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Transport Vehicle Route Decision Based on Particle Swarm Optimization Algorithm in Logistics Distribution Management

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In recent years, the economic boom has prompted various industries to usher in better development prospects, including the continuous development of the logistics industry. In all aspects of logistics, the most important issue is the issue of distribution, which corresponds to the issue of transportation timeliness. The transportation timeliness is closely related to the route of the transportation vehicle to a large extent, so the optimal selection of the transportation route plays an important role in solving the timeliness problem of distribution. In order to better optimize the transportation route of transportation vehicles, this paper will use particle swarm optimization algorithm to solve such decision-making problems. And through the logistics distribution and transportation vehicle route optimization problem, the logistics transportation optimization method based on the traditional particle swarm optimization algorithm and the logistics distribution method of the improved particle swarm optimization algorithm are used to construct the decision-making of the transportation vehicle transportation route. Through the simulation experiment of transportation route optimization based on particle swarm optimization, the particle optimization algorithm was run 99 times, of which the optimal solution is 57 times, and the probability of achieving the final efficient delivery success reaches 57%. The corresponding optimal solution results of 57.1 and 25.1 show that the transportation vehicle route based on the particle swarm optimization algorithm can successfully obtain the optimization results for the route, achieving the timeliness of distribution in logistics transportation.

Keywords: Logistics Distribution Management, Particle Swarm Optimization Algorithm, Transportation Vehicle Route, Decision Optimization

1. INTRODUCTION

The concept of logistics emerged a long time ago, and with the various economic developments over time, the form of this concept is also changing. With the rapid development of the Internet, e-commerce has elevated the virtual economy, and the sustained development of this industry now depends to a greater extent on the mature development of the logistics industry. In the large system of logistics, the problem of logistics distribution and the optimization result of the transportation route corresponding to this problem is the dominant one. Vehicle transportation is the main form of commodity circulation in the inland areas, and the planning of vehicle routes is complex, making the selection of the optimal route for vehicle transportation a problem that must be solved.

Only by rationally optimizing the transportation routes of transportation vehicles, can the overall efficiency of logistics distribution be improved, which also guarantees the development of the transportation industry relying on vehicles. This kind of problem can be handled with the help of advanced information technology. In this paper, the optimization algorithm of particle swarm is used to

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optimize the route of the transport vehicle, so that this kind of problem can be resolved successfully. Through the use of particle swarm algorithm, it can offer a good reference for the transportation vehicles in the planning of the route, and also provide a basis for the final decision.

The innovation of this paper is that (1) it focuses on the problem of distribution in logistics, optimizes and improves the transportation route of transportation vehicles, which leads to an improvement in the efficiency of the logistics industry. (2) By using the particle swarm optimization algorithm in the intelligent algorithm to solve the optimization problem of the transportation route, the application of the intelligent algorithm will have a broader scope.

2. RELATED WORK

As an integral part of contemporary economic development, logistics distribution, the key link in logistics, has been studied by many researchers in order to improve the efficiency of logistics distribution. Kumar studies the problem of reducing the transportation cost in cement transportation, hoping to obtain more profits through transportation optimization [1]. Maloni optimizes the process of logistics and transportation by studying the labor cost in logistics and transportation [2]. Godlevskyi made some improvements to the logistics distribution system through a different mode of logistics management [3]. Ning built a multi-item logistics distribution optimization model by studying the psychological factors of logistics distribution users [4]. Yadavalli employed a new distribution model to optimize the movement of packages in and out of the distribution system [5].This previous research work on the logistics distribution link in the logistics system aimed to improve the overall logistics distribution efficiency from different perspectives. It can be seen that there are various factors that affect the logistics distribution efficiency. It is an entry point for reform. In the end, logistics still has to rely on land vehicle transportation. If reasonable planning is carried out in this regard, logistics distribution will greatly improve the efficiency of the industry and improve the decision-making power in regard to vehicle deployment. In this paper, the corresponding processing is implemented in the step of vehicle transportation to realize the optimization of decision-making for the transportation route.

In this paper, the particle swarm optimization algorithm is used to deal with these logistics distribution problems, and to optimize the logistics distribution transportation route. The related research is as follows. When Martinson used particle swarm optimization to optimize the transportation route of transportation vehicles, he calculated the optimal cost of a single factor model, which provided better results for the optimization results [6]. Li attempted to reduce the cost by passing the transportation route of vehicle transportation through the particle swarm optimization algorithm [7]. Li transformed various factors involved in vehicle transportation into multiple objectives, and optimized the model with the help of the particle swarm algorithm [8]. Yin optimized the route of vehicle transportation by using particle swarm optimization to strengthen the relationship between customers and transporters in logistics transportation [9]. Bhuvaneswari compared various algorithms for the route transportation problem of transport vehicles, in order to determine the effectiveness of the particle swarm optimization algorithm [10]. The above researchers conducted studies related to the results and purposes of particle swarm optimization algorithm in handling the transportation route problem of transportation vehicles, which also proves that the research direction of this paper is in line with the general direction of route optimization research. However, this paper will focus mainly on optimizing the transportation route in vehicle transportation, so as to provide support for the decision-making of the vehicle route.

3. DECISION-MAKING METHOD OF LOGISTICS VEHICLE TRANSPORTATION ROUTE BASED ON PARTICLE SWARM OPTIMIZATION ALGORITHM

3.1 Logistics Distribution and Transportation Vehicle Route Optimization Problem

Nowadays, the importance of the logistics industry is undisputed. With China's rapid economic development and increasing openness to the outside world, logistics at the national level has been combined for the international transportation of goods and the development of various internal industries is especially evident. The role of logistics in economic development is reflected in many aspects, with both direct and indirect effects on economic improvement [11]. Therefore, optimizing the logistics distribution can improve the overall work efficiency of the logistics industry from a deeper level. The general process of logistics transportation can be represented by Figure 1:

As can be seen from the entire logistics process depicted in Figure 1 above, after the goods are received from the receiving point, between each point, it relies on the transportation of vehicles, but since the route between the locations is There are various, in order to improve the efficiency of the entire distribution process, the most important thing is to optimize the transportation route. The problem of optimizing the transportation route of transportation vehicles (VRP) emerged a long time ago, and the principle of this type of problem has been refined to a certain extent, because this problem involves a system. The elements within it are rationally optimized and can be solved using many related disciplines, including operations research, applied analytical mathematics, logistics, and computer science. The principle corresponding to the route optimization problem of transport vehicles is shown in Figure 2.

Figure 2 above describes the two situations of route optimization in the logistics distribution process. It can be seen from the figure that this type of problem is mainly related to the distribution of consumers. When the transported vehicle is under certain conditions, such as the needs of consumers during the transportation of the vehicle, the length of the delivery task, etc., the transport route of the vehicle

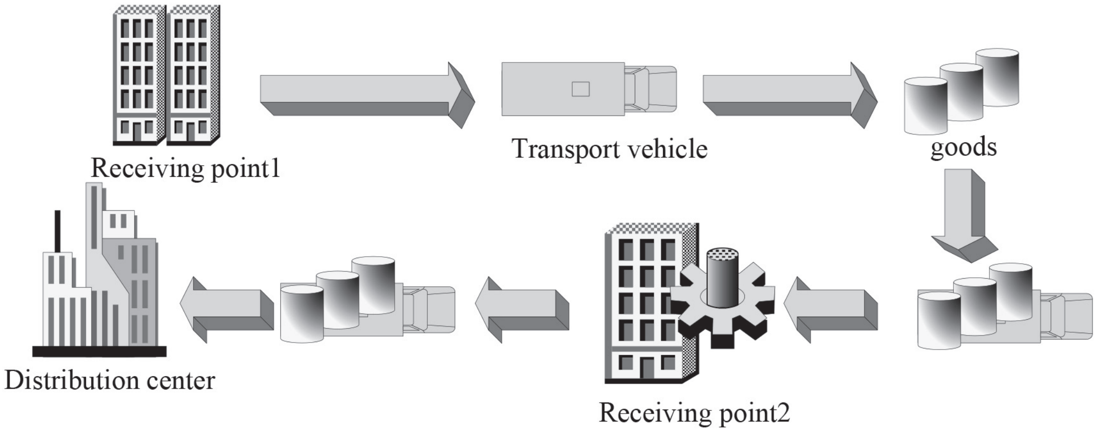


Figure 1 Diagram of the logistics and transportation process.

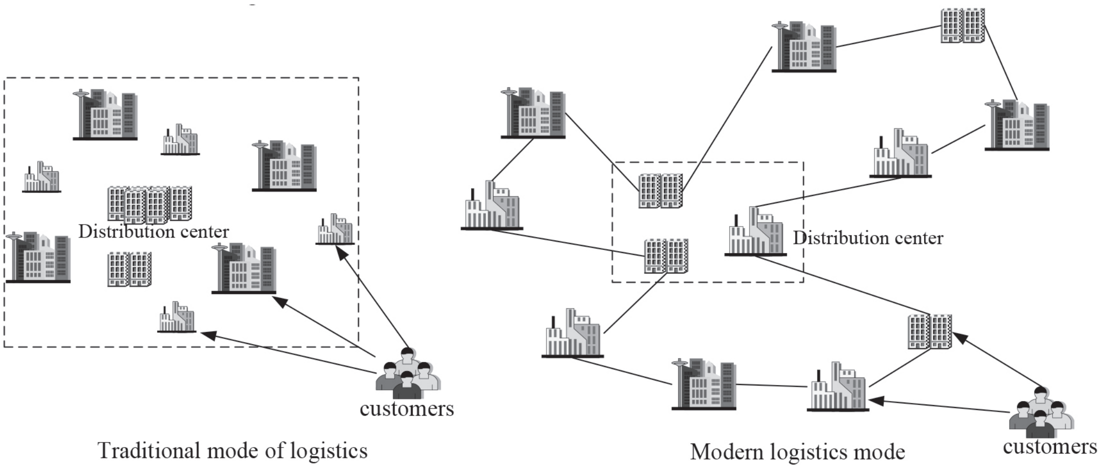


Figure 2 Two modes of route optimization problem for logistics vehicle transportation.

Table 1 Problem types for vehicle transportation route optimization.

Classification criteria		**Classification criteria**	
Execution characteristics	Loading problem	Relationship between cars and yards	Open vehicle issues
	Unloading problem		Closed vehicle issues
	Loading and unloading problems	Loading condition	Sufficient cargo
Car number	A parking lot problem		Insufficient cargo
	Multi depot problem	Task time	Time constrained problem
Type of vehicle	A vehicle type problem		Time unconstrained problem
	Problems with multiple models	Optimization factors	Single factor problem
			Multiple factor problem

is reasonably formulated, and the consumer's goods are delivered in a timely and orderly manner. It is also the ultimate goal of solving such problems. According to the above-mentioned principle of path optimization problem [12], this kind of problem can be divided into different categories. These are presented in Table 1.

In Table 1, the route problem of vehicle transportation is classified and summarized, and the standard of each classification is also an influencing factor for the vehicle transportation process [13]. The above-mentioned problems related to various transportation routes are actually related to the logistics system. The construction of the current logistics distribution system relies on computer science, etc., which mainly involves data processing, as depicted in Figure 3.

The system model in Figure 3 above is the main component of the contemporary logistics system. According to the processing structure of logistics distribution in the figure, most of the data pertaining to the logistics process uses computer science to digitize the information. It is applied in the construction of logistics system [14]. This also provides the hardware basis for the application of more intelligent algorithms in this problem, including the particle swarm optimization algorithm used in this paper. After digitization, the route optimization can be represented by a certain system structure, as shown in Figure 4.

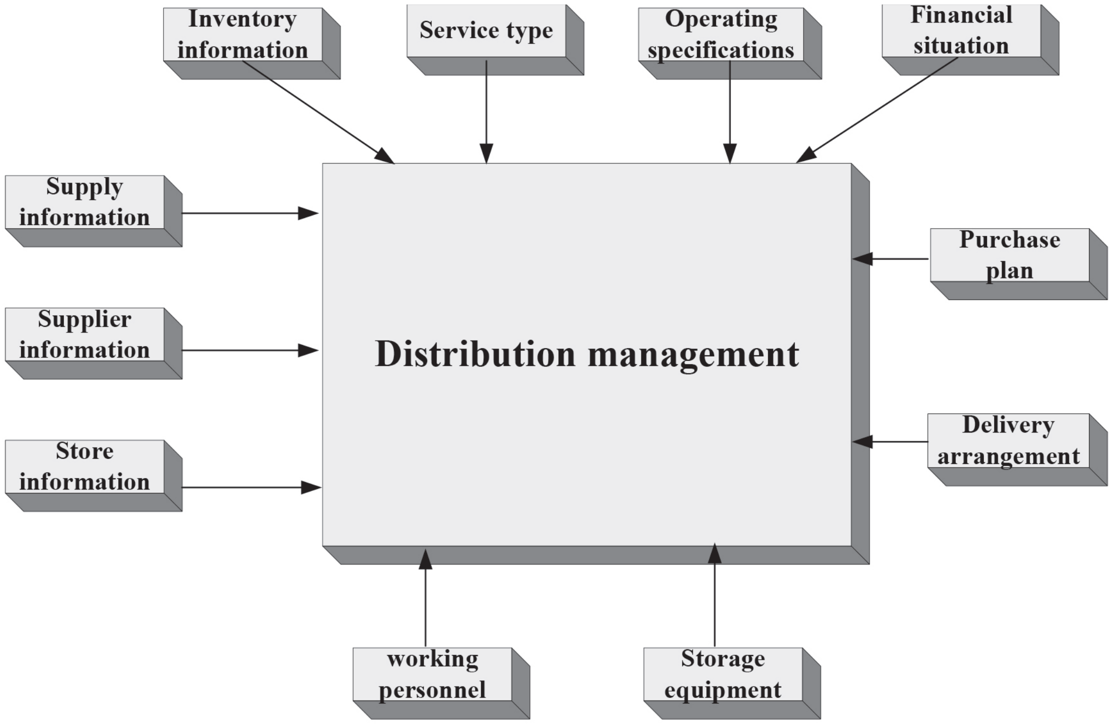


Figure 3 Structure diagram of logistics distribution system.

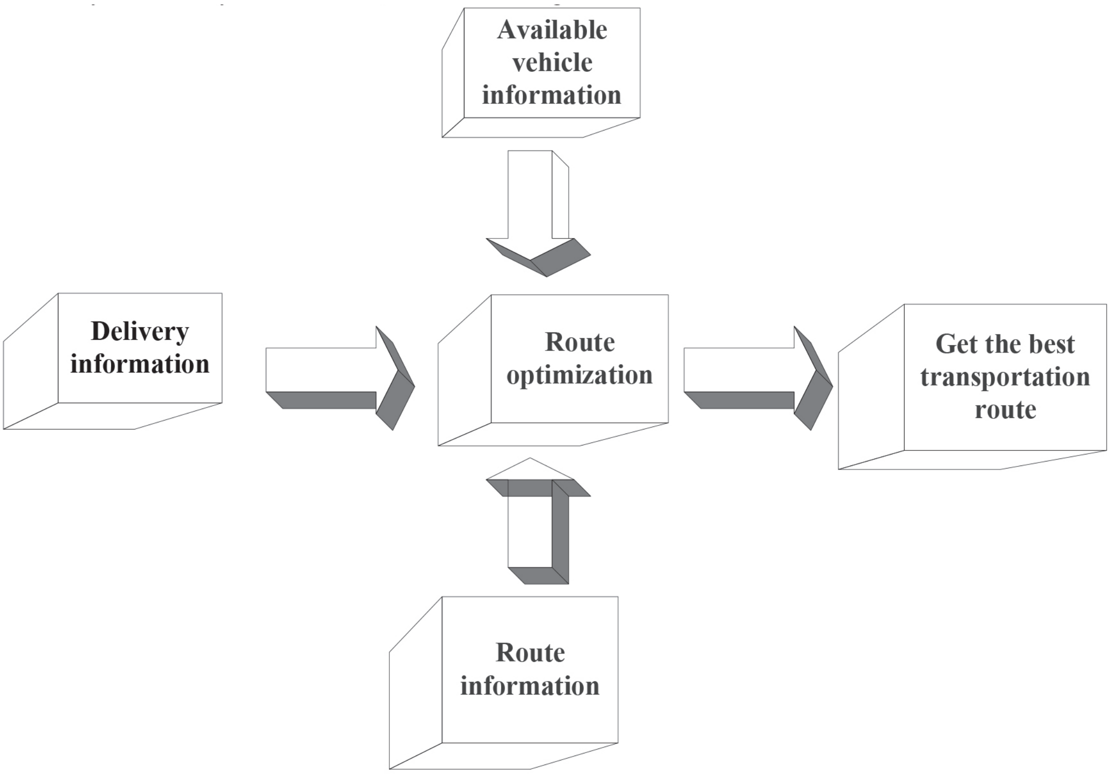


Figure 4 Diagram of the optimized structure of logistics and distribution transportation routes.

The structure in Figure 4 above is a link in the logistics distribution management system, and this step is very important for the efficiency of the entire distribution. Each of its parts is extremely critical because the management system of logistics transportation involves arrangements for the distribution center of the goods and the distribution business. Finally, the result of route optimization can be automatically obtained according to the corresponding data information, which also directly saves the cost of transportation. After the introduction of logistics transportation and route optimization problems, it is necessary to construct mathematical models for such problems [15]. The first is the generalized modeling for this type of problem. Suppose there are M vehicles, there are A customers who need these to be delivered to them, vehicles $m = 1, 2, \cdots M$, customers $a = 1, 2 \cdots A$, and there are variables X and Y, the formula is as follows:

$$Y_a^m = \begin{cases} 1, \text{Car M delivers to user a} \\ 0, \text{otherwise} \end{cases} \quad (1)$$

$$X_{ab}^{nm} = \begin{cases} 1, \text{User a to user b use the M} - \text{Car of N field} \\ 0, \text{otherwise} \end{cases} \quad (2)$$

The above formula takes the two cases as two different variables in the route optimization problem, and then it is necessary to define the optimal result brought by the most route, such as the least transportation cost, the least transportation time and the shortest transportation time. Transportation routes are obtained withthe following formula:

$$\min Q = \sum_{m=0}^{M} \sum_{a=1}^{A} \sum_{b=1}^{A} C_{ab} X_{ab}^{m} \quad (3)$$

C_{ab}in the formula (3) represents the cost incurred from user a to user b [16]. In addition to the setting of the above optimal value, some conditions need to be set. The formula is:

$$\max \frac{1}{M} = \sum_{a=1}^{M} \varepsilon_a t_a \quad (4)$$

The $\varepsilon_a t_a$in the above formula represents the user's satisfaction with the transportation result, and it can also represent the transportation time, etc. In order to allow each user of logistics transportation to obtain the delivery of goods in time, the conditions of the following formula need to be met:

$$\sum_{m=1}^{M} Y_a^m = 1 \quad (5)$$

On the basis of the above, it is also necessary to ensure that each user is served more than once, which is expressed by this formula:

$$\sum_{a=1}^{M} X_{ab}^{m} = Y_b^m \quad (6)$$

In order to obtain the result for the final route optimization, it is necessary to cancel the selection of other routes that may appear. The formula is:

$$\sum_{a,b \in l \times l}^{A} X_{ab}^{m} \leq |l| - 1, l \in \{1, 2, \cdots, A\} \quad (7)$$

When all the above conditions are met, it is also necessary to ensure that the car is not overloaded. The corresponding formula is:

$$\sum_{a=1}^{A} u_a Y_a^m \leq p_m \quad (8)$$

The modeling of the route optimization problem above has taken into account various factors involved. The construction is also a general form of the route optimization problem in vehicle transportation [17] and it contains a variety of model structures. In practical applications, the modeling process needs to be modified and adjusted to a certain extent, because the model constructed according to the actual situation needs to add more constraints so that the logistics can be realized. Of course, in order to obtain a better route, it is then necessary to use the particle swarm algorithm for processing.

3.2 Logistics and Transportation Optimization Method Based on Traditional Particle Swarm Optimization

Logistics transportation involves the delivery of goods to consumers via a certain route in a timely and efficient manner, and this process is very similar to the original model of particle swarm optimization [18]. The original particle swarm algorithm is based on the foraging behavior of birds, where individual birds represent particles in the foraging process. The efficiency and time of foraging define the problem in this process, which is then abstracted to form the final particle swarm algorithm model. The similarity between the two lies in the pursuit of the optimal solution of the route, which also provides an entry point for the application of particle swarm optimization in the optimization of vehicle transportation routes. The principle of particle swarm optimization is depicted in Figure 5.

Figure 5 above shows the particle swarm clearly, and also includes several important factors of the particle swarm: the position of the particle, the speed of the particle, and the degree of adaptation of the particle. In the original model above, the group of birds has not been shown, because each bird is moving for the group's foraging until the bird that finds the food the fastest appears [19]. This is very closely related to the transportation of vehicles. Through a process similar to the above model, finding the most efficient transportation route for logistics distribution is the answer to the most problematic route. The operation of this algorithm is described in mathematical form. Suppose there is a particle group $G = \{G_1, G_2, \cdots, G_m\}$, the particle a in the X space can be expressed as X_a, the speed of the particle is expressed as v_a, and the best position of a particle in the space X is Q_a, the best position among all the particles in the particle swarm is Q_c. After the foraging behavior of the particle swarm, the corresponding velocity of the particles and their respective positions can be expressed as:

Location:

$$X_{ab}^{u+1} = X_{ab}^{u} + v_{ab}^{u+1} \quad (9)$$

speed:

$$v_{ab}^{u+1} = v_{ab}^{u} + d_1 t_1 \left(Q_{ab}^{u} - X_{cb}^{u}\right) + d_2 t_2 \left(Q_{cb}^{u} - X_{ab}^{u}\right) \quad (10)$$

where u represents the number of times that the current particle swarm algorithm has undergone operations, $d_1$and $d_2$represent the learning variable values of an algorithm, and t_1 and $t_2$represent random values within the range [20]. The above formula also includes the changes within the particle

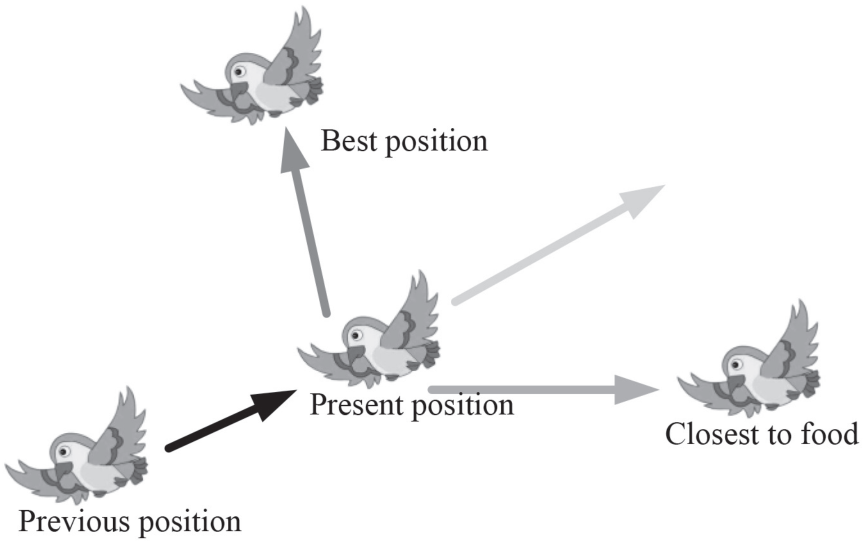


Figure 5 Original model of particle swarm optimization.

swarm; that is, the algorithm is constantly changing, through the particle's own speed, foraging experience and particle swarm experience, until the final optimal position is obtained. This process is a simple mathematical description, and it is necessary to analyze the characteristics of the algorithm, that is, the particle swarm algorithm itself has the speed of aggregation and the quality of aggregation. First, on the basis of the above formula, weights are added to improve the evolution of the particle swarm. The particle velocity after weighting can be expressed as:

$$v_{ab}^{u+1} = \beta v_{ab}^{u} + \alpha d_1 t_1 \left(Q_{ab}^{u} - X_{cb}^{u}\right) + \eta d_2 t_2 \left(Q_{cb}^{u} - X_{ab}^{u}\right) \tag{11}$$

The purpose of weighting is to minimize the impact on the particle velocity, which has a greater effect on the particle's seeking ability. At the same time, in order to improve the aggregation characteristics of the particle swarm, an aggregation factor needs to be introduced. The corresponding aggregation formula is expressed as:

$$v_{ab}^{u+1} = \lambda \left[v_{ab}^{u} + \varepsilon_1 t_1 \left(Q_{ab}^{u} - X_{cb}^{u}\right) + \varepsilon_2 t_2 \left(Q_{cb}^{u} - X_{ab}^{u}\right)\right] \tag{12}$$

In the above formula, $\varepsilon_1 = \varepsilon_2 = 2.10$ and λ represent the aggregation factor. The corresponding formula is expressed as:

$$\lambda = \frac{2}{\left|2 - \varepsilon - \sqrt{\varepsilon^2 - 4\varepsilon}\right|} \tag{13}$$

The above-mentioned weighting and aggregation processing for the particle swarm algorithm are intended to improve the accuracy of the algorithm and the efficiency of the work. Combining the above formulas creates the mathematical model structure of particle swarm optimization [21]. In order to better apply the particle swarm algorithm to practical application, it is also necessary to discuss the improved particle swarm algorithm.

3.3 Logistics Distribution Method Based on Improved Particle Swarm Optimization Algorithm

The original model for particle swarm algorithm is the foraging of birds. In this original model, since the foraging ability of individual particles will be affected by factors such as time and distance, it is necessary to make necessary improvements because, if the original particle swarm model continues to develop, there may be some problems. The improved algorithm also plays an important role in preventing these problems [22]. After the improvement, the search ability of particles can be enhanced, and it is also possible to actively avoid local optimization. This paper will redefine the fitness of the particles in the particle swarm, the formula for which is:

$$\eta^2 = \sum_{a=1}^{n} \left(\frac{f_a - f_{bc}}{f'}\right)^2 \tag{14}$$

The above formula is the calculation of variance, and this result is used to express the degree of adaptation of the particle. For the above formula, there are:

$$f = \max\left\{1, \max_{1 \le a \le M} |f_a - f_{bc}|\right\} \tag{15}$$

For the degree of adaptation, f in the formula plays a role in controlling its size, M represents the number of particles in the particle swarm, and f_a represents the function of obtaining the degree of particle fitness, among which there are:

$$f_{bc} = \frac{1}{m} \sum_{a=1}^{m} f \tag{16}$$

Where f_{bc} represents the average function expression of the particle fitness degree. When the function value of the fitness degree is better than the function value of the average fitness degree, it can be obtained by weighting:

$$\lambda = \lambda - (\lambda - \lambda_{\min}) \times \frac{|f - f_{bc}|}{f_n - f_{bc}} \tag{17}$$

Table 2 Consumer Location Information.

consumer number	**1**	**2**	**3**	**4**	**5**
X coordinate	80	37	23	61	11
Y coordinate	27	33	71	97	21
consumer number	6	7	8	9	10
X coordinate	92	31	78	32	87
Y coordinate	7	61	73	53	53

Table 3 Information about transport vehicles.

consumer number	**7**	**8**	**9**
X coordinate	23	71	53
Y coordinate	23	47	3
Number of cars	3	3	3

If the function value of fitness is worse than the function value of average fitness, the result of weighting is as follows:

$$\lambda = 2.3 - \frac{1}{\left[1 + u_1 \exp\left(-u_2 \left| f_n - f'_{bc} \right|\right)\right]} \tag{18}$$

After the above improvement process, the particle swarm algorithm is still faced with the phenomenon of particle aggregation that may occur in the algorithm itself. The occurrence of this phenomenon may cause the algorithm to have serious deviations. In order to solve this problem, the variance of the degree of adaptation is used to quantitatively determine the aggregation. By comparing the calculated variance value with the theoretical value, the result of the optimal foraging route can be obtained. It can also be corrected by mutation to expand the space where the particle swarm is located. Its formulaic expression is:

$$P_t = (P_{\max} - P_{\min}) \left(\frac{\eta_t^2}{m}\right) + (P_{\min} - P_{\max}) \frac{2\eta_t^2}{m} + P_{\max} \tag{19}$$

The above formula gives the probability of mutation. η_t^2 in the formula represents the variance value of the corresponding adaptation degree of the particle swarm algorithm in the t-th operation, and P_t represents the possibility of mutation in the particle swarm. $P_{\max}$, $P_{\min}$ represent the maximum and minimum values of mutation, respectively. The formula shows that under certain conditions, there is an inverse relationship between the degree of adaptation of particles and the possibility of variation [23]. That is, when the variance is small, the distance between the corresponding particles is less, and variation is more likely to occur, and vice versa. The above is the improvement of the particle swarm algorithm. The purpose of this is to avoid the aggregation phenomenon that may occur under the natural development of the particle swarm algorithm, so that the final result obtained by the algorithm is the optimal solution for the entire system under test conditions. When the optimization of the transportation route of the transportation vehicle is combined with the application of this algorithm, the key is to select the optimal transportation route from several routes. The application of the algorithm can effectively adjust the efficiency of route searching and ensure that the final result is as close to the optimal as possible. The optimization of the transportation route is similar to the foraging behavior in the particle swarm algorithm. The combination of the two means that the vehicles in transportation are converted into particles, and the overall optimal answer is achieved according to the algorithm model and the improved model [24–25].

4. RESULTS AND DISCUSSION

4.1 Route Optimization Related Data of Logistics Distribution

The focus of this study is the optimization of transportation routes in logistics transportation. Through the optimization of routes, the efficiency of logistics distribution can be improved. It can be seen from the above analysis that there are many factors that affect the optimization of the transportation route, the first of which is the geographic location of the cargo receiver and the route between the distribution center, and the number of vehicles that can participate in the distribution. Firstly some key information needs to be presented, shown in Table 2 and Table 3.

From the statistical results in Tables 2 and 3 above, it can be seen that in the experiment, the distribution simulation was carried out for the goods of 10 consumers, and the corresponding number of vehicles is 9. It can be seen from the above position distribution that, there are various differences from place to place. In addition, it is also necessary to determine the demand for the user's goods, and consider the load in the vehicle transportation at one time. Taking the goods A as an example, the resultant statistics are shown in Table 4.

The results presented in Table 4 are the statistics for logistics distribution of goods. The maximum load of the transport vehicles in the above is 200 items. The goods for the above 10 consumers are delivered, and the quantity of delivered goods is unified with the delivery route. The results are shown in Table 5.

The results presented in Table 5 are conversion values obtained after unification. When the conversion value

Table 4 Statistics for consumer demand for goods.

Consumer number	**1**	**2**	**3**	**4**	**5**
Cargo volume	73	68	83	81	97
Consumer number	6	7	8	9	10
Cargo volume	51	63	71	59	83

Table 5 Uniform relationship of cargo volume.

Consumer number	**1**	**2**	**3**	**4**	**5**
Cargo volume	0.27	0.17	23	0.19	0.07
Consumer number	6	7	8	9	10
Cargo volume	0.18	0.11	0.29	0.09	0.15

Table 6 Results of optimization of other factors in transportation routes under weighting.

Weight	**Degree of satisfaction**	**Driving expenses**	**Driving time**
1	0.935	211.3	671.3
2	0.957	271.5	817.6
3	0.917	311.7	1273.5
4	0.971	413.7	1571.6

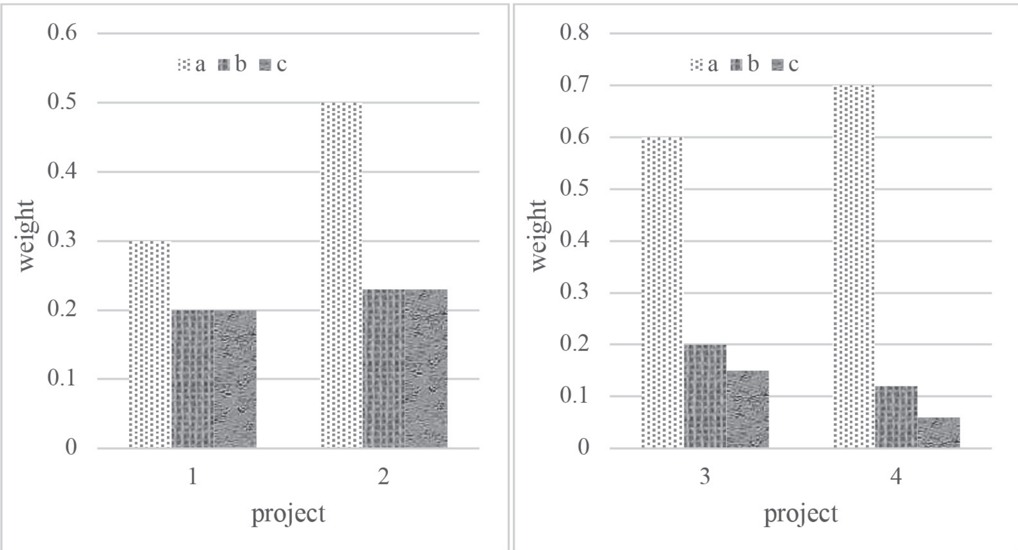


Figure 6 Weights corresponding to different weighting methods.

corresponding to the quantity of goods is less than 1, the delivery of the vehicle will be implemented; otherwise, it cannot be delivered. In the actual situation, several other problems are also involved in the transportation of vehicles, and the relationship between them and the weights of each problem are shown in the results presented in Table 6.

Table 6 shows the optimization results of three different factors corresponding to the weighting of the transportation process. These three factors are: the satisfaction of consumers, the cost of driving, and the time on the road. The results in Table 6 show that consumers' satisfaction with the delivery results is above 90%, and the highest is 97.1%, indicating that the entire transportation process has little impact on consumers. However, the changes corresponding to the other two factors are larger. The highest driving cost and driving time are 413.7 and 1571.6 respectively, while the lowest driving cost and driving time are 211.3 and 671.3 respectively. This change is relatively high obviously, because when the weight is reduced, the corresponding result is less optimized. For the weighted optimization involved in the above, the corresponding results of the four different methods are also different. The results are shown in Figure 6:

The weight results in Figure 6 above are just special values in a large number of weighted calculations. In order to clarify the relationship between the three influencing factors and the weighted weights above, and for the final route optimization result by weighting. In addition to the analysis of the results presented in Figure 6, the weight model of $a=0.3, b=0.2, c=0.2$ will be adopted in this paper because the corresponding optimization result under this mode may be the optimal value.

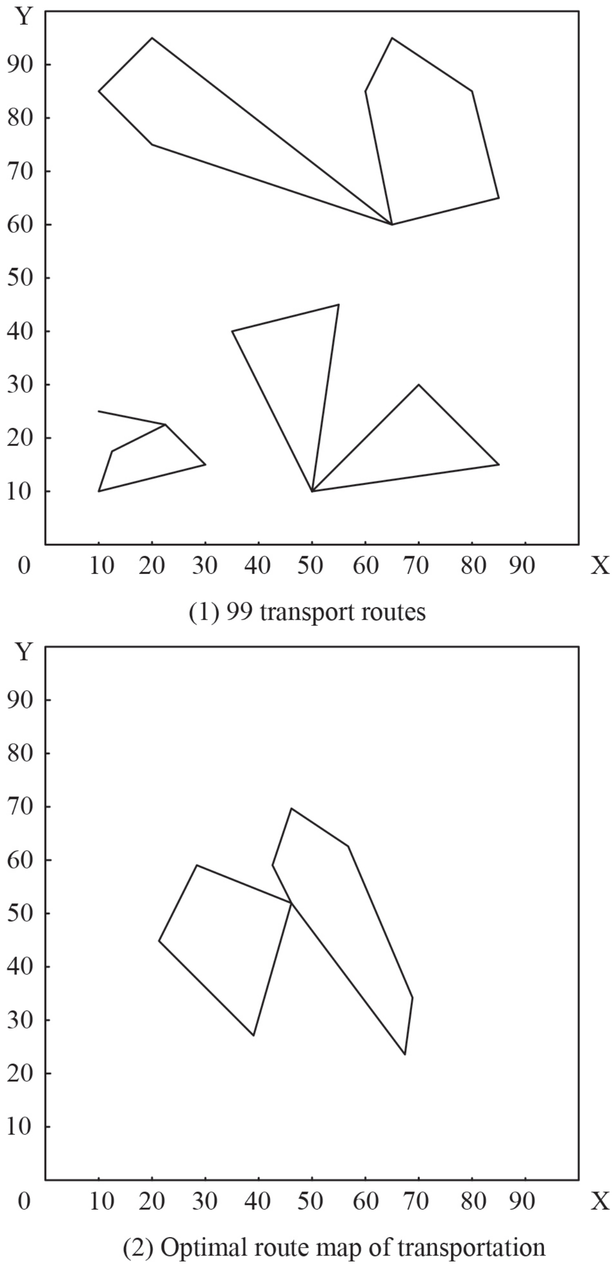


Figure 7 Roadmap for logistics distribution.

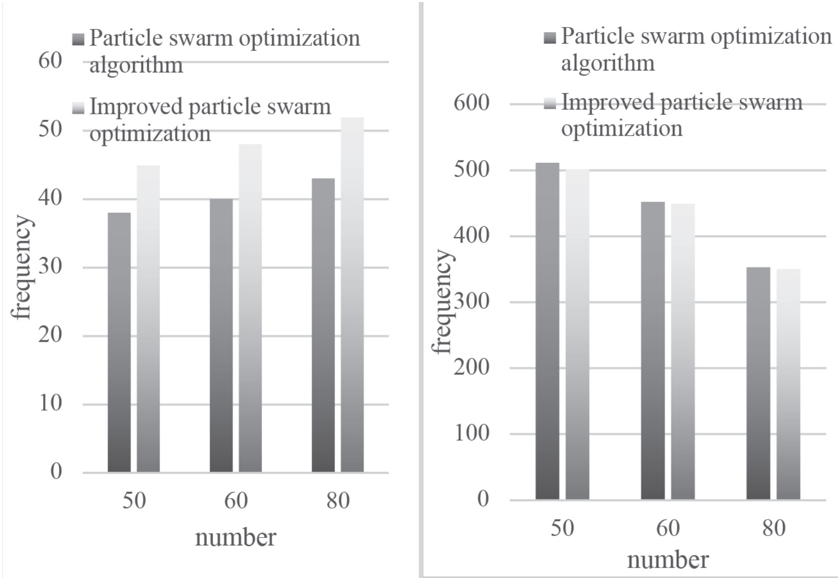
4.2 Optimization of Transportation Route Based on Particle Swarm Optimization

The route optimization based on particle swarm optimization, in addition to the above data statistics and the influence of some results, also requires particle swarm simulation experiments for vehicle transportation in order to prove that the algorithm used in this paper has practical applicability. It is assumed that the optimal vehicle transportation route problem under the particle optimization algorithm model has been repeatedly calculated 99 times. The results are presented in Figure 7.

It can be seen from (1) in Figure 7 that the particle optimization algorithm runs 99 times, of which the optimal solution is 57 times, and the probability of achieving the final efficient delivery success reaches 57%; the corresponding optimal solutions are 57.1 and 25.1. This result enables vehicle transportation to achieve the optimal result under this circumstance, that is, the most efficient transportation route. In this route, the aggregation speed of the particle algorithm is faster, so the result corresponding to this method is very high. Figure 7 (2) shows the simulation results of the shortest route for logistics transportation and the route that takes the least time, indicating that the actual optimal results are different under different distribution situations.

4.3 Comparison of Original Particle Swarm Algorithm and Improved Algorithm

The improved particle swarm algorithm has better aggregation performance for solving the problem of route optimization for vehicle transportation. The two use simulation experiments, and the number of particles is 50, 60, and 80 groups. Two



(1) The number of times the optimal solution is reached
(2) The number of times the algorithm runs

Figure 8 Number of particles versus optimal solution and number of iterations.

different experiments are carried out for these three groups of different numbers of particle swarms. The results are shown in Figure 8.

The results presented in Figure 8 above show that the number of times the improved particle swarm algorithm reaches the optimal solution is better than the one before the improvement when the number of particles is 50, 60, and 80, and when the number of particles with the largest increase is 80. This corresponds to a 21% improvement. In terms of the number of algorithm iterations, the improved algorithm will reduce the number of times under different particle numbers, and the best is reduced by 1.95%. This small reduction indicates that the particle swarm algorithm is more effective in reaching the optimal solution.

5. CONCLUSIONS

This article presents the research on the optimization of distribution routes in logistics and transportation. When the social economy and corresponding aspects are developing rapidly, the rise of the logistics industry is inevitable. How to achieve more efficient logistics distribution within the same time as before has become a hot research topic in the logistics and transportation industry. Inspired by intelligent algorithms, the particle swarm algorithm used in this paper is based on the phenomenon of bird foraging, and uses mathematical language to construct mathematical models, which is highly suitable for processing optimization problems. In this paper, the optimization of vehicle transportation routes is carried out with the help of such algorithms, and the distribution points are abstracted as individual particles so that the algorithm for such problems can be applied. The application of particle swarm algorithm can achieve the organic combination of various factors in vehicle transportation, giving a more comprehensive understanding of the optimal solution.

6. FUNDING

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