Research Article

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

Huaixiao Wang, Wanhong Zhu, Jianyong Liu, Ling Li, and Zhuchen Yin

College of Field Engineering, PLA University of Science and Technology, Nanjing 210007, China

Correspondence should be addressed to Jianyong Liu; 15850717015@163.com

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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 \( \mu_{ik} (x_i) \) \((\mu_{ik} \text{ for short})\). The expression of the objective function \( J_b \) is

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

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 \( i \)th sample \( x_i \) and the \( k \)th 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, \( \sum_{i=1}^{c} \mu_{ij}(x_i) = 1, i = 1, 2, \ldots, n \).

The calculation formula of membership degree \( \mu_{ik} \) is

\[
\mu_{ik} = \frac{1}{\sum_{l=1}^{c} (d_{ik}/d_{lk})^{2/(b-1)}} = \frac{1}{\sum_{l=1}^{c} \left( \frac{\sum_{j=1}^{m} (x_{ij} - v_{lj})^2}{\sqrt{\sum_{j=1}^{m} (x_{ij} - v_{kj})^2}} \right)^{2/(b-1)}}
\]

(2)

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

\[
v_{ij} = \frac{\sum_{k=1}^{n} (\mu_{ik})^b x_{kj}}{\sum_{k=1}^{n} (\mu_{ik})^b}.
\]

Set \( I_k = \{ i \ | \ 2 \leq c < n; \ d_{ik} = 0 \} \), 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; \( \alpha \) and \( \beta \) 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, \( Q_i, (i = 1, 2, \ldots, N_p) \), is the \( i \)th qubit string in the \( t \)th iteration; correspondingly, the other group of \( N_g \) bit strings of \( N_g \) real
numbers is $P^t_i$, $(i = 1, 2, \ldots, N_p)$; $P^t_i$ is maintained. Each $Q_i$ has $N_q$ qubits, which stands for the probability amplitude of $\alpha_i$. 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; $\alpha_i$ and $\beta_i$ 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 ith iteration. The $N_e$ solution strings $P^t_j, (j = 1, 2, \ldots, N_e)$, of the ith family are generated by $Q^t_i, P^t_i$, and $P^t_{\text{best}}$ (the solution string with best fitness currently found). The fitness of $P^t_j$ is calculated after the constraint conditions are determined.

The flow chart of generation of $P^t_{\text{best}}$ 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 $N_e$ neighborhood solution strings. The best out of these $C^t_i$ is determined for each family. If $C^t_i$ is better than $P^t_i$, then $C^t_i$ replaces $P^t_i$ to be $P^t_{i+1}$. The best value of all $P^t_{i+1}$ (if it is better than $P^t_{\text{best}}$) replaces $P^t_{\text{best}}$ to be $P^t_{\text{best}+1}$.

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 $t$th generation, $N_q$ quantum bits $Q_i$ there are $N_q$ elements in each $Q_i$. NO1 is used to generate solution strings $P^t_j, (j = 1, 2, \ldots, N_e)$, each of which has $N_q$ elements.

The array $R_{ij}$ with $N_q$ elements is generated, whose elements are $+1$ or $-1$, randomly. $P^t_{ijk}$ is the $k$th element of $R_{ij}$; then

$$\theta^t_{ijk} = \theta^{t-1}_{ijk} + \rho_{ijk} \delta^t,$$

where $\delta^t$ is the alteration of angle, $\theta^t_{ijk}$ is the rotation angle, and $\theta^{t-1}_{ijk} = \arctan(\beta_{ijk}/\alpha_{ijk})$. If $\rho_{ijk} = -1$, $\delta^t$ is a random number in the range $[0, \pi/2 + \theta^t_{ijk}]$; if $\rho_{ijk} = +1$, $\delta^t$ is a random number in the range $[0, \pi/2 - \theta^{t-1}_{ijk}]$ (Figure 2).

The formula of calculating the probability amplitude is

$$\begin{bmatrix} \alpha^t_{ijk} \\ \beta^t_{ijk} \end{bmatrix} = \begin{bmatrix} \cos \delta & \sin \delta \\ -\sin \delta & \cos \delta \end{bmatrix} \begin{bmatrix} \alpha^{t-1}_{ijk} \\ \beta^{t-1}_{ijk} \end{bmatrix}.$$  

Then, the formula to calculate the individual elements is

$$P^t_{ijk} = \left(\alpha^t_{ijk}^2 \right) \left( P_{k_{\text{max}}} - P_{k_{\text{min}}} \right) + P_{k_{\text{min}}}.$$  

where $P_{k_{\text{max}}}$ and $P_{k_{\text{min}}}$ 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 $P_{\text{best}}$. NO2 utilizes formula (6) to determine $P^t_{ijk}$, where, $P_{k_{\text{max}}} = \max(P_{\text{best}i} C^t_i)$, $P_{k_{\text{min}}} = \min(P_{\text{best}i} C^t_i)$, $C^t_i$ 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

$$F_{\text{NO1}} = 90 - \frac{80t}{T},$$

$$F_{\text{NO2}} = 10 + \frac{80t}{T},$$

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 $t$th iteration.

<table>
<thead>
<tr>
<th>Fitness</th>
<th>Element value $\Delta \theta$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$X$</td>
<td>$C_{ij} = P_{\text{BEST},j}$</td>
</tr>
<tr>
<td>$F(p) &gt; F(P_{\text{BEST}})$</td>
<td>$C_{ij} &gt; P_{\text{BEST},j}$</td>
</tr>
<tr>
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<td>$C_{ij} &lt; P_{\text{BEST},j}$</td>
</tr>
<tr>
<td>$F(p) = F(P_{\text{BEST}})$</td>
<td>$C_{ij} &gt; P_{\text{BEST},j}$</td>
</tr>
</tbody>
</table>

The solutions generated by given strings are different with the given strings in a great tendency; NO2 is better in exploitation performance, for $P_t$ will converge to $P_{\text{best},j}$ 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 String. 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 $k$th element of $P_t$ and $P_{\text{best},j}$ in the $t$th 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 $\theta_t$ is the size of rotation angle in $t$th iteration, $\theta_t = \theta_{\text{max}} - ((\theta_{\text{max}} - \theta_{\text{min}})/T) \times t$, $\theta_{\text{max}}$ is the maximal rotation angle, $\theta_{\text{min}}$ 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 $Q^t_i$ in the local migration; $P_{\text{best}}$ is used to update $Q^t_i$ 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].
<table>
<thead>
<tr>
<th>Result</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td>Run time(s)</td>
<td>0.2584</td>
<td>0.3267</td>
<td>0.1066</td>
<td>0.1205</td>
<td>0.1356</td>
<td>0.2607</td>
<td>0.2915</td>
<td>0.2704</td>
<td>0.1876</td>
<td>0.2433</td>
</tr>
</tbody>
</table>

### 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 $f_i$ ($i = 1, 2, \ldots, \text{sizepop}$) 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 $\mu_k$ and the fitness value $f_j^i$ of the $c$ cluster centers of the new generated individual. If $f_j^i > f_j$, 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.

<table>
<thead>
<tr>
<th>Rounds</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td>(J_b)</td>
<td>3.3035</td>
<td>3.3035</td>
<td>3.3035</td>
<td>3.3035</td>
<td>3.3035</td>
<td>3.3035</td>
<td>3.3035</td>
<td>3.3035</td>
<td>3.3035</td>
<td>3.3035</td>
</tr>
<tr>
<td>Run time(s)</td>
<td>1.6408</td>
<td>1.5358</td>
<td>1.6716</td>
<td>1.6614</td>
<td>1.4342</td>
<td>1.5683</td>
<td>1.4286</td>
<td>1.6284</td>
<td>1.4849</td>
<td>1.5947</td>
</tr>
</tbody>
</table>

Table 4: Simulation result of RQECA.

<table>
<thead>
<tr>
<th>Rounds</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
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<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td>(J_b)</td>
<td>3.3035</td>
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<td>3.3035</td>
<td>3.3035</td>
<td>3.3035</td>
<td>3.3035</td>
<td>3.3035</td>
</tr>
<tr>
<td>Run time(s)</td>
<td>0.6619</td>
<td>0.6350</td>
<td>0.5476</td>
<td>0.5563</td>
<td>0.5910</td>
<td>0.5127</td>
<td>0.5896</td>
<td>0.6657</td>
<td>0.6721</td>
<td>0.7345</td>
</tr>
</tbody>
</table>

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: \(n_1 = 10, \bar{x}_1 = 1.56487, \) and \(s_1^2 = 0.0083; n_2 = 10, \bar{x}_2 = 0.61664, \) and \(s_2^2 = 0.0047. \) Then, \(s^2_w = 0.0065 \) 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
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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