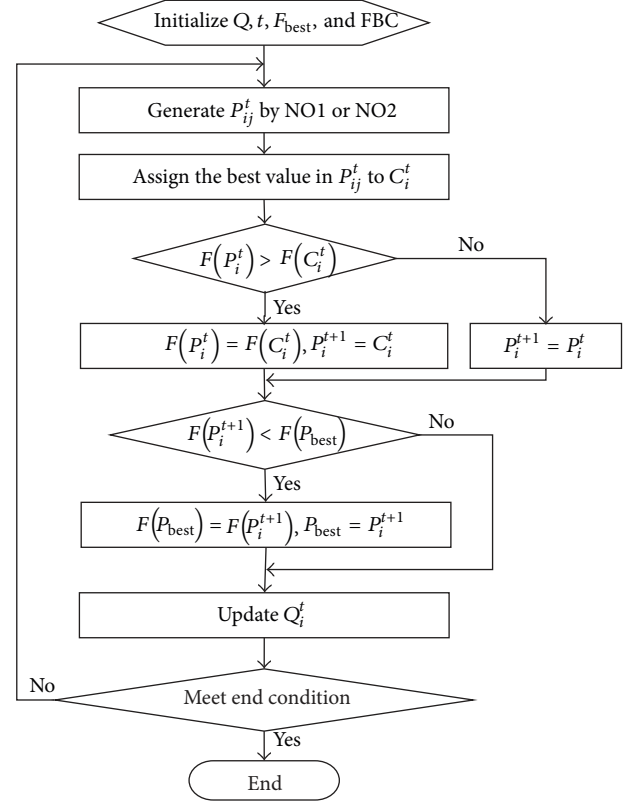

FIGURE 3: The flow chart of RQIEA.

4.1. Coding and the Initialization of Population. The coding of algorithm consists of two parts: the real number coding of clustering center and the corresponding quantum bit encoding. Coding is carried out after the size of the number of distribution centers c, the scale of the population n, and scope of the distribution center location are determined.

The real number coding of the clustering center of the population is initialized as

$$\begin{bmatrix} q_{11} & q_{12} & \cdots & q_{1c} \\ q_{21} & q_{22} & \cdots & q_{2c} \\ \vdots & \vdots & \ddots & \vdots \\ q_{n1} & q_{n2} & \cdots & q_{nc} \end{bmatrix}, \tag{8}$$

where q_{ij} ($i = 1 \cdots n$, $j = 1 \cdots c$) is the jth cluster center of the ith individual.

The corresponding quantum bit coding of clustering center of the population is

$$\begin{bmatrix} \alpha_{11} & \alpha_{12} & \cdots & \alpha_{1c} \\ \beta_{11} & \beta_{12} & & \beta_{1c} \\ \alpha_{21} & \alpha_{22} & \cdots & \alpha_{2c} \\ \beta_{21} & \beta_{22} & & \beta_{2c} \\ \vdots & \vdots & \ddots & \vdots \\ \alpha_{n1} & \alpha_{n2} & \cdots & \alpha_{nc} \\ \beta_{n1} & \beta_{n2} & & \beta_{nc} \end{bmatrix}, \tag{9}$$

where α_{ij} and β_{ij} ($i = 1 \cdots n$, $j = 1 \cdots c$) are initialized to 0.707.

TABLE 2: Simulation result of FCM.

Result	Rounds									
	1	2	3	4	5	6	7	8	9	10
J_b	3.3046	3.3051	3.3191	3.3453	3.4091	3.4250	3.3036	3.3041	3.4468	3.4171
Run time(s)	0.2584	0.3267	0.1066	0.1205	0.1356	0.2607	0.2915	0.2704	0.1876	0.2433
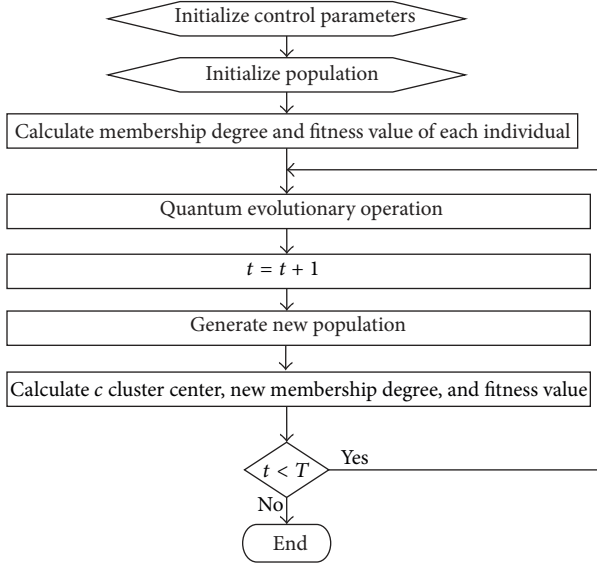
FIGURE 4: Flow chart of the clustering algorithm based on RQIEA.

FIGURE 5: 400 random data of the sample.

4.2. The Iterative Process. Preset the exponent for the partition matrix U, maximum number of iterations, and minimum amount of improvement. The process of iteration is as follows.

(1) Initialize the control parameters such as population size and the maximum evolutionary iteration T.

(2) Randomly initialize c clustering centers, and generate the initial population. Apply formula (2) to calculate the membership degree and the corresponding individual fitness value f_i ($i = 1, 2, \ldots,$ sizepop) for every clustering center.

(3) Set the loop counter variable $t = 0$.

(4) Carry out the quantum evolutionary operation. Apply formulas (2) and (3) to calculate the membership degree of the sample μ_{ik} and the fitness value f_i' of the c cluster centers of the new generated individual. If $f_i' > f_i$, accept the new individual or give up the new individual.

(5) If $t < T$, then $t = t + 1$; go to step (4) or end the algorithm.

The flow chart of the clustering algorithm based on RQIEA is shown in Figure 4.

Introducing RQIEA into clustering analysis and design of the encoding and fitness function according to the actual situation of clustering problem makes the algorithm more quickly and effectively converge to the global optimal solution [19].
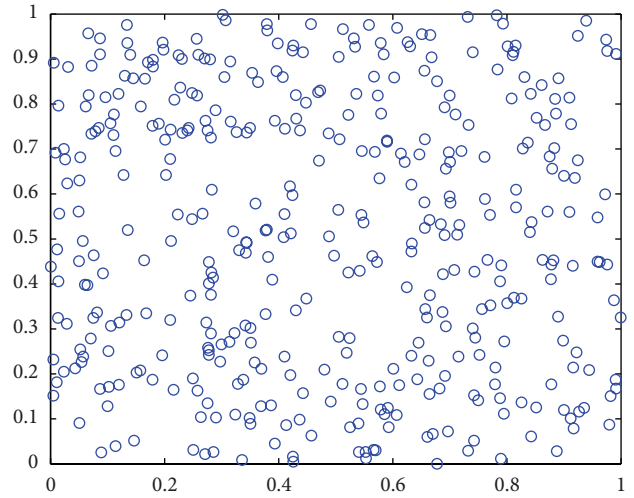
5. Simulation Analyses

FCM, CSAGA, and RQECA are tested on random data to do comparative analysis. Produce 400 two-dimensional plane points which is shown in Figure 5. The number of distribution center is 4, the initial temperature of the CSAGA is 100, the cooling factor is 0.8, terminal temperature is 1, exponent for the partition matrix U is 3, maximum number of iterations is 20, minimum amount of improvement is $1e - 6$, the number of individuals is 5, the maximal genetic generation is 10, and the size of the binary bits is 4.

Use the random initial cluster centers for the FCM clustering. Ten rounds of experiments are presented in this paper. We performed the experiments in each round for 10 tests, taking the average of the results as the final simulation results. The results of the FCM are shown in Table 2.

The clustering figure of FCM when $J_b = 3.3191$ is shown in Figure 6. Where the triangles are the clustering centers of each cluster, the points are divided into 4 clusters, and the different color represents the points in different clusters.

The results of the CSAGA are shown in Table 3. Compare the results in Tables 2 and 3; the values of J_b in Table 3 are all the optimal value 3.3035. But the run time in Table 3 is greatly longer than the run time in Table 2.

The results of the RQECA are shown in Table 4. Compare the results in Tables 2, 3, and 4. The values of J_b in Tables 3 and 4 are all the optimal value, and the run time of RQECA is shorter than CSAGA.

Contrast the data in Tables 2, 3, and 4; it can be obtained that the convergence of FCM is the poorest; the convergence of CSAGA is as good as RQECA, but the evolution time of CSAGA is longer. The values of J_b in Table 2 do not converge

TABLE 3: Simulation result of CSAGA.

Result	Rounds									
	1	2	3	4	5	6	7	8	9	10
J_b	3.3035	3.3035	3.3035	3.3035	3.3035	3.3035	3.3035	3.3035	3.3035	3.3035
Run time(s)	1.6408	1.5358	1.6716	1.6614	1.4342	1.5683	1.4286	1.6284	1.4849	1.5947

TABLE 4: Simulation result of RQECA.

Result	Rounds									
	1	2	3	4	5	6	7	8	9	10
J_b	3.3035	3.3035	3.3035	3.3035	3.3035	3.3035	3.3035	3.3035	3.3035	3.3035
Run time(s)	0.6619	0.6350	0.5476	0.5563	0.5910	0.5127	0.5896	0.6657	0.6721	0.7345

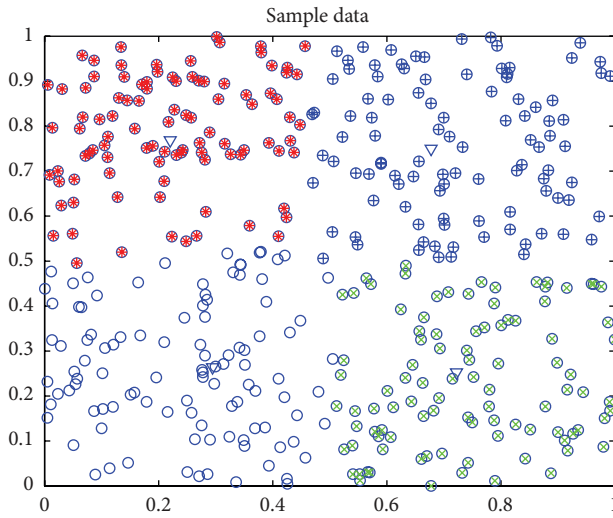FIGURE 6: Clustering figure of FCM.

FIGURE 7: The clustering figure after optimization.

to the minimum value 3.3035, but all the values of J_b in Tables 3 and 4 are 3.3035. So, the convergence of CSAGA and RQECA is obviously improved. Apply the test method of mean difference of two normal populations (t test) to analyze the running time of CSAGA and RQECA.

The data of running time of the two methods can be considered to be samples from normal population $N(\mu, \sigma^2)$. The means of the sample of the two methods are $\overline{X_1}$ and $\overline{X_2}$, respectively, and the variances are S_1^2 and S_2^2. The t-statistic is introduced to be the test statistic:

$$t = \frac{\left(\overline{X_1} - \overline{X_2}\right) - \delta}{S_w \sqrt{(1/n_1) + (1/n_2)}}, \tag{10}$$

where $\delta = \mu_1 - \mu_2$ and $S_w^2 = ((n_1 - 1)S_1^2 + (n_2 - 1)S_2^2)/(n_1 + n_2 - 2)$, $S_w = \sqrt{S_w^2}$.

The form of rejection region is $|((\overline{x_1} - \overline{x_2}) - \delta)/s_w \sqrt{(1/n_1) + (1/n_2)}| \geq k$.

If {Reject H_0 when H_0 is true} $= P_{\mu_1 - \mu_2 = \delta}\{|((\overline{x_1} - \overline{x_2}) - \delta)/s_w \sqrt{(1/n_1) + (1/n_2)}| \geq k\} = \alpha$, then $k = t_{\alpha/2}(n_1 + n_2 - 2)$.

So the rejection region is $|t| = |(\overline{x_1} - \overline{x_2}) - \delta|/s_w \sqrt{(1/n_1) + (1/n_2)} \geq t_{\alpha/2}(n_1 + n_2 - 2)$.
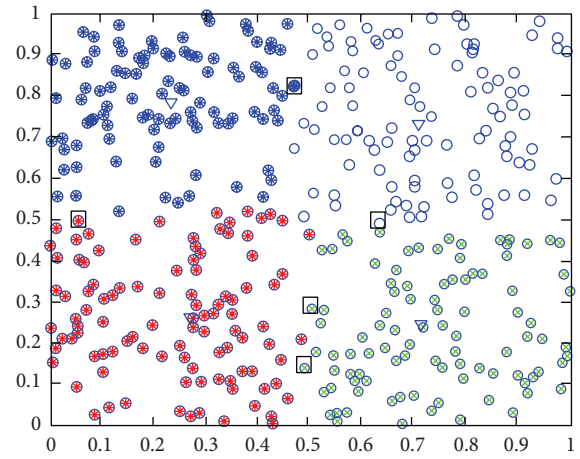
The hypotheses $H_0, \mu_1 - \mu_2 < 0$, and $H_1, \mu_1 - \mu_2 \geq 0$, need to be tested.

The mean and variance of running time of CSAGA and RQECA are as follows: $n_1 = 10$, $\overline{x_1} = 1.56487$, and $s_1^2 = 0.0083$; $n_2 = 10$, $\overline{x_2} = 0.61664$, and $s_2^2 = 0.0047$. Then, $s_w^2 = 0.0065$ and $t = 26.3002 > t_{0.005}(18) = 2.8784$. So reject H_0; that is, the running time of CSAGA is longer with probability of more than 99.5% than the RQECA.

The clustering figure of $J_b = 3.3035$ is shown in Figure 7, where the triangles are the clustering centers of each cluster. The different point between the clustering figure after optimized and clustering figure of FCM is marked with "□."

The evolutionary figure of three kinds of algorithms is shown in Figure 8. Where the blue curve is the evolutionary curve of FCM; the red curve is the evolutionary curve of CSAGA; and the black curve is the evolutionary curve of RQECA. x-axis represents the evolutionary time and y-axis represents the value of J_b. Through the comparison of the three algorithms, it can be concluded that the evolutionary speed of RQECA is fastest and the efficiency of RQECA is best.

6. Conclusions

RQECA is the combination of RQIEA and FCM. It can be used to effectively solve the problem of multidistribution
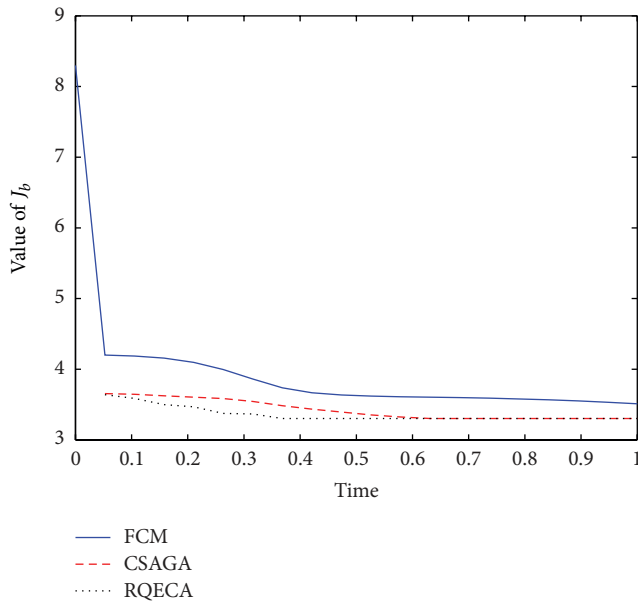
Figure 8: Evolutionary figure of three kinds of algorithms.

center location. The global search ability of RQECA is powerful. RQECA avoids the defect that FCM easily falls into local minimum and reduces the sensitivity to the initial value. The superiority of RQECA will be more obvious when the size of the data is more. The only objective of multidistribution center location in this paper is to minimize the distance without regarding complex constraints. The distribution center location problem with complex constraint conditions can be studied in the future.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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