The Research on the Shaanxi International Inland Port Logistics Path Optimization Based on the Improved Ant Colony Algorithm under the Belt and Road Background

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Abstract

The Belt and Road is not only an important content in Chinese 13th Five-Year planning, but also the new Chinese economic growth point. Shaanxi as the connection point of The Silk Road Economic Belt, plays an very important role in the logistics industry. The logistics path optimization is one of the key links in the logistics system optimization. It can improve the economic efficiency and the realization of the logistics to optimize the logistics path. The ant colony algorithm is a novel simulated evolutionary algorithm. It has many excellent properties and can solve the problem of logistics path optimization better. In this paper, we propose an improved ant colony algorithm. This algorithm combines the ant colony algorithm with the hill climbing method to improve the efficiency of the algorithm. We apply the improved ant colony algorithm to the optimization of the logistics path. The experimental results show that the proposed algorithm can effectively optimize the logistics path and obtain better results.

Keywords: The belt and road, Logistics, Path, Ant Colony.

1. INTRODUCTION

The Belt and Road is short for The Silk Road Economic Belt and the 21st-Century Maritime Silk Road. The Belt and Road is an important means for China to carry out domestic reform, global economic integration and accelerate economic growth. Shaanxi has an important position in The Belt and Road strategy, and the international land port in Shaanxi will promote the development of Belt and Road greatly.

With the development of the economy, the logistics plays an increasingly important role in the process of the social production. The logistics transportation is an important part in the logistics system (Lebeau et al., 2016; Hua et al., 2016). The logistics path optimization is a key link in the optimization of the logistics system. It is also an important part of the logistics system (Das et al., 2016; Zhang and Ding, 2016). The research on the theory and the method of the logistics distribution path optimization is the basis of the logistics intensive development, the establishment of integrated logistics system, the establishment of the modern dispatching command system, the development of the intelligent transportation system and the development of electronic commerce (Liu et al., 2016).

Cao Erbao studied several kinds of the logistics distribution vehicle routing problem model and algorithm. On the basis of analyzing the theoretical and practical background, he proposed the mathematical model and constructed several effective sub heuristic algorithms to solve the related problems. The author had the effectively integrated the vehicle routing problem of the forward logistics and the reverse logistics. At the same time, under the condition of the uncertain information, the author studied the three special cases of the delivery and picked up vehicle routing problem simultaneously. Then the author established the relevant uncertainty model and gave the solving algorithm. The author used the numerical experiments to test the validity of the model and algorithm (Cao, 2007). On the basis of the defining the connotation of the distribution center, Shi Zhao introduced the discrete location methods according to the need of the research. Then, he designed the improved asymptotic coverage and minimum envelope clustering model to solve the location problem. Among them, the incremental coverage model optimized the node allocation principle and algorithm. On the basis of improving the decision conditions, the minimum envelope clustering model considered the service time and spatial distribution of each node (Zhao, 2014). Aiming at the problem of the logistics distribution routing selection and combined with the characteristics of the logistics distribution path selection, Chen Jianjun proposed a method of using the ant colony algorithm to select the logistics distribution path. This algorithm
established the mathematical model of the optimization of the logistics distribution path. Then the algorithm adopted the ant colony algorithm to solve the mathematical model (Chun, 2011). The simulation results showed that the ant colony algorithm had the strong global optimization ability and the quick search speed. It could find the optimal solution of the logistics distribution path in the shortest time. It was an effective algorithm to solve the optimization problem of logistics distribution routing problem. At the same time, Wu Jieming (2011), Wang Huadong (2012) and other people also studied the logistics path optimization.

The ant colony algorithm is a new search optimization technology. It is produced from the research of ant colony behavior. The ant colony algorithm produces the pheromone according the individual. With the help of the selection strategy, the pheromone updates and other operations and it approaches the optimal solution (He and Ma, 2013). Inspired by the promising performance of heuristic algorithms to solve combinatorial problems, Min Liu and other people proposed an improved quantum ant colony algorithm (QACA) for exhaustive optimization of the evacuation path that people could evacuate from hazardous areas to safe areas (Liu et al., 2016). In comparison with ACO (ant colony optimization) based method, QACA had the capability of finding a good solution faster using fewer individuals and possessed strong robustness, as a result of the quantum representation and updating of pheromone. Piotr Sitarz and Bartosz Powałka put forward a new estimation method of modal parameters for dynamical systems. The problem of parameter estimation had been simplified to optimisation which was carried out using the ant colony system algorithm (Sitarzand Powałka, 2016). The combination of deterministic constraints of the solution space with modified ant colony system algorithms produced excellent results for systems in which mode shapes were defined by distinctly different natural frequencies and for those in which natural frequencies were similar. Weiqin Wu, Yu Tian and Tongdan Jin proposed a multi-attribute Label-based Ant Colony System (LACS) algorithm to tackle this complex optimization problem (Wu et al., 2016). The features of the ant colony system included swarm intelligence and searching robustness. A variety of benchmark instances were used to demonstrate the computational advantage and the global optimality of the LACS algorithm.

In this paper, we propose an improved ant colony algorithm in order to make a better research on Shaanxi international port logistics path optimization. This algorithm combines the ant colony algorithm with the mountain climbing method to improve the search efficiency the optimization effect. The structure of this paper is as follows. The first part is instruction. In this part, we mainly introduce the research background of this paper. The second part is the ant colony algorithm. In the second part, we simply introduce the ant colony algorithm. The third part is the improved ant colony algorithm. In this part, we combine the climbing method with the ant colony algorithm. Then, we propose the improved ant colony algorithm. The fourth part is the numerical test and the last part is the conclusion.

2. ANT COLONY ALGORITHM

Ant colony algorithm was put forward by Italy expert M Dorigo in 1991 at the first artificial life conference (Jovanovic et al., 2016). He gave the basic model of the ant colony algorithm. In 1992, he analyzed the core idea of ant colony algorithm in his doctoral thesis (Scimemi et al., 2016).

In order to simulate the behavior of real ants, we define the following symbols

\[ n \] City scale
\[ b(t) \] The number of the ant in the element \( i \) at time \( t \)
\[ m \] the total number of the ant
\[ tabu_k \] Tabu list of the ant \( k \)
\[ C=\{c_1, c_2, \ldots, c_n\} \] Set of \( n \) cities
\[ allowed_k=\{C-tabu_k\} \] The city that the ant \( k \) chooses
\[ \alpha \] Information elicitation factor
\[ \beta \] Expected information factor
\[ d_{ij} \] the distance between the city \( i \) and the city \( j \)
\[ \tau_{ij} \] Pheromone intensity from \( i \) to \( j \)
\[ \eta_{ij} \] Heuristic function

The transition probability of the ant \( k \) from \( i \) to \( j \) at the time \( t \) is
Transition probability $P^k_{ij}(t)$ is proportional to $\tau_{ij}$ and $\eta_{ij}$. Compared with real ants, an artificial ant colony system has a memory. In order to satisfy the requirements of all the ants through the cities, we establish the data structure for each ant which calls tabu table. The tabu list records the cities that the ants have passed at the time $t$ (Scimemi et al., 2016). In this cycle, the ants are not allowed to go through the city again. At the end of the cycle, the tabu list is used to account for the current solution, which is the ant's path. Then, the tabu list will be empty, and the ant will re select the path again (Liu et al., 2013).

In order to prevent the residual information too much to cover up the inspiration of information, we need to update the pheromone after the steps or the completion of the whole city trip. This mechanism is similar to the human brain (Özkale and Figlah, 2013).

Information content can be calculated by:

$$\tau_{ij}(t+n) = (1-\rho)\tau_{ij}(t) + \Delta \tau_{ij}(t,n)$$  \hspace{1cm} (2)

$$\Delta \tau_{ij}(t,n) = \frac{M}{\sum_{n=1}^{N} \Delta \tau_{ij}(t,n)}$$  \hspace{1cm} (3)

The meaning of each symbol is:

- $\rho$: Pheromone volatile coefficient
- $1-\rho$: Pheromone residue coefficient
- $\Delta \tau_{ij}(t,n)$: Pheromone increment in the middle of this cycle
- $\Delta \tau_{ij}(0) = 0$: Initial moment
- $\Delta \tau_{ij}^k(t,n)$: Information content that the ant $k$ leave on the path at this circle

According to the different pheromone update strategies, M Dorigo proposed several different basic ant colony algorithm models. The difference of these models is in the solution $\Delta \tau_{ij}^k$ of the methods. These models are Ant-Cycle model, Ant-Quantity model and Ant-Density model.

Ant-Cycle model

$$\Delta \tau_{ij}^k(t,n) = \begin{cases} Q/L_k, & \text{if } \text{ant}_k\text{ pass}(i,j) \\ 0, & \text{otherwise} \end{cases}$$  \hspace{1cm} (4)

Ant-Quantity model

$$\Delta \tau_{ij}^k(t,n) = \begin{cases} Q/d_{ij}, & \text{if } \text{ant}_k\text{ pass}(i,j) \\ 0, & \text{otherwise} \end{cases}$$  \hspace{1cm} (5)

Ant-Density model

$$\Delta \tau_{ij}^k(t,n) = \begin{cases} Q, & \text{if } \text{ant}_k\text{ pass}(i,j) \\ 0, & \text{otherwise} \end{cases}$$  \hspace{1cm} (6)

$Q$ is the Pheromone intensity. It can affect the convergence speed of the algorithm. $L_k$ is the total length of the path that the ant $k$ passed.
Ant-Quantity model and Ant-Density model use the local information. It means that the ant updates the pheromone after each step. Ant-Cycle model use the global information. This means that the ant updates the pheromone after the completion of a cycle. In solving the TSP problem, the Ant-Cycle model is better to solve the problem. So, the Ant-Cycle model is generally used as the basic model of the algorithm (Vatankhah et al., 2012).

The basic steps of ant colony algorithm are:

Step1: Initialization parameters. Time $t=0$. Cycle times $N_c = 0$. Maximum cycle times $N_{cmax}$. Mants are at $n$ cities. Initial information of each side is $\tau_{ij}(t) = const$, const is constant. $\Delta \tau_{ij} = 0$.

Step2: $N_c = N_c + 1$
Step3: $k = 1$
Step4: $k = k + 1$
Step5: According to the probability, the ants choose the next city $j$
Step6: Adjust the taboo table pointer. We put the visited city in the tabu list
Step7: Update information
Step8: If the algorithm meets the end conditions, namely $N_c \geq N_{cmax}$, the loop is terminated and the calculation result is output. Or, we empty the tabu list and jump to Step2

The flow chart of ant colony algorithm is shown below

![Flow chart of ant colony algorithm](image)

**Figure1. Flow chart of ant colony algorithm**

### 3. THE IMPROVED ANT COLONY ALGORITHM

We set the number of the investigation ants and the search ants are $m_1$ and $m_2$. The number of the cities are $n$. The limiting conditions among the parameters are $m_1 = n$ and $m_2 < n$.

The investigation range of the investigation ants is the MAXPC number of the cities which are the most close the current city. $PC_i$ is a circular which uses the each city as the center in the optimal solution and makes the $R$ as the radius. $R$ increases from zero until the number of cities recorded in the circle recorded in the city’s neighboring city. MAXPC is the maximum value of the $PC_i$. When the numbers of the cities are less than 100, the MAXPC is less than ten.

For the investigation ant, we put $m_1$ number of the investigation ants into the $n$ number of the cities. The each ant investigates the $n-1$ number of the cities which makes the city as the center. Then, it combines the
investigation results with the prior knowledge to constitute the investigation pheromone. We note it as \( X_{ij} \). Among them, \( i, j=1, 2, ..., n-1, i\neq j \). The calculated formula of the \( X_{ij} \) is as follows.

\[
X_{ij} = \begin{cases} 
\min(d_{ij})/d_{ij}, & j \in \text{MACPX}, \\
0, & \text{otherwise}
\end{cases}
\]

(7)

At the start time, the amount of information on each path is

\[
\tau_{ij}(0) = \begin{cases} 
W \cdot X_{ij}, & \text{if } X_{ij} \neq 0 \\
G_1 \cdot W \cdot \min(d_{ij})/\max(d_{ij}), & \text{otherwise}
\end{cases}
\]

(8)

Where, \( W \) is the constant. \( G_1 \) is the weighted coefficient and the range of the values is \((0, 1)\). This can make the ants search the optimal path to be the best path. The research ants will use the investigation pheromone and combine with the probability transfer formula to choose the nest city. Therefore, for the search ants, the probability for the ant \( k \) from the city \( i \) to the city \( j \) at \( t \) time is

\[
p_{ij}^k(t) = \begin{cases} 
\sum_{x \in \text{allowed}_k} \frac{\tau_{ij}^x(t) \cdot \eta_{ij}^x(t)}{\tau_{ij}^x(t) \cdot \eta_{ij}^x(t)}, & \text{if } j \in \text{allowed}_k \text{ and } X_{ij} \neq 0 \\
\sum_{x \in \text{allowed}_k} \frac{\tau_{ij}^x(t) \cdot \eta_{ij}^x(t)}{\tau_{ij}^x(t) \cdot \eta_{ij}^x(t)}, & \text{if } j \in \text{allowed}_k \text{ and } X_{ij} = 0 \\
0, & \text{else}
\end{cases}
\]

(9)

The transfer strategy is

\[
j = \begin{cases} 
\text{choice j according to the probability} & \text{max} \{ p_k \}, p \leq r_0 \\
\text{choice j according to the } & \text{max} \{ \tau_{ij}^x(t) \cdot \eta_{ij}^x(t) \}, p > r_0
\end{cases}
\]

(10)

In the above formula, \( \text{allowed}_k \) is the city that the ant \( k \) can visit. The weighted coefficient is \( G_2 > 1 \). However, we need to consider that the probability is less than the overall direction. \( \alpha \) is the pheromone heuristic factor. \( \beta \) is the expected heuristic factor. \( p \) is the random number. It obeys the uniform distribution on the interval \((0, 1)\). \( r_0 \) adjusts dynamically on the interval \((0, 1)\) with the evolutionary process of the algorithm. In the initial stage, the choice scope of the ant is larger. Therefore, \( r_0 \) should be larger. In the intermediate stage, if the convergence rate of the algorithm is slow, \( r_0 \) should be decreased. If the convergence rate of the algorithm is fast, \( r_0 \) should be enlarged. If the algorithm falls into local solution, \( r_0 \) should be enlarged. We let the ants to carry out the random selection. After all of the ants complete the cycle, the amount of the information on each path adjusts according to the following formula.

\[
\tau_{ij}(t+1) = \begin{cases} 
\rho_1 \cdot \tau_{ij}(t) + (1-\rho_1) \cdot \Delta \tau_{ij}(t), & \text{if } X_{ij} \neq 0 \\
\rho_1 \cdot \tau_{ij}(t), & \text{otherwise}
\end{cases}
\]

(11)

Where, the definition of \( \Delta \tau_{ij}(t) \) is,

\[
\Delta \tau_{ij}(t) = \sum_{k=1}^{\infty} \Delta \tau_{ij}^k(t)
\]

(12)
\[
\Delta t^*_i(t) = \begin{cases} 
    \frac{Q(\min(d_{ij}), d_{kj})}{L_q} & \text{if } \text{ant pass}(i, j) \& X_{ij} \neq 0 \\
    0, & \text{otherwise}
\end{cases}
\]

\[\rho(t) = \begin{cases} 
    \Omega \cdot \rho(t-1), & \Omega \cdot \rho(t-1) > \rho_{\text{min}} \\
    \rho_{\text{min}}, & \text{otherwise}
\end{cases}\]

Where, \(\rho\) is the pheromone volatile coefficient. \(Q\) is the pheromone intensity. \(\rho_{\text{min}}\) is the minimum value of \(\rho\) and \(\Omega \in [0.9, 0.95]\). We quote the time variant function to replace the pheromone intensity \(Q\). We use the following step function.

\[Q(t) = \begin{cases} 
    Q_1, & t \leq T_1 \\
    Q_2, & T_1 \leq t \leq T_2 \\
    Q_3, & T_2 \leq t \leq T_3 \\
    Q_4, & \text{else}
\end{cases}\]

Where, \(Q_1, Q_2, Q_3, Q_4\) get different values in the different time and interval. From the pheromone updating formula, we can see that the search ants is to leave the pheromone on the path where may be the optimal solution path. We combine the local search investigation ants of the local search with the global search ability of the search ants. Then we add the weighting factors and introduce the time varying function instead of the pheromone intensity. These practices are in order to improve the search efficiency.

The selection mechanism of the ant colony algorithm is to make good the path with the higher probability to be selected. The existence of the positive feedback mechanism will promote the path more competitive advantage in the future. When the search is being trapped in the local optimal solution, according to the traditional algorithm, the algorithm cannot jump out from the local minimum value point. Therefore, we introduce the negative feedback mechanism. It references the min max thought to limit the amount of the information of each path in a fixed range. It can reduce the concentration of the pheromone gap among the path in a certain extent. It urges the algorithm to jump out of the local minimum point. If there is the stagnation, the amount of the negative feedback information is added when the global updates in order to reduce the amount of pheromone on the corresponding path of the local solution.

We mix the mountain climbing method to the solution process of the ant colony algorithm. Then we improve the optimal solution for each generation. We set that the optimal solution is consisted of \(p\) sub circuits. It notes \(\{L_1, L_2, ..., L_p\}\). In fact, the process of the improvement is to use the mountain climbing method for each sub circuit. We set that \(W_k\) is the orderly arrangement that the path \(L_k\) goes through. \(W_k = \{v_0, v_1, ..., v_n\}\) and \(v_i\) and \(v_j\) are the two vertexes which are selected randomly from \(W_k\). We change the positions of the two points and get \(L_k'\). \(C_N\) is the maximum number of cycles without any improvement. The steps of the mountain method are as follows.

The first step is to initialize the loop number variable \(t = 1\). The current optimal solution is \(S* = S\) and the length is \(L(S*)\).

The second step is to select the two vertexes \(v_i\) and \(v_j\) randomly from \(W_k\). \(v_i\) and \(v_j\) are not adjacent.

The third step is to calculate the distance \(\Delta C_k = [d(x_{i+1}, x_i) + d(x_i, x_{j+1})] - [d(x_{i+1}, x_i) + d(x_i, x_{j+1})]\). If \(\Delta C_k > 0\), it does not exchange. \(t++\), then it turns to the step four. Otherwise, we exchange them and update \(W_k\). The corresponding solution is \(S'\). The optimal solution is \(S*' = S', t+1\) and turns to the step two.

The fourth step is as follows. If \(L(S*)\) does not decrease in the last \(C_N\) cycles, the algorithm ends. Otherwise, it turns to the step two.

The algorithm steps are as follows.
The first step is to initialize the parameters.

The second step is to take the $m_1$ investigation ants to the $n$ cities. Each investigation ant takes the city as the axis point to investigate the remaining cities.

The third step is to set the iteration number $N_c=1$.

The fourth step is to research the investigation pheromone and the amount of the information.

The fifth step is to adjust the information pheromone of the path and find out the feasible solution.

The sixth is to adopt the mountain climbing method to optimize each feasible solution in the feasible solution concentration. Then we calculate the optimal path.

The seventh step is as follows. If the If the algorithm is stuck, the pheromone on the path is adjusted according to the negative feedback mechanism and enlarges $r_0$. Otherwise, we update the information pheromone according to the global update rules.

The eighth step is as follows. If $N_c=N_{\text{max}}$, the cycle ends and outputs the optimal solution. If $N_c<N_{\text{max}}$, $N_c=N_c+1$.

The specific flow chart is shown in the following.

**Figure 2.** Improved ant colony algorithm flow chart

### 4. NUMERICAL EXPERIMENT

In order to verify the improved ant colony algorithm performance, we use the improved ant colony algorithm to operate the E-n22-k4, E-n51-k5, E-n76-k10, M-n101-k10 and M-n121-k7 problem. The operation results are shown in the following table.
### Table 1: The operation result of the improved ant colony algorithm

<table>
<thead>
<tr>
<th>Problem</th>
<th>Result</th>
<th>Average</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>E-n22-k4</td>
<td>364.21</td>
<td>376.43</td>
<td>5.98</td>
</tr>
<tr>
<td>E-n51-k5</td>
<td>523.11</td>
<td>527.02</td>
<td>17.66</td>
</tr>
<tr>
<td>E-n76-k10</td>
<td>814.84</td>
<td>826.58</td>
<td>83.17</td>
</tr>
<tr>
<td>M-n101-k10</td>
<td>799</td>
<td>813.75</td>
<td>210.78</td>
</tr>
<tr>
<td>M-n121-k7</td>
<td>967</td>
<td>1002.1</td>
<td>465.25</td>
</tr>
</tbody>
</table>

In the Table 1, the result is the optimal solution obtained by the algorithm in this paper. Average is the average value of the algorithm after running 10 times. Time is the time to consume the optimal solution.

Seen from the above table, we can see that the improved ant colony algorithm has achieved the desired results when operates the E-n22-k4, E-n51-k5, E-n76-k10, M-n101-k10, M-n121-k7 problems. The improved ant colony algorithm gets a good performance in terms of solution time and the path length. This algorithm reflects the good solution performance and convergence performance. When deal with larger scale example, the improved ant colony algorithm also shows the high stability.

### Table 2: The sensitivity of parameter $\rho$

<table>
<thead>
<tr>
<th>$\rho$</th>
<th>0.1</th>
<th>0.3</th>
<th>0.5</th>
<th>0.7</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Optimum solution</td>
<td>Time</td>
<td>Optimum solution</td>
<td>Time</td>
</tr>
<tr>
<td>Test 1</td>
<td>341.83</td>
<td>6.12</td>
<td>341.83</td>
<td>6.38</td>
</tr>
<tr>
<td>Test 2</td>
<td>341.83</td>
<td>2.16</td>
<td>372.11</td>
<td>2.31</td>
</tr>
<tr>
<td>Test 3</td>
<td>341.83</td>
<td>4.38</td>
<td>364.58</td>
<td>1.46</td>
</tr>
<tr>
<td>Optimum solution</td>
<td>341.83</td>
<td>2.16</td>
<td>341.83</td>
<td>1.46</td>
</tr>
<tr>
<td>Worst solution</td>
<td>341.83</td>
<td>6.12</td>
<td>372.11</td>
<td>6.38</td>
</tr>
<tr>
<td>Average solution</td>
<td>341.83</td>
<td>4.22</td>
<td>359.51</td>
<td>3.38</td>
</tr>
</tbody>
</table>

When the parameter $\rho$ changes, the best solution obtained by the algorithm is the optimal value 341.83 at present. When the parameter $\rho$ increases, algorithm worst solution and the average solution show a gradually increasing trend. When the parameter $\rho$ is 0.1, the average solution is the smallest of all the tests.

After that, we test the sensitivity of the parameter. We test the effect of the change of $\rho$ on the results. The test results are shown in the following table.

### Table 3: Comparison of the results of the algorithms

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Failure times</th>
<th>Success ratio</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>Genetic algorithm</td>
<td>10</td>
<td>90%</td>
<td>9.8s</td>
</tr>
<tr>
<td>Ant colony algorithm</td>
<td>4</td>
<td>96%</td>
<td>3.9s</td>
</tr>
<tr>
<td>Particle swarm algorithm</td>
<td>6</td>
<td>94%</td>
<td>4.7s</td>
</tr>
<tr>
<td>Improved ant colony algo</td>
<td>1</td>
<td>99%</td>
<td>1.3s</td>
</tr>
</tbody>
</table>

From the above table, we can see that the performance of the improved ant colony algorithm in Shaanxi international land port logistics path optimization is very good. The algorithm gets the least number of failures, the highest success rate and the shortest time. Therefore, the improved ant colony algorithm applied to the Shaanxi international land port logistics path optimization research achieves good results.
5. CONCLUSION

Shaanxi international inland port logistics is not only an important industrial park in The Belt and Road strategy, but also an important node of the new Eurasian Continental Bridge. Therefore, the Shaanxi international land port is very dependent on the development of logistics. Logistics path optimization problem is a hot issue in the field of logistics management. Because of the complexity and diversity of the logistics path optimization problem, how to arrange the logistics path and receive the goods at the lowest cost is a challenging problem. Because of the advantages of ant colony algorithm in solving the discrete problem and the sensitivity of the path, ant colony algorithm has been concerned about the path planning problem. In this paper, we propose an improved ant colony algorithm. And we use this algorithm to study the logistics path optimization problem. At the same time, we study the parameter sensitivity of this algorithm. The main contents of this paper are as follows. (1) We summarize the research background of this paper. (2) We introduce the ant colony algorithm briefly. (3) An improved ant colony algorithm is proposed. (4) The improved ant colony algorithm is used to study the logistics path optimization problem, and the sensitivity of the parameters is tested. Experimental results show that the algorithm proposed in this paper can effectively optimize the logistics path problem and obtain better results.

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