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Research on the Optimization of Distributed Logistics Routing Based on Particle Swarm Optimization Algorithm and Ant Colony Algorithm

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Abstract

Aiming at the traditional logistics distribution path that paid much emphasis on cost factors but ignoring the factor of the delivery time, leading the problem of the long working time of driver affecting the quality of service, optimization of logistics distribution routing problem is a kind of NP complete problem with very high practical value. In view of the shortcomings of the traditional heuristic optimization algorithm, such as slow searching speed, being easy to fall into local optimal solution, we put forward a kind of the multi depot vehicle routing scheduling method based on particle swarm optimization algorithm and ant colony algorithm. Gave the vehicle scheduling model and the coding method of particle of multi distribution center, through the particle swarm optimization algorithm to optimize the heuristic factor a, b and adjust the distribution of initial pheromone to eliminate the effect of the parameter selection on the performance of ant colony algorithm, so it has strong global search ability. Simulation results show that compared with several other commonly used algorithm, the results of fusion algorithm is closer to the current optimal solution. The simulation results show that, the algorithm has strong global search ability and convergence speed, and can effectively solve the problem of logistics distribution routing.

Key words: DISTRIBUTED LOGISTICS, PATH OPTIMIZATION, PARTICLE SWARM OPTIMIZATION ALGORITHM, ANT COLONY ALGORITHM

1. Introduction

The problem of optimization of logistics distribution routing is an important part of logistics distribution, the reasonable arrangement of the number of vehicles and vehicle routing being an important means to reduce waste, improve economic efficiency, having the important influence to the speed, cost, benefit of the whole logistics distribution.

The problem of optimization of logistics distribution routing is typical combinatorial optimization problem, which belongs to the NP (non-deterministic polynomial complete NPC) problem, the distribution line arranged by the traditional manual arrangement having been difficult to meet the needs of modern enterprise business, using the computer to carry on the route arrangement being imperative. There are many methods to solve the problem of the optimization of distribution route, mainly being divided into 2 categories: the exact and heuristic algorithm. The exact method mainly has listing technique and dynamic programming and so on, this kind of method having great amount of calculation and storage, being only suitable for small scale of optimization of logistics distribution routing; The heuristic algorithm can obtain high quality solutions in a relatively short period of time, such as genetic algorithm, simulated annealing algorithm, particle swarm optimization algorithm, ant colony algorithm and other optimization methods of logistics distribution path. Ant colony algorithm (Ant Colony Algorithm, ACA) has the advantages of good ability of finding optimal solution, strong robustness and excellent distributed computing, being mostly applied in the optimization of logistics distribution path, becoming an important research direction, but ACA having some defects, such as slow convergence speed, being easy to fall into local optimum and so on. Quantum ant colony algorithm (Quantum Ant Colony Algorithm, QACA) is the combination of quantum computation and ant colony algorithm, introduced the state vector and quantum rotation gate of quantum computation into the ant colony algorithm, accelerating the convergence rate of the algorithm. The algorithm is successfully used in TSP solution, image rendering, function optimization and other problems of multi-objective combination optimization.

In order to obtain a better solution of optimization of logistics distribution path, we put forward a quantum ant colony algorithm to optimize logistics distribution path. Firstly, establishing mathematical model of the optimization of logistics distribution path, then using the quantum ant colony algorithm to solve the problem, finally we used the simulation experiment to test the superiority and effectiveness of this paper.

2. The Problem of the Optimization of Logistics Distribution Routing

2.1. The Description of Problem

The essence of the satisfaction problem of drivers is a problem of the delivery time, but it being not a simple problem of linear time, while the vehicle running time will be affected by the weather, accidents, vehicles and other factors, it being a problem of probability. Before giving the description of the problem, the paper gave several defines of fuzzy sets.

Definition 1 (the definition of fuzzy set): Fuzzy set A can be defined as a set of order pairs $A=\{(x,\mu_A(x))|x\in R\}$, in which, $\mu_A(A)$ known as the membership functions of fuzzy sets.

Definition 2 (normal fuzzy set): if the fuzzy set A had at least one point $x\in R$, meeting $\mu_A(x)=1$, the fuzzy set A being called normal fuzzy set.

Definition 3 (convex fuzzy set): If for any x, y and $\lambda\in[0,1]$, meeting the conditions:

$$\mu_A(\lambda x+(1-\lambda)y)\geq\min\{\mu_A(x),\mu_A(y)\} \tag{1}$$

So called the fuzzy set A is convex.

Definition 4 (fuzzy sets): if the fuzzy number on the line meet the normal (definition 2) and convex (definition 3), it can constitute a fuzzy set.

γ-cut is an important concept of fuzzy sets, assuming A being any given fuzzy sets defined on X, for any $\gamma \in [0,1]$, γ-cut (${}^{\gamma}A$) and strong γ-cut, (${}^{\gamma+}A$) can be respectively defined as:

$$\begin{cases} {}^{\gamma}A = \{x | A(x) \geq \gamma\} \\ {}^{\gamma+}A = \{x | A(x) > \gamma\} \end{cases} \tag{2}$$

We know that with the increase of vehicle running time, it will lead to the reduction of job satisfaction, affect the quality of work. So we assume that the working time $t < t_l$, the working efficiency and the highest quality of service of the activities with the highest satisfaction of the drivers. When the working time $t \in [t_l, t_u]$, the satisfaction of drivers shows linearly decreases with the time increasing. When $t > t_u$, the work efficiency and service quality decrease to a minimum. In this paper we made the following two assumptions. (1) The delivery time is the normal variable with a certain mean and variance. (2) The driver satisfaction is a function of the delivery time, and within a certain time interval showing linear change. The function curve of the driver satisfaction varying with time is shown in Figure 1 as.

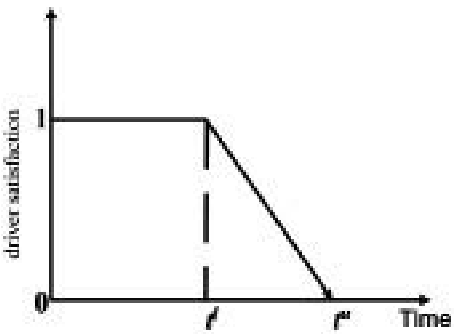


Figure 1. The time curve of driver satisfaction

Based on this we can build a random distribution model. If t_γ is the longest journey time of the γ satisfaction, the normal distribution function can be expressed as:

$$y = a_1 x_1 + a_2 x_2 + \cdots + a_n x_n \tag{3}$$

Then y is the normal distribution function that meet the $y \sim \mathcal{N}\left(\mu_y, \sigma_y^2\right)$. In which:

$$\begin{cases} \mu_y = a_1\mu_1 + a_2\mu_2 + \cdots + a_n\mu_n \\ \sigma_y^2 = a_1^2\sigma_1^2 + a_2^2\sigma_2^2 + \cdots + a_n^2\sigma_n^2 \end{cases} \tag{4}$$

If t_{ij}^v expressed the delivery time from node i to node j of the vehicle, in which t_{ij}^v meeting the normal distribution series of $t_{ij}^v \sim \mathcal{N}\left(\mu_{ij}, \sigma_{ij}^2\right)$. For all drivers of distribution, the delivery time t_γ of γ satisfaction is the same. Then in the ideal condition, the total business hours should satisfy the constraints:

$$\sum_{i=1}^{n} t_i^v \sum_{j=1}^{n} x_{ij}^v + \sum_{i=1}^{n}\sum_{j=1}^{n} t_{ij}^v x_{ij}^v \leq t_\alpha \tag{5}$$

In the formula, $i \neq j$, $v = 1, \cdots, NV$, NV is the total vehicle of distribution, x_{ij}^v being the decision parameters, which usually takes the value of either 0 or 1.

Extending the formula (4) we can the following formula:

$$\begin{gathered} t_1\left(x_{12}^v + \cdots + x_{1N}^v\right) + \cdots + t_N\left(x_{N1}^v + \cdots + x_{NN-1}^v\right) \\ + \left(t_{12}^v x_{12}^v + \cdots + t_{1N}^v x_{1N}^v\right) + \cdots + \\ \left(t_{N1}^v x_{N1}^v + \cdots + t_{NN-1}^v x_{NN-1}^v\right) \leq t_\alpha \end{gathered} \tag{6}$$

Then the percentage probability can be expressed as

$$p\left(\sum_{i=1}^{n} t_i^v \sum_{j=1}^{n} x_{ij}^v + \sum_{i=1}^{n}\sum_{j=1}^{n} t_{ij}^v x_{ij}^v \leq t_\alpha\right) \geq \alpha \tag{7}$$

Then delivery time of the normal distribution can be expressed as:

$$\begin{cases} A = \sum_{i=1}^{n}\sum_{j=1}^{n} t_{ij}^v x_{ij}^v \sim \mathcal{N}\left(\mu_A, \sigma_A^2\right) \\ \mu_A = \sum_{i=1}^{n} \mu\left(t_i^v\right) \sum_{j=1}^{n} x_{ij}^v + \sum_{i=1}^{n}\sum_{j=1}^{n} \mu\left(t_{ij}^v\right) x_{ij}^v \\ \sigma_A^2 = \sum_{i=1}^{n} \sigma^2\left(t_i^v\right) \sum_{j=1}^{n} \left(x_{ij}^v\right)^2 + \sum_{i=1}^{n}\sum_{j=1}^{n} \sigma^2\left(t_{ij}^v\right) x_{ij}^v \end{cases} \tag{8}$$

We can get the conclusion:

$$p\left(A \leq t_\alpha\right) \Rightarrow p\left(\frac{A - \mu_A}{\sqrt{\sigma_A^2}} \leq \frac{t_\alpha - \mu_A}{\sqrt{\sigma_A^2}}\right) \geq \alpha \tag{9}$$

The extended equation of formula (8) can be expressed as:

$$\frac{t_\alpha^v - \left(\sum_{i=1}^{n} \mu\left(t_i^v\right) \sum_{j=1}^{n} x_{ij}^v + \sum_{i=1}^{n}\sum_{j=1}^{n} \left(t_{ij}^v\right) x_{ij}^v\right)}{\sqrt{\sum_{i=1}^{n} \sigma^2\left(t_i^v\right) \sum_{j=1}^{n} \left(x_{ij}^v\right)^2 + \sum_{i=1}^{n}\sum_{j=1}^{n} \sigma^2\left(t_i^v\right)^2 x_{ij}^v}} \geq Z_\alpha \tag{10}$$

By this method the VRPS problem can be extended to the optimization problem that takes into account of delivery time and time distribution.

2.2. Object Function

In the suggested nonlinear programming model, the customers connecting by a connecting line, connecting line represents the map of the distribution routes between nodes. This map having n nodes, the customer is represented by each node having the demand of distribution, and the warehouse located in node 1. Total number of delivery vehicles is NV, each vehicle capacity being K_v, t_i^v being the time of vehicle v servicing for customer i, t_{ij}^v being time of the vehicle v from customer i to customer j, C_{ij} being the transportation costs from customer i to customer j, S being the collection of client nodes, being defined as: $S=\{i|i=1,\cdots,n\}$

The objective function can be defined as follows:

$$z=\min\sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{v=1}^{NV}c_{ij}x_{ij}^v \tag{11}$$

The constraint conditions are:

$$\sum_{j=1}^{n}\sum_{v=1}^{nv}x_{ij}^v=1, i=1,\cdots,n \tag{12}$$

$$\sum_{j=1}^{n}\sum_{v=1}^{nv}x_{ij}^v=1, i=1,\cdots,n \tag{13}$$

$$\sum_{i=1}^{n}x_{ip}^v-\sum_{v=1}^{nv}x_{pi}^v=0, p=1,\cdots,n \tag{14}$$

$$\frac{t_{ij}^v-\left(\sum_{i=1}^{n}E\left(t_i^v\right)\sum_{j=1}^{n}x_{ij}^v+\sum_{i=1}^{n}\sum_{j=1}^{n}\left(t_{ij}^v\right)x_{ij}^v\right)}{\sqrt{\sum_{i=1}^{n}\sigma^2\left(t_i^v\right)\sum_{j=1}^{n}\left(x_{ij}^v\right)^2+\sum_{i=1}^{n}\sum_{j=1}^{n}\sigma^2\left(t_i^v\right)^2x_{ij}^v}}\geq Z_\alpha \tag{15}$$

$$\sum_{i=2}^{n}d_i\left(\sum_{j=1}^{n}x_{ij}^v\right)<k_v, v=1,\cdots,NV \tag{16}$$

$$\sum_{j=1}^{n}x_{ij}^v=1, v=1,\cdots,NV \tag{17}$$

$$\sum_{k=1}^{k}\sum_{j\in S}\sum_{j\notin S}x_{ij}^k\leq|S|-r(S),\forall S\subseteq A-\{1\} \tag{18}$$

In the above models, the formula is mainly to minimize the transportation cost and transportation time, constraints (12) (13) being mainly used to limit each customer by only one vehicle to service. Limitation(14) is mainly to express that the vehicle that reached the client nods should leave the nods next, so as to ensure the continuity of distribution path. Limitation (15) indicates that normal distribution function of working time of driver should be greater than z_α. Limitation (16) says the vehicle should not overload. Limitation (17)says the warehouse is the starting point of each car.

3. The Quantum Ant Colony Algorithm of the Optimization of Logistics Distribution Path

Li Panchi inspired by the quantum evolutionary algorithm (Quantum-Inspired Evolutionary Algorithm, QEA), combining quantum computation and ant colony algorithm, proposing quantum ant colony algorithm (QACA) [12]. In this algorithm, firstly, each ant carried a group of quantum ratio said the current location information of the ant, based on the pheromone intensity and the selective probability of visibility structure to choose the moving goal of ant; secondly, using quantum rotation gate to update the quantum bit the ants carried, taking the move of ants; using the quantum non gate to achieve the variation of position of ants, increasing the diversity of the position; finally, according to the location after moving to complete the update of the pheromone intensity and visibility of the ant colony, can be better to solve the the slow convergence and being easy to fall into the local optimization of the ant colony algorithm in solving the problems.

3.1. The Information Coding of Quantum

In quantum computation, we use the quantum bits (quantum, bit, qubit) to represent the information. A simple quantum bit is a binary system; we can use the probability amplitude $\begin{bmatrix}\alpha\\\beta\end{bmatrix}$ to express a qubit. Then the individual probability amplitude having n qubit can be expressed as:

$$\left[\begin{array}{c|c|c|c}\alpha_1&\alpha_2&\cdots&\alpha_n\\\beta_1&\beta_2&\cdots&\beta_n\end{array}\right] \tag{19}$$

In the formula, α_i, β_i meeting $|\alpha_i|^2+|\beta_i|^2=1$, i=1,2,…,n, the quantum individual can express arbitrary quantum superposition state.

In QACA, using quantum bits to represent the path pheromone, the quantum information coding of the k ant in the path can be expressed as:

$$Q\tau_k=\begin{pmatrix}\begin{pmatrix}\alpha_{11}\\\beta_{11}\end{pmatrix}&\begin{pmatrix}\alpha_{12}\\\beta_{12}\end{pmatrix}&\cdots&\begin{pmatrix}\alpha_{1n}\\\beta_{1n}\end{pmatrix}\\\begin{pmatrix}\alpha_{21}\\\beta_{21}\end{pmatrix}&\begin{pmatrix}\alpha_{22}\\\beta_{22}\end{pmatrix}&\cdots&\begin{pmatrix}\alpha_{2n}\\\beta_{2n}\end{pmatrix}\\\vdots&\vdots&\vdots&\vdots\\\begin{pmatrix}\alpha_{n1}\\\beta_{n1}\end{pmatrix}&\begin{pmatrix}\alpha_{n2}\\\beta_{n2}\end{pmatrix}&\cdots&\begin{pmatrix}\alpha_{nn}\\\beta_{nn}\end{pmatrix}\end{pmatrix} \tag{20}$$

In the formula, n is the number of customers, $\begin{pmatrix}\alpha_{ij}\\\beta_{ij}\end{pmatrix}$ expressing the probability amplitude of pheromone of the delivery path between customer i and customer j, and having:

$$\begin{cases} |\alpha_{ij}|^2 + |\beta_{ij}|^2 = 1, & if \ \ i \neq j \\ |\alpha_{ij}|^2 = |\beta_{ij}|^2 = 0, & if \ \ i = j \end{cases} \tag{21}$$

For the customer I and j, when the ant went through path the customer I to j, the pheromone probability amplitude of the path would increase and the pheromone would be enhanced; On the contrary, the path pheromone would have some volatile.

3.2. The Pheromone Updating Rule

When all the ants constructed path, the pheromone of each path length would be updated. First of all, the pheromone of edge would reduce a constant factor, and then the pheromone of the path the ant went through would increase. According to the following formula to perform the evaporation of pheromone:

$$\tau_{ij} = (1-\rho)\tau_{ij}, \forall (i,j) \in E \tag{22}$$

In the formula, ρ is evaporation rate of pheromone, having $0 < \rho \le 1$, the function of parameter ρ being to avoid the unlimited accumulation of pheromone. After steps of evaporation of pheromone, all ants in the path they passed to release pheromone:

$$\tau_{ij} = \tau_{ij} + \sum_{k=1}^{m} \Delta\tau_{ij}^{k}, \forall (i,j) \in E \tag{23}$$

In the formula, $\Delta\tau_{ij}^{k}$ is the amount of pheromone the k ant released to the path it went through.

3.3. The Adjustment of the Quantum Rotation Gate

Assuming that there is m ants, the $n \times n$ matrix R is the solution path the distribution center of logistics system of n customers to all customers. R[i,j]=1 expressed the path R having the edge from customer i to customer j. When i=j it must have R[i,j]=0. Using the matrix Rk in algorithm, k=1,2,…,m to record the k ant's obtained path, Rbest recording the optimal solutions in the process of operation. Using quantum rotation gate to update the probability amplitudes of the quantum of ants in the path, the adjusting way of quantum rotation gates is:

$$\begin{pmatrix} \alpha_{ij}^{t+1} \\ \beta_{ij}^{t+1} \end{pmatrix} = \begin{pmatrix} \cos(\theta) & -\sin(\theta) \\ \sin(\theta) & \cos(\theta) \end{pmatrix} \begin{pmatrix} \alpha_{ij}^{t} \\ \beta_{ij}^{t} \end{pmatrix} \tag{24}$$

In the formula, $\left(\alpha_{ij}^{t}, \beta_{ij}^{t}\right)^T$ is the probability amplitudes of the path between customer i to customer j of the t iteration; θ expresses the rotation angle of the quantum from path i to path j, being used to control the convergence rate.

3.4. The Solving Steps of the Optimization of the Logistics Distribution Path

Step1: Setting the values of the parameters α,β,ρ,γ, the number of ants being m, the maximum number of iterations being NMAX, the current number of iterations being t=0, the pheromone $\tau_{ij}(0) = 1$. In order to make all states occur with the same probability in the algorithm of initial search, all the values of α_{ij}, β_{ij} of quantum information coding of ants are $1/\sqrt{2}$.

Step2: Assuming to put m ants in logistics and distribution center, each ant constructed a solution independently. According to the constraints of logistics and distribution of equation (22), selecting the next customer according to formula (25), repeat the application of the state transition rule until the k ant completed logistics and distribution of all customers.

$$j = \begin{cases} \arg\max\limits_{l \in N_i^k} \{\tau_{il} (\eta_{il})^{\delta}\}, & if \ \ q \le q_0 \\ J & , \ otherwise \end{cases} \tag{25}$$

In the formula, is the pheromone concentration of the path (i,l); $\eta_{il} = 1/C_{il}$, being on behalf the amount of self enlightenment of the distribution path (I, l); δ being the weight of self-inspiration; N_i^k representing the collection of adjacent customer that the ant K located in the customer i can directly, that is the collection of customer that having not been visited bu ant k.

The customer j is a random variable produced by using the roulette way according to the probability distribution of equation (15).

$$p_{ij}^{k} = \frac{[\tau_{ij}]^{\alpha} [\eta_{ij}]^{\beta}}{\sum\limits_{l \in N_i^k} [\tau_{il}]^{\alpha} [\eta_{il}]^{\beta}}, \ if \ j \in N_i^k \tag{26}$$

In the formula, α and β are two parameters, which respectively determines the relative influence of pheromone and heuristic information; p_{ij}^{k} refers to the probability of ant k located in customer i choosing customer j as next customer.

Step 3: If the M ants constructed their solutions, then switch to Step4, or Step2.

Step 4: According to the current optimal solution, applying the rule of quantum rotation gate to update probability amplitude of quantum information of ants in each distribution path, according to formula (7) and (8) to update pheromone.

Step 5: If meet the end conditions, namely t>Nmax, outputting optimal solution, getting the optimal scheme of logistics distribution path, or t=t+1, to switch to Step2, to continue the implementation.

4. Simulation Experiment

4.1. Classical Function Test

Selecting 3 kinds of classic multi peak function to test, and comparing the test results with the ant colony algorithm (ACA). 3 classical test functions are as follows:

(1)Rastrigin function

$$f(x)=\sum_{i=1}^{n}(x_i^2-10\cos(2\pi x_i)+10) \tag{27}$$

(2)Ackley function

$$f(x)=-20\exp\left(-0.2\sqrt{\frac{1}{30}\sum_{i=1}^{n}x_i^2}\right)-\exp\left(\frac{1}{30}\sum_{i=1}^{n}\cos 2\pi x_i\right)+20+e \tag{28}$$

(3)Schaffer function

$$f(x)=\frac{\sin^2\sqrt{x_1^2+x_2^2}-0.5}{(1+0.001(x_1^2+x_2^2))^2}-0.5 \tag{29}$$

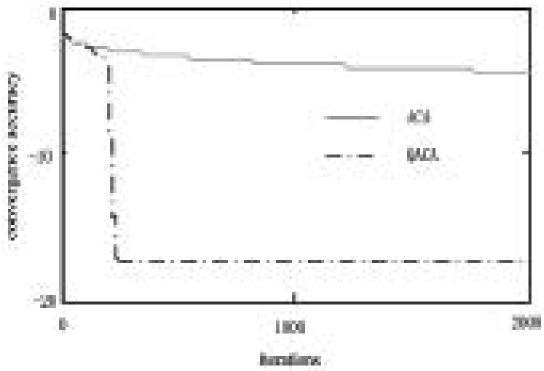
Figure 2 shows the evolution curve of the fitting numerical of test function(Note: in order to facilitate the display and observation of evolution curve, this paper took denary logarithm as the fitness value.) From Figure 1 we can see, for all the functions, the QACA can quickly reach the theoretical minimum at 0 and -1. The convergence speed of QACA algorithm is better than that of ACA, mainly due to the QACA with quantum bits to encode pheromone, quantum rotation gate updating the pheromone in the link to avoid the premature stagnation phenomenon and trapping in local optimization.

4.2. The Simulation Test of Optimization of Logistics Distribution Path

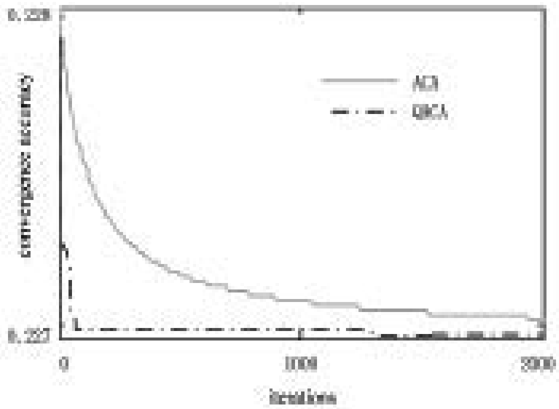
A company having a logistics distribution center, there are 5 sets of goods transport vehicles (the load of each vehicle is 1 ton). They need to delivery to 7 customers, the coordinate and the freight transportation demand of each customer as shown in Table 1 (0 distribution centers; 1~7 client).

Table 1. The coordinates and the customer demand

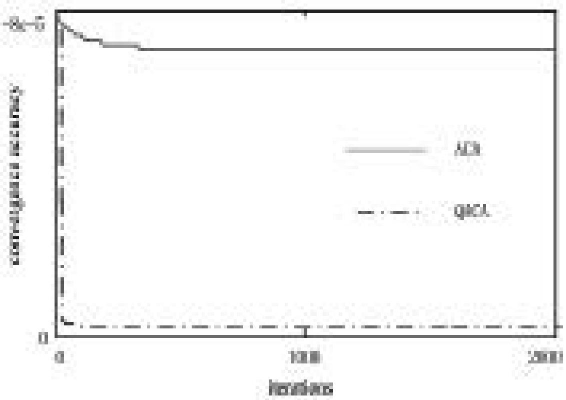
Customer number	Coordinate	Demand
0	(40,40)	
1	(10,20)	1
2	(15,50)	1.6
3	(25,40)	1.3
4	(30,60)	2.4
5	(35,15)	1.5
6	(55,45)	1.1
7	(65,10)	1.6



(a) The curve of fitness convergence of Rastrigin function



(b) The curve of fitness convergence of Ackley function



(c) The curve of fitness convergence of Schaffer function

Figure 2. Comparison of convergence performance of QACA algorithm and ACA

The number of ants of QACA n=5, $\alpha=1,\beta=5,\rho=0.9$, $\gamma=2\sim4$, the prior knowledge $q_0=0.05$, Max evolution algebra NMAX=500. The initial pheromone of each side was 1, respectively using ACA and QACA to solve the problem of the optimization of logistics distribution routing of Table 1, the results being shown in Figure 2 and 3.

From Figure 3 we can see, the logistics distribution path of ACA is divided into 2 routes, route 1: 0 - 4 - 2 - 3 - 1 - 0, the total length of the path being 110.547km; Route 2: 0 - 5 - 7 - 6 - 0, the total length of the path is 108.121km, so the total length of the

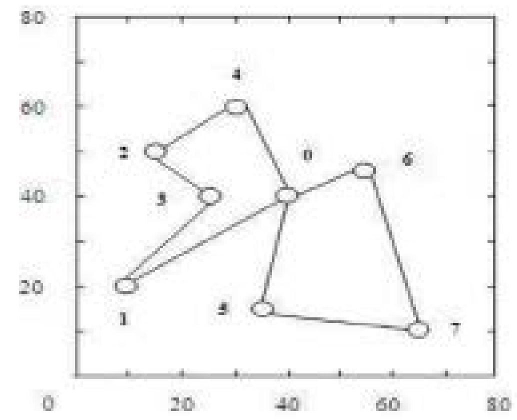


Figure 3. The logistics distribution route of ACA

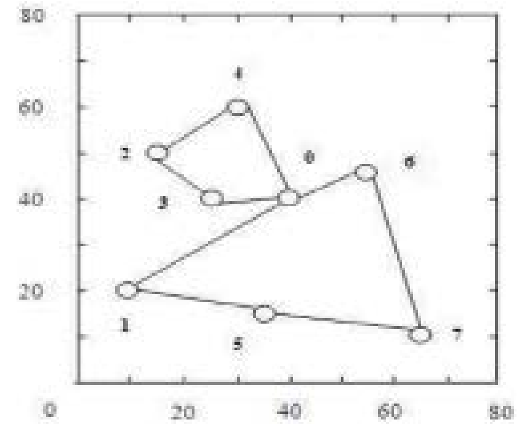


Figure 4. The logistics distribution route of QACA

path of logistics distribution routing schemes of ACA being 218.668km.

From Figure 4 we can see, the logistics distribution path of QACA is divided into 2 routes, route 1: 0 - 4 - 2 - 3 - 0, the total length of the path being 64.491km; Route 2: 0 - 1-5 - 7 - 6 - 0, the total length of the path is 144.177km, so the total length of the path of logistics distribution routing schemes of QACA being 208.668km.

Comparing the results of Figure 2 and figure 3 we can see, QACA can find the logistics distribution routing scheme that be better than the logistics distribution routing scheme of ACA. This is mainly because QACA uses quantum bits to encode the pheromone of distribution path, quantum rotation gate updating the pheromone of the distribution path, improved the searching capability of the algorithm, effectively avoiding the algorithm to fall into local optimum and to prevent premature convergence, improved the efficiency of search.

Conclusion

Taking optimization and adjustment of the parameters of ant colony algorithm by using particle swarm optimiz`ation algorithm, avoiding the artificial way to set its parameters, improves the efficiency of ant colony algorithm. Simulation results showing that, the proposed fusion algorithm is superior to other algorithms, being more close to or to reach the optimal path. The rest of parameters of ant colony algorithm also need to be optimized and adjusted, according to the characteristics of optimization of logistics distribution routing and the deficiency of ant colony algorithm, put forward the strategy of optimization of logistics distribution path of quantum ant colony algorithm. Experimental results show that QACA can quickly and efficiently obtain the optimal solution of the optimization of logistics distribution route, having a certain reference value on the research of problems of ant colony algorithm and logistics distribution routing.

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