Improved particle swarm algorithm for logistics distribution path optimization

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Abstract. In this paper, the logistics distribution path problem is studied in depth, and the general steps of model establishment are analyzed and summarized through the study of logistics distribution models with many different objectives, and the logistics distribution model of multiple vehicles in multiple car parks based on the shortest path is established, while the number of customers served by the vehicles is restricted and new constraints are added from the perspective of controlling vehicle mileage. At the same time, multiple algorithms are analyzed and compared, and finally the particle swarm algorithm is chosen as the research object. By studying the shortcomings of the traditional particle swarm algorithm, an adaptive variation particle swarm optimization algorithm is designed. The article introduces fuzzy classification, adaptive variation mechanism, adding new variation probability and adjustable adaptation variance to achieve the purpose of adaptive adjustment of current particles, so as to avoid premature convergence and form a new adaptive variation particle swarm optimization algorithm. Finally, simulation experiments are conducted on the contents made through the platform to verify the corresponding conclusions. The simulation contents are to verify the feasibility and superiority of the optimization algorithm with the multi-vehicle model established in the paper, and to verify the different logistics distribution schemes obtained from the distribution models based on different target premises with the two models based on the shortest path least vehicle and based on customer satisfaction given in the previous paper. Two conclusions are obtained from the simulations, which are that the present algorithm has better features than the traditional particle swarm algorithm in solving such problems, maintaining a better global search capability and effectively avoiding premature convergence of the algorithm.

Keywords: logistics distribution problem; mathematical modeling; particle swarm algorithm; adaptive

1 Introduction

With the rapid development of modern science and technology, the impact of logistics on economic activities is gaining more and more attention [1]. The need for storage has diminished in importance in the modern logistics and distribution process, and in its place, distribution has become the most important aspect[2]. The collection of vehicles,

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goods equipped and delivery process, and the optimization of vehicle distribution routes are the most central part of the whole logistics distribution, and the impact on the cost, transportation speed and efficiency of the whole logistics is very important [3].

A large number of domestic and foreign scholars have researched logistics distribution problems and proposed corresponding solution algorithms, which mainly include two types of algorithms: exact solution and heuristic solution [4]. However, with the development of modern logistics, the number of distribution paths is large and the number of customers is large, so it is difficult for the exact algorithm to obtain the optimal solution, and it takes a long time [5]. Logistics distribution path optimization is a multi-objective optimization problem, heuristic algorithm is more suitable for the solution of this problem [6]. So it becomes the main research direction at present, there are genetic algorithm, particle swarm algorithm and forbidden search algorithm, etc., which can achieve better results compared with the exact solution algorithm [7]. A large number of research results show that these algorithms sometimes fall into local extremes, the phenomenon of "premature", search speed and other defects, affecting the speed of logistics distribution path optimization, find the optimal logistics distribution route is slow [8]. In recent years, many domestic and foreign scholars have done a lot of research work on the improvement of heuristic algorithms, with the common goal of increasing the search speed, improving the global convergence of the algorithm, and broadening its application areas [9].

In view of the logistics distribution path problem and the current situation of particle swarm algorithm, the article conducts an in-depth study of particle swarm algorithm, analyzes its defects, introduces new optimization means, improves the existing particle swarm algorithm, and establishes a logistics distribution model for solution by adding corresponding constraints according to the demand, which plays a corresponding role for practical application and also lays the foundation for the next research work[10 -11]

2 Mathematical modeling of logistics distribution path optimization

First, custom variables. Mostly x and y . Initial conditions are set for the requested variables, i.e., if the variable is 1, it is served, and if the variable is 0, it is unserved. For example:

$$y_i^k = \begin{cases} 1 & \text{Customer i is delivered by vehicle k} \\ 0 & \text{Otherwise} \end{cases} \tag{1}$$

$$x_{ij}^{mk} = \begin{cases} 1 & \text{Car k of depot m travels from user i to j} \\ 0 & \mathit{Otherwise} \end{cases} \tag{2}$$

The second step is to set minimization goals. Such as minimized cost, minimized time, or minimized path. For example:

$$minZ = \sum_{K=0}^{K}\sum_{i=1}^{N}\sum_{j=1}^{N} c_{ij}x_{ij}^{k} \tag{3}$$

In the third step, customize the fulfillment conditions. Such as customer satisfaction, total number of vehicles assigned or transit time. For example:

$$\max \frac{1}{N}\sum_{i=1}^{N}\mu_i(t_i) \tag{4}$$

The fourth step is to ensure that every customer is served. For example:

$$\sum_{k=1}^{K} y_i^k = 1 \tag{5}$$

Step 5 ensures that each client is served once. Sometimes step 4 and step 5 can be combined. For example:

$$\sum\nolimits_{i=1} x_{ij}^k = y_j^k \tag{6}$$

The sixth step ensures the elimination of subloops.

$$\sum\nolimits_{i,j\in s\text{x}s}^{n} x_{ij}^k \le |\ s| - 1 s \in \{1.2, \ldots N\} \tag{7}$$

The seventh step is to ensure the carrying capacity of the vehicle. For example:

$$\sum_{i=1}^{N} g_i y_i^k \le q_k \tag{8}$$

The analysis and summary of the model ideas and each constraint are necessary to facilitate the actual requirements. It is necessary to analyze and summarize the model ideas and each constraint, so that we can build the corresponding model according to the actual requirements, and add the corresponding constraints according to our own requirements to improve the model and make it more suitable for the actual requirements. It is necessary to analyze and summarize the model ideas and each constraint.

3 Logistics distribution path optimization model

3.1 Improved particle swarm algorithm

In the PSO algorithm, each particle is considered as a feasible solution to the problem, and the particle dynamically adjusts its flight speed and direction in the solution space according to its own flight experience and that of its peers, and finally finds the optimal solution to the problem by tracking the current and historical optimal particles. In each iteration, the particle velocity and position are updated as follows.

$$v_{id}(i+1) = \omega \times v_{id}(i) + c_1 \times rand() \times (P_{best} - x_{id}(i) + c_2 \times rand() \times (g_{best} - x_{id}(i)) \tag{9}$$

$$x_{id}(i+1) = x_{id}(i) + v_{id}(i+1) \tag{10}$$

Based on this principle, this paper combines the fuzzy adaptive principle and the introduction of adaptive variation mechanism to solve the standard algorithm. The algorithm first divides the particles into different small populations according to their fitness, and uses relatively small inertia weights for those with higher fitness and larger inertia weights for those with lower fitness, and then reclassifies them at each iteration, and judges the aggregation degree of each particle population during the iteration, when the particles tend to aggregate prematurely. Adaptive variation operation is performed on the position information so that the particle positions can be recalculated when the search tends to stagnate and the other directions of the solution space are searched. In this way, the new optimal solution appears during the subsequent search. After an iterative loop, the global optimal solution can be found. The position of each particle is reflected by the fitness function value, so a quantitative description of the degree of aggregation of each particle can be performed by studying the change in the fitness function values of all particles of the population.

The traditional fitness variance, with relatively weak self-adjustment, σ^2 is defined in this paper as the following equation:

$$\sigma^2 = \sum_{i=1}^{m} \left(\frac{f_i - f_a v}{f} \right)^2 \tag{11}$$

Among them $f = \max\{1, \max_{1 \le i \le N} | f_i - f_{av} |$ The role of f is to limit the size of σ^2, f_i : the value of the fitness function of particle i. $f_{av} = \frac{1}{n} \sum_{i=1}^{n} f$ is the average fitness function value for each particle;

When the particle swarm optimization algorithm appears to be either locally converging or globally converging, it will produce a common phenomenon, which is the aggregation phenomenon, that is, the particles have the same fitness, which is next inferred using Equation 11, the fitness variance. The variance of the fitness of the particle swarm is used to judge the degree of convergence of all particles, the smaller the variance of the fitness, the more the particle swarm tends to converge, the larger the variance of the fitness, the particle swarm is still in the search state, when the variance of the fitness is 0, the whole particle swarm algorithm reaches an optimal state, that is, the global optimum or local optimum, the local optimum is the premature algorithm described in this paper. Then the optimal solution at this point is compared with the theoretical optimal solution to determine whether it is the global optimal solution or the local optimal solution, and the local optimal is the premature algorithm.

3.2 Particle encoding

This subsection discusses the application of the PSO algorithm to the multiple vehicle problem for multiple yards in the distribution path and designs a particle coding model. The encoding pattern allows the discrete combinatorial problem to be continuous so that the improved particle swarm algorithm in the previous section can be applied directly. Suppose there are N customer points and M vehicle yards (number of vehicles M) in the multiple vehicle path problem in multiple vehicle yards; construct a 2N-dimensional vector that It has two N-dimensional subsectors, X_r and X_V. X_V is used to express the vehicle information and takes values in the range [1, L]. X_r is used to express the path information. When decoding, we can determine which vehicle will be dispatched from which yard according to that. For example, suppose there are 17 customer points, 3 car parks, 2, 3, 2 vehicles in each car park, and these 7 vehicles are coded as 1 to 7. The particle codes are as follows. This is shown in Table 1.

Table 1. Particle code lists

Client	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
X v	1	1	1	2	2	3	3	4	4	4	4	5	5	6	6	7	7
X r	1	2	3	1	2	2	1	2	1	3	4	2	1	1	2	2	1

This encoding method can clearly represent the vehicle path information and facilitate decoding. In practical applications, the number of the car park is superimposed on the last digit of the user, and the same car park vehicles are sorted to facilitate the coding representation and the convenience of decoding later.

3.3 Specific steps of algorithm implementation

The specific implementation of the algorithm relies on the following steps, as shown in Figure 1, which is a series of steps and processes of the algorithm.

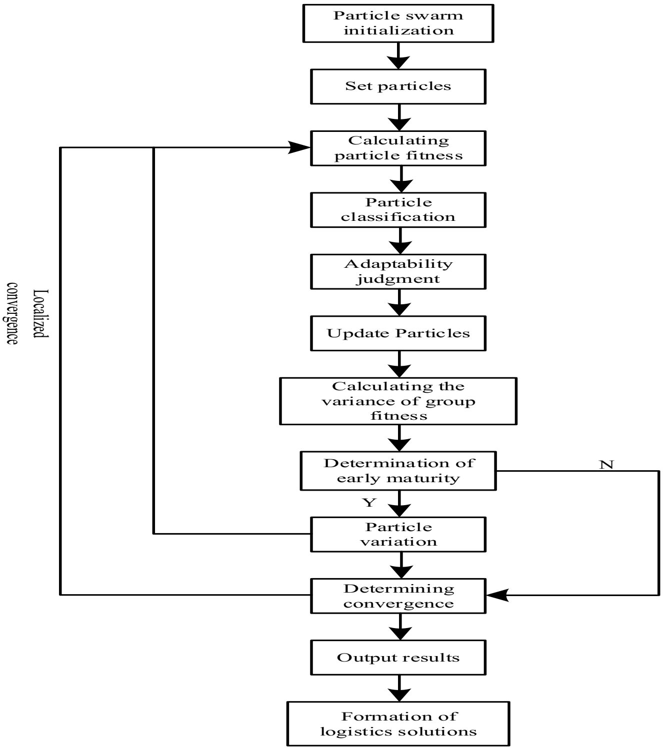

Fig. 1. Algorithm flowchart

4 Experiment and Simulation

In order to comprehensively verify the scientific and correctness of the improved optimization-based particle swarm logistics distribution path algorithm designed in this paper, and also to study that the distribution paths obtained from different optimal distribution targets are not the same. Based on the theoretical basis and the analytical design of the previous chapters, simulation experiments and results analysis are conducted in this chapter under the environment.

4.1 Simulation Environment

Environmental simulation mainly studies a variety of natural environment and induced environment artificial reproduction technology and experiments in the simulation environment, it uses the principle of system analysis, establishes the theory or entity model of the environmental system, under artificial control conditions, by changing specific parameters to observe the model response, pr-edict the behavior and characteristics of the actual system under real environ-mental conditions. The simulation environment created for better experiments is shown in Table 2.

Table 2. Simulation environment

Operating System	Windows 7 Home Edition
CPU	Intel Dual Core i5 650,3333MHz
RAM	2048M
Simulation software environment	MATLAB 2011a
Graphic Interface	OpenGL 3.0

4.2 Algorithm feasibility analysis

4.2.1 Simulation experimental data.

Let the number of customer points be 16, the number of car parks be 3, and each car park has two vehicles, i.e., the total number of vehicles is 6. Table 1 shows the location of customer points, and Table 3 indicates the location of car parks and the number of vehicles in each car park, Table 4 shows the parking space information.

Table 3. Customer information

Customer Number	1	2	3	4	5	6	7	8
X coordinate	78	39	20	65	9	90	33	79
Y coordinate	30	31	76	98	23	9	65	75
Customer Number	9	10	11	12	13	14	15	16
X coordinate	55	88	9	35	73	63	33	11
Y coordinate	35	55	12	93	85	70	13	20

Table 4. Parking space information

Depot number	17	18	19
X coordinate	20	75	50
Y coordinate	20	45	8
Number of vehicles	2	2	2

4.2.2 Algorithm feasibility study.

First, simulation software is used to demonstrate the feasibility of the optimized particle swarm algorithm in the logistics distribution problem. In this paper, the number of experimental particles in this problem is 100, and it is repeated 100 times. The experimental results are shown in Table 5, and the income distribution path chart is shown in Figure 2.

Table 5. Optimal situation

Clients	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
X coordinate	6	5	3	4	1	6	3	4	5	4	2	3	4	4	2	2
Y coordinate	1	1	2	1	1	2	1	4	2	5	2	3	3	1	1	3

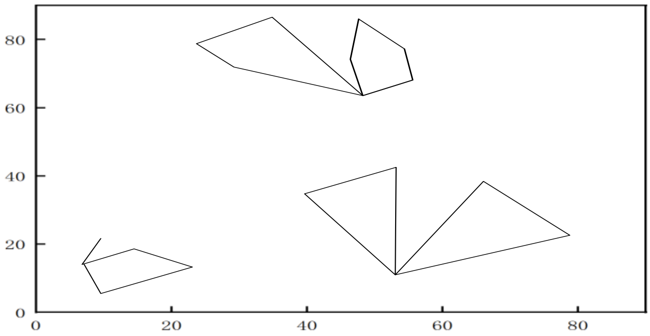

Fig. 2. The income distribution path chart

As can be seen from the figure, the improved particle swarm algorithm can quickly obtain the optimal logistics distribution path, mainly because of the dynamic change of the inertia weights w of the basic particle swarm algorithm, overcoming the emergence of local optimum and "premature" phenomenon, improving the logistics distribution path search efficiency and finding the optimal logistics distribution path faster. The simulation results show that the improved particle swarm algorithm is an effective logistics distribution path optimization method.

4.2.3 Analysis of results with other algorithms.
In order to test the superiority of the improved particle swarm algorithm, the basic particle swarm algorithm, genetic algorithm and ant algorithm were used for comparison simulation, and each swarm algorithm was run 10 times, and the average result was taken as the final result. The simulation test results of all algorithms are shown in Table 6.

Table 6. simulation test results

Algorithm	Number of failures	Success rate
Genetic Algorithm	12	87%
Ant colony algorithm	5	56%
Particle swarm algorithm	7	94%
Improved particle swarm algorithm	2	98%

From Table 6, it can be seen that the success rate of finding the optimal logistics distribution path of the improved particle swarm algorithm is more than 98%. At the same time, the average search time for finding the most logistic distribution path is the least. The comparison results show that the improved particle swarm algorithm improves the success rate of logistic distribution path optimization and effectively prevents the defects of falling into local optimum and premature convergence that exist in other algorithms.

4.3 Simulation results based on different target models

4.3.1 Experimental data.

In the following, two different restrictions are selected and simulated to verify the different distribution paths under the premise of different restrictions. The customer information is shown in Table 7.

Table 7. Customer information

Clients	1	2	3	4	5	6	7	8	Distribution center
X coordinate	12	40	35	30	28	10	20	48	30
Y coordinate	48	45	15	55	45	35	15	25	35

4.3.2 Simulation results.

(1) Distribution results based on the shortest path with the least number of vehicles, the income distribution chart is shown in Figure 3.

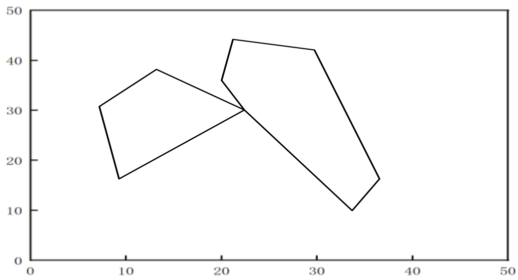

Fig. 3. Income distribution chart

The resulting distribution path is: Vehicle 1：0-1-6-7-3-0

Vehicle 2：0-5-4-2-8-0

(2) Distribution results based on customer satisfaction

The customer information in the table above is given different levels of importance to form the table below. The following is the table that expresses customer information and importance, which is table 8.

Table 8. Customer information and importance

Clients	1	2	3	4	5	6	7	8	Distribution center
X coordinate	12	40	35	30	28	10	20	48	30
Y coordinate	48	45	15	55	45	35	15	25	35
Importance	1	2	3	4	5	6	7	8	

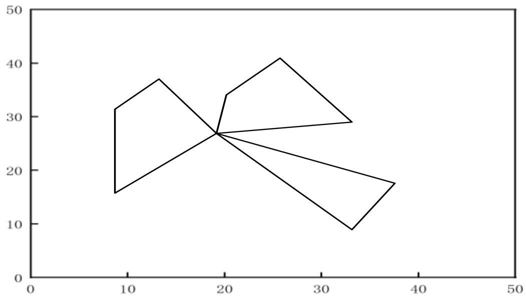

Fig. 4. Income distribution chart

The resulting distribution path is: Vehicle 1：0-1-6-7-0

Vehicle 2：0-2-4-5-0

Vehicle 3：0-3-8-0

According to the simulation results in Fig. 3 and Fig. 4, it can be found that the simulation results of the model with the shortest vehicle path and the least number of vehicles are two vehicles to complete the distribution task, while the simulation results of the logistics distribution scheme based on customer satisfaction require three vehicles, and the order of the two distribution schemes is different in the distribution process. It can be summarized that the two optimal distribution objectives are different, the required vehicles are different and the distribution order is different. Thus, it can be understood that the distribution solutions obtained under different optimal distribution objectives are different according to different actual situations.

5 Simulation results Conclusion

In view of the defects of current heuristic algorithms in logistics distribution path optimization, an improved particle swarm algorithm for logistics distribution path optimization is proposed. The simulation results show that the improved particle swarm algorithm improves the success rate of logistics distribution path optimization, has better solution results and solution efficiency, and has certain reference value for the research of other heuristic algorithms and logistics distribution path optimization problems.

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