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Research on Logistics Distribution Routes Optimization Based on ACO

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***Abstract*—Aiming at the problem of route optimization, a multi-objective optimized route distribution model is constructed with the goal of the smallest total transportation cost and the shortest total delivery route. In order to overcome the shortcomings of ant colony optimization, such as too long search time and easy to fall into local optimum, the ant colony pheromone volatilization coefficient is improved by the method of adaptive change value, which improves the adaptability of ant colony optimization. Therefore, the improved ant colony optimization is used to solve the logistics distribution route optimization problem. The experimental results show that the improved ant colony optimization can obtain a better logistics distribution route plan, which provides valuable reference information for improving the economic benefits of logistics enterprises.**

Keywords- vehicle routing problem; ant colony optimization (ACO); logistics distribution; multi-objective optimization

I. Introduction

With the continuous acceleration of the process of economic globalization, the logistics activities of enterprises have become increasingly frequent, and the rapid development of e-commerce has made logistics an important part of enterprises [1]. In the process of logistics and distribution, the choice of logistics transportation path is very critical. It can not only reduce logistics transportation costs and shorten transportation time, but also improve transportation service quality and the company's core competitiveness. Therefore, choosing a low-cost, high-efficiency delivery route has important research significance.

The research on path optimization problems in foreign countries started early and is widely used. After continuous accumulation, development, improvement and perfection, excellent research results of a large scale have been successively produced. Wang Yuan fused the ant colony optimization algorithm and the simulated annealing algorithm to solve the periodic vehicle routing problem with time windows and service selection problems [2]. Rajeev Kumar Goel used the firefly optimization algorithm and simulated annealing algorithm to improve the local optimization problem of the ant colony algorithm, and obtained a better convergence and solution scheme [3]. Artur Pessoa proposed a bifurcation and price algorithm based on heterogeneous vehicle routing, which can better solve the problem of multi-warehouse and site vehicle routing [4]. Taking advantage of population evolution, Yan, X.M. proposed a graph-based fuzzy evolution algorithm to solve the two-echelon vehicle routing problem. This method integrates the graph-based fuzzy allocation scheme into the iterative evolutionary learning process to avoid excessive fitness evaluations of unpromising moves in different satellites [5]. Xiaoshu Xiang et al. considered the diversification of actual needs, and combined heuristic algorithms and ant colony algorithms to efficiently respond to the diverse needs of customers [6]. YaoJiang Gu proposed a dynamic pheromone ant colony optimization algorithm based on CW saving algorithm. A general path range is found by CW saving value algorithm, and the pheromone matrix can be reasonably configured, so that the ant colony algorithm can quickly get a better solution in the initial optimization [7]. Xu Kun et al. used the random search mode of Levi flight to find the global optimal solution, and the search mode combining small step size and occasional large step size search improved the problem of easy stagnation of ant colony algorithm iteration and long search time. This method speeds up the solution efficiency and accuracy of the ant colony algorithm [8].

Aiming at the problems of low solution efficiency and simple constraint conditions in current logistics distribution route design methods, a logistics distribution route optimization method based on improved ant colony algorithm is proposed. Through specific examples, the improved ant colony algorithm is analyzed and applied to the logistics distribution route plan.

II. Construction of Path Optimization Model for Logistics Distribution

A. Problem Description

Generally, the problem of logistics distribution route optimization can be defined as: For distribution service points in a known area, and a certain number of distribution vehicles, through reasonable planning and arrangement, the most suitable distribution route is selected so that the distribution vehicles can have Distribute services to all service points in an orderly and non-repetitive manner. In addition, certain targets must be met under certain constraints. The problem of vehicle routing optimization is mainly composed of such elements as distribution center, distribution vehicle, distribution goods, customers, constraints, optimization goals and so on [9].

Assuming there are M customer points, and the demand and location of each customer point are also known, there are a total of N cars from the distribution center to each demand point, and it is stipulated that after the distribution task is completed, it will return to the logistics center. The weight is constant.

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B. Model Establishment

Analysis of logistics and distribution problems shows that different optimization goals can be selected according to the actual situation. The multi-objective optimization of this model is selected with two objective functions: the lowest total transportation cost and the shortest delivery distance. The total transportation cost is divided into fixed cost and variable cost. Regardless of the total fixed cost, the variable cost of transportation will increase with the increase of the distance traveled by the vehicle during the distribution process. It is directly proportional to the transportation distance of the vehicle. The variable transportation cost of the distribution vehicle is as follows:

$$\mathrm{C} = \mathrm{r}\sum_{k=1}^{n}\sum_{i=0}^{m}\sum_{j=0}^{m} x_{ij}^{k}\, d_{ij} \quad (1)$$

In formula (1):m is the total number of customers that need to be delivered, n is the total number of vehicles that can participate in the delivery, r represents the transportation cost per unit distance, d_{ij} is the distance between customer point i and customer point j, and x_{ij}^{k} represents vehicle k driving from customer i to customer j, otherwise 0.

The shortest objective function of the total distribution path is:

$$f = min\sum_{k=1}^{n}\left(\sum_{i=1}^{S_k} d_{r_k}^{i-1} r_k^{i} + d_{r_k}^{S_k}\right) sign(S_K) \quad (2)$$

In formula (2): R_k is a collection of customer points where vehicle k is dispatched for delivery. When $S_k = 0$, R_k is the empty set, when $S_k \neq 0$, $R_k = \{r_k^1, r_k^2, \cdots, r_k^{S_k}\}$, Where r_k^i is that the position of the customer point in the delivery route of vehicle k is i. S_k is the total number of customers delivered by vehicle k. $sign(S_K)$ is a symbolic function.

The constraints of the logistics distribution route optimization model are as follows:

1) Vehicle load constraints: The total amount of goods delivered on each vehicle does not exceed the maximum load capacity of the delivery vehicle.

$$\sum_{i=1}^{S_k} y_i^k q_i < E_K \quad (3)$$

In formula (3): y_i^k means that the goods of customer i are delivered by vehicle k, and E_k is the maximum load of vehicle k.

2) Delivery vehicle constraints: In the distribution process, each vehicle can perform distribution tasks to multiple customers, but each customer has and only one distribution vehicle for distribution.

$$\sum_{k=1}^{n} y_i^k = 1 \quad (4)$$

3) Travel distance constraint: Vehicles depart from the distribution center, and each time a delivery activity is completed, the driving distance of each vehicle does not exceed the maximum driving distance.

$$\sum_{i=1}^{m}\sum_{j=1}^{m} x_{ij}^{k}\, d_{ij} \leq D_k \quad (5)$$

In formula (5): D_k is the maximum travel distance of vehicle k.

4) Customer quantity constraint: The number of customers delivered per vehicle is less than the total number of customers.

$$\sum_{k=1}^{n} S_k = n \quad (6)$$

In summary, the logistics distribution route optimization problem is a typical combinatorial optimization problem, and the ant colony optimization algorithm is a heuristic search algorithm that solves the problem through positive feedback and distributed collaboration. When the ant colony is looking for food, it always looks for the shortest path from the food source to the ant colony, which is very similar to the logistics distribution route optimization problem. Therefore, an improved ant colony optimization algorithm is introduced to solve it.

III. IMPROVED ANT COLONY ALGORITHM TO OPTIMIZE PATH MODEL

The basic principle of the ant colony algorithm is described as follows: Based on the study of the collective foraging behavior of real ant colonies in nature, the real ant colony collaboration process is simulated. The algorithm uses several ants to jointly construct the solution path. By leaving and exchanging pheromone on the solution path, feedback information is used to improve the quality of the solution, and then find the shortest path to achieve the goal of optimization[9].

The basic idea of applying ant colony algorithm to solve the path optimization problem is: use the walking path of the ants to represent the feasible solution of the problem to be optimized, and all paths of the entire ant colony constitute the solution space of the problem to be optimized. Ants with a shorter path release more pheromone. As time progresses, the accumulated pheromone concentration on a shorter path gradually increases, and the number of ants that choose this path increases. In the end, the entire ant will be concentrated on the best path under the effect of positive feedback, at this time the corresponding is the optimal solution of the problem to be optimized.

A. Improvement of ant colony algorithm

Because the ant colony algorithm has some shortcomings, such as long search time and premature convergence, which affects the solution of logistics distribution routes, this article improves it. The pheromone volatilization coefficient ρ indicates the persistence of the pheromone amount, that is, the degree of mutual influence between ants.

If the value of ρ is too large, it means that the pheromone volatilizes quickly, which will cause the pheromone to play a very limited role in the path selection of ants, and it will not highlight the advantages of the ant colony algorithm. In practical examples, it often appears that the pheromone has not yet worked It has been volatilized and it is difficult to find the optimal solution. If the value of ρ is too small, it means that the pheromone is not easy to volatilize, which will lead to excessive accumulation of pheromone on the local path. The probability of ants choosing the selected path to run will greatly increase, which will restrict the algorithm's global search ability and make it difficult to find the optimal solution. Therefore, it is necessary to set a reasonable value for the pheromone volatilization coefficient to improve the performance of the algorithm. This article adopts the method of adapting to change to speed up the convergence speed and reduce the probability of premature convergence, as follows:

$$\rho = \begin{cases} 0.1 & Iter \in [0, 0.25Iter\_max] \\ 0.2 & Iter \in [0.25Iter\_max, 0.5Iter\_max] \\ 0.3 & Iter \in [0.5Iter\_max, 0.75Iter\_max] \\ 0.4 & Iter \in [0.75Iter\_max, Iter\_max] \end{cases} \quad (7)$$

In the formula (7), Iter and Iter_max respectively represent the current and maximum iteration times. That is, in the early stage of operation, a smaller pheromone volatilization coefficient is used to increase the algorithm's optimization ability and speed up its convergence speed, and gradually increase the ρ value in the middle and later stages to ensure the algorithm's global search ability and avoid the algorithm from forming a local optimum.

B. *Improved algorithm to solve the model of logistics distribution route*

Applying the improved ant colony algorithm to the logistics distribution route optimization model, the solution steps are as follows:

- Establish the model of logistics distribution route optimization problem.
- Initialize the relevant parameters, including ant colony size, pheromone factor, heuristic function factor, pheromone volatilization factor, pheromone constant, and maximum number of iterations, etc., and read the data into the program and perform preprocessing, such as Transform the coordinate information of the city into the distance matrix between cities.
- The ant colony is initialized, ants are randomly placed at different starting points, and the next city to be visited is calculated for each ant until an ant has visited all cities and the initial pheromone on all paths is the same.
- Set the initial times of iterations of the algorithm to 0.
- Calculate the path length of each ant and the probability of each ant choosing the next crawling node.
- Record the optimal solution for the current iteration times, and update the pheromone on the path between adjacent nodes.
- When all ants crawl the entire path, update the pheromone on the entire path, and increase the times of iterations by 1.
- If the current times of iterations is greater than the maximum times of iterations, then the optimal logistics distribution path is output.

IV. Test Results and Analysis

A. *Test Case*

In order to analyze the impact of the improved ant colony algorithm on the solution performance of the logistics distribution route optimization model, Matlab R2019 is used as the simulation software. The computer operating environment is as follows: CPU is 3.40GHz, memory is 8GB, and operating system is Windows 10.

The initial value of each parameter of the algorithm is set to: $\alpha = 1, \beta = 5, \rho = 0.1, Iter\_max = 200$, the total number of ants is 50.

To simulate the actual distribution business scenario, a distribution center has 5 distribution vehicles with a load of 5000kg, and 31 customers are required to deliver goods. The distribution target location is known to the horizontal and vertical coordinates of the map and the required weight of the goods, and the path is optimized for this situation Problem solving.

B. *Result analysis*

In the ant colony algorithm, the influence of parameter selection on the performance of the algorithm is complementary and mutually restrictive. The algorithm is based on the optimization of the pheromone volatilization coefficient ρ , and under the same other conditions, six sets of experimental data are used to combine the values of α and β to simulate the effect of the algorithm performance. The results are shown in Table I.

TABLE I. The Influence of Different Parameters on Algorithm Performance

Number	**The influence of each parameter value on the result**			
	α	***β***	***Optimal path length / Km***	***Times of iterations***
1	0	0	32290.0711	8
2	0.5	1	19722.0391	166
3	0.5	5	15872.4598	169
4	1	1	16548.2748	159
5	1	5	15601.9151	140
6	1	10	15611.9195	93

It can be seen from Table I that when the values of α and β are too large, the algorithm tends to converge prematurely and it is difficult to obtain better search results; the values of α and β are too small, the algorithm converges slowly and it is difficult to obtain the optimal solution. Better search results can only be obtained by selecting α and β appropriately. Generally, the following combinations are selected: $(\alpha = 0.5，\beta = 1)$ or $(\alpha = 1, \beta = 5)$.

$\alpha = 1, \beta = 5$ is selected in the comparison experiment before and after the algorithm optimization. When the improved ant colony algorithm iterates to about 120 times, the algorithm basically stabilizes. The performance comparison before and after the improvement is shown in Table II.

TABLE II. THE PERFORMANCE COMPARISON BEFORE AND AFTER ALGORITHM IMPROVEMENT

Before algorithm optimization		**After algorithm optimization**	
Time of iterations	***Optimal path length / Km***	***Time of iterations***	***Optimal path length / Km***
10	17086.3565	10	16928.4869
40	16910.7845	40	16660.3816
70	16695.3369	70	16187.5269
100	16438.1562	100	16187.5269
130	16227.3854	130	15601.9151

Comparing the number of iterations before and after the algorithm improvement and the optimal path length, it can be seen from Table 2 that the number of iterations of the improved ant colony algorithm to find the optimal logistics distribution path is significantly less than that of the ant colony algorithm, which speeds p the efficiency of solving the optimal path , can be very applied to the actual large-scale logistics distribution route optimization problem.

V. CONCLUSIONS

With the rapid rise of the logistics and transportation industry today, reasonable planning of driving routes can not only save resources and time, but also reduce environmental pollution, which is of great significance to the future development of the country and enterprises. The logistics distribution route optimization problem is a typical combination optimization problem, and the calculation process is more complicated. Through in-depth research on the logistics route optimization problem, it is found that the ant colony algorithm is regarded as a more efficient intelligent algorithm.

Since the ant colony optimization uses positive feedback and distributed collaboration to obtain the shortest path, which is very similar to the path optimization model, an improved ant colony algorithm is introduced to solve the route distribution model problem. A multi-objective optimization model is established with the least total transportation cost and the shortest total delivery path. By optimizing the relevant parameters of the ACO, the actual logistics distribution problem model is solved. Through experimental tests, the optimal path or approximate optimal path of delivery vehicles in a certain area is given, and the performance comparison test with the improved ant colony algorithm is carried out. The results show that the improved ant colony optimization can obtain a better logistics distribution route plan. And the search efficiency is high, which has a certain practicality and reference value for the actual logistics distribution route optimization.

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