Hindawi
Journal of Advanced Transportation
Volume 2023, Article ID 7651100, 11 pages
https://doi.org/10.1155/2023/7651100

*Research Article*

# Dynamic Path Optimization Based on Improved Ant Colony Algorithm

**Juan Cheng**

*Jinling Institute of Technology, Nanjing 211169, China*

Correspondence should be addressed to Juan Cheng; apriljj@163.com

Received 20 June 2022; Revised 19 December 2022; Accepted 18 March 2023; Published 17 April 2023

Academic Editor: Wen Liu



Dynamic path optimization is an important part of intelligent transportation systems (ITSs). Aiming at the shortcomings of the current dynamic path optimization method, the improved ant colony algorithm was used to optimize the dynamic path. Through the actual investigation and analysis, the influencing factors of the multiobjective planning model were determined. The ant colony algorithm was improved by using the analytic hierarchy process (AHP) to transform path length, travel time, and traffic flow into the comprehensive weight-influencing factor. Meanwhile, directional guidance and dynamic optimization were introduced to the improved ant colony algorithm. In the simulated road network, the length of the optimal path obtained by the improved ant colony algorithm in the simulation road network is 3.015, which is longer than the length of the optimal path obtained by the basic ant colony algorithm (2.902). The travel time of the optimal path obtained by the improved ant colony algorithm (376 s) is significantly shorter than that of the basic ant colony algorithm (416.3 s). The number of iterations of the improved ant colony algorithm (45) is less than that of the basic ant colony algorithm (58). In the instance network, the number of iterations of the improved ant colony algorithm (18) is less than that of the basic ant colony algorithm (26). The travel time of the optimal path obtained by the improved ant colony algorithm (377.1 s) is significantly shorter than that of the basic ant colony algorithm (426 s) and the spatial shortest distance algorithm (424 s). Compared with the basic ant colony algorithm and the spatial shortest distance algorithm, the results of the optimal path obtained by the improved ant colony algorithm were more accurate, and the effectiveness of the improved ant colony algorithm was verified.

## 1. Introduction

In intelligent transportation systems, path optimization is an essential part. Obtaining real-time and accurate traffic information is important for estimating the traffic conditions at the next moment and has a significant position in traffic guidance. Path optimization helps the traveler to constantly adjust his driving route according to the actual traffic conditions during driving, and reach the destination quickly and efficiently. The ultimate goal of path optimization is to optimize the distribution of traffic flow throughout the road network, thus solving urban traffic congestion problems fundamentally, improving road capacity and travel comfort, and alleviating environmental pollution caused by automobile exhaust.

To solve the traffic congestion, traffic accidents, traffic pollution, and other problems existing in the current road traffic, it is impossible to rely on traffic demand management alone. It is urgent to implement an intelligent transportation system to improve the utilization rate of the existing road network. In the face of increasingly serious traffic problems, traffic managers and traffic participants need to obtain real-time and accurate traffic information of road sections in time to provide basis for dynamic management decisions and travel decisions. Because link travel time and dynamic path optimization can effectively improve travel efficiency in the driving process, travel time estimation and prediction and dynamic path optimization have become one of the issues in the traffic field.

Through investigation and analysis, the dynamic road multiobjective planning model is established with the path length, travel time, and traffic flow as the targets. The analytic hierarchy process (AHP) is used to transform the path length, travel time, and traffic flow into the comprehensive weight-influencing factor, and then the ant colony algorithm is improved. The improved ant colony algorithm is used to optimize the dynamic path.

The rest of the paper is structured as follows: a brief review is given in the next section. Section 3 discussed the dynamic path multiobjective programming model followed by Section 4, which describes the improved ant colony algorithm. Results and discussion are presented in Section 5. Finally, the conclusions are outlined in Section 6.

## 2. Literature Review

Dynamic path optimization can not only integrate real-time traffic information, but also accurately predict traffic flow parameters in future time based on detected real-time traffic information. The dynamic path optimization algorithm provides path planning to the driver, which can be planned before travel or during travel. Researchers have carried out a lot of study on dynamic path optimization algorithms and achieved fruitful results. Bauer et al. [1] introduced layering technology and target acceleration technology in the Dijkstra algorithm, which improved the data storage capacity of the road network and the efficiency of the algorithm. Wei and Meng [2] optimized the dynamic path using the improved Dijkstra algorithm, a weight function was introduced to the improved algorithm, and the weight was determined according to the degree of traffic congestion. The $A^*$ algorithm for the unbalanced search was proposed by Pijls and Post [3]. The proposed algorithm improved the path search ability and narrowed the search range. However, the stability of the solution obtained by this method was poor. Atila et al. [4] applied the improved genetic algorithms for route guidance with the shortest travel time, which introduced a genetic search method in the crossover operation of genetic algorithms. The experimental results showed that the improved genetic algorithm enhanced the computational efficiency compared with the traditional genetic algorithm. An improved ant colony algorithm was developed by D'Acierno et al. [5]. The algorithm divided ants into two categories, one for path selection and one for setting signals at intersections. The improved ant colony algorithm solved the problem of asymmetric traffic assignment. Yu et al. [6] presented an improved ant colony algorithm. In this algorithm, the path length, road slope, and traffic condition were equivalent to the weight of the path, and the improved ant colony algorithm was applied to the TSP problem. Experimental results showed that the improved ant colony algorithm was feasible. Kobayashi et al. [7] studied the dynamic path optimization algorithm of the traffic network. Taking the shortest distance and the shortest travel time as constraints, a road network with 12 light-controlled intersections was simulated. Che et al. [8] proposed an improved ant colony optimization algorithm based on the particle swarm optimization algorithm. Experiment results demonstrate that improved ant colony optimization algorithm is more effective and feasible in path planning for autonomous underwater vehicles than the traditional ant colony algorithm. Research on trajectory optimization to realize real-time collision avoidance under complex driving conditions, a hierarchical three-layer trajectory planning framework was presented by Zhang et al. [9]. The simulation results showed that the proposed scheme is effective in various scenarios. In order to avoid subsequent collisions and stabilize vehicles, Wang et al. [10] proposed a postcollision motion planning and stability control method for autonomous vehicles. Through the hardware in the loop test, the proposed scheme is verified in the integrated driving scenario. Zhang et al. [11] made a comprehensive and systematic review of chassis-coordinated control methods for full-line control vehicles, summarized the research progress in recent years, and introduced the identification methods of different working conditions under steering and braking conditions.

In summary, the application of dynamic path optimization in the traffic field is more and more mature. The dynamic path optimization algorithms include Dijkstra algorithm, heuristic algorithm [12], genetic algorithm, ant colony algorithm, and so on. The algorithm used in the existing literature employed the path length as the weight, the dynamic travel time calculation generally used the BPR function, and the data obtained from the fixed detector data or traffic simulation data. However, the path optimization under a dynamic road network not only requires the optimal path search based on real-time traffic information, but also requires stability, fast convergence, and low complexity of the algorithms. Therefore, artificial intelligence algorithms that can realize dynamic characteristics are the development trend of dynamic path optimization algorithms.

The ant colony algorithm has the characteristics of parallelism, positive feedback, and self-organization ability. Therefore, the ant colony algorithm is introduced to optimize the dynamic path. To make the ant colony algorithm more suitable for dynamic path optimization, the ant colony algorithm is improved in this paper. The novelties in this paper are as follows: (1) path length conversion, (2) add directional guidance, and (3) dynamic optimization.

## 3. Dynamic Path Multiobjective Programming Model

At present, most of the path optimization has a single selection criterion, which is the minimum travel time or the shortest travel distance. However, surveys have shown that in London and Paris, 42% of travelers use the combination of the minimum travel time and the shortest travel distance to select the optimal path, and 56% of travelers use the minimum travel time as the standard for the optimal path. In Munich, 71% of travelers use the combined standard with the minimum travel time and the shortest travel distance to select the path, and only 27% of travelers use the minimum travel time as the path selection criterion [13]. It can be seen that travelers prefer multiple criteria rather than a single criterion when optimizing travel routes.

*3.1. Dynamic Path Multiobjective Programming Model.* In the dynamic traffic network, the factors affecting the travelers should be considered comprehensively to find the optimal path. In order to understand the factors affecting travelers, questionnaires were used to investigate the factors that influence path optimization. In the questionnaire, the factors that affect path optimization were path length, road width, travel time, traffic flow, road slope, road performance, traffic speed, number of intersections, weather, and so on. The questionnaires issued in the survey were 890. In addition to the survey conducted by the conventional method, the survey was conducted using QQ and WeChat. Finally, 543 valid questionnaires were collected. Through the analysis of the recovered questionnaire, it was found that the path length, travel time, and traffic flow were the three main factors affecting path optimization. Therefore, the influence of path length, travel time, and traffic flow on path optimization should be considered comprehensively in the process of path optimization. The statistical distribution of various influencing factors is shown in Figure 1.

The traveler will choose the path with the shortest travel distance and the minimum travel time in the traffic state of free-flow. While in the traffic state of transition and congestion, the traveler will choose the path with less travel time and travel distance relatively short and try to avoid crowded paths.

*3.1.1. Optimal Path Based on the Shortest Travel Distance.* The shortest travel distance refers to the shortest path chosen from the starting point $O$ to the ending point $D$, as shown in the following equation:

$$W_1 = \min\left\{L_k^{od}\right\},\quad \text{s.t.}\begin{cases} L_k^{od} = \sum_i l_i \delta_{i,k}^{od}, \\ i \in A, k \in K_{od}, \end{cases} \tag{1}$$

where $l_i$ is the geometric length of road $i$. $\delta_{i,k}^{od}$ is 1 if road $i$ is on the feasible path $k$ connecting the $OD$, otherwise $\delta_{i,k}^{od}$ is 0.

*3.1.2. Optimal Path Based on the Minimum Travel Time.* The minimum travel time indicates the path with the least travel time from the starting point $O$ to the ending point $D$, which is shown in the following equation:

$$W_2 = \min\left\{T_k^{od}\right\},\quad \text{s.t.}\begin{cases} T_k^{od} = \sum_i t_i(t)\delta_{i,k}^{od}, \\ i \in A, k \in K_{od}, \end{cases} \tag{2}$$

where $t_i(t)$ is the average travel time of road $i$ at time $t$. $\delta_{i,k}^{od}$ is 1 if road $i$ is on the feasible path $k$ connecting the $OD$, otherwise $\delta_{i,k}^{od}$ is 0.

*3.1.3. Optimal Path Based on the Least Traffic Flow.* Traffic flow is an indicator of congestion. The least traffic flow is the path with the minimum traffic flow from the starting point $O$ to the ending point $D$, that is, the path with the least congestion is selected, as indicated in the following equation:

$$W_3 = \min\left\{Q_k^{od}\right\},\quad \text{s.t.}\begin{cases} Q_k^{od} = \sum_i q_i(t)\delta_{i,k}^{od}, \\ i \in A, k \in K_{od}, \end{cases} \tag{3}$$

where $q_i(t)$ is the average traffic flow of road $i$ at time $t$. $\delta_{i,k}^{od}$ is 1 if road $i$ is on the feasible path $k$ connecting the OD, otherwise $\delta_{i,k}^{od}$ is 0.

Through the abovementioned analysis, the influence of path length, travel time, and traffic flow should be considered in the dynamic path optimization process. Consistent with the method used by Yu et al. [6], the AHP is also used to calculate the weight of each influencing factor, and then transforms the factors affecting the path optimization into a comprehensive weighting influencing factor.

*3.2. Analytic Hierarchy Process.* The AHP was proposed by the American operations researcher Professor Saaty in the mid 1970 s. AHP can classify various factors that affect the problem, determine the relationship between the various factors, and establish a multilevel structural model of the influencing factors [6].

*3.2.1. Establishing the Hierarchy Model.* In this paper, the structure of the model is divided into two layers, namely, the target layer A and the criterion layer B. The weight of the path optimization in the target layer is $w_{ij}$, and the weights of the path length, travel time, and traffic flow in the criterion layer are $w_1$, $w_2$, and $w_3$, respectively, as shown in Figure 2.

*3.2.2. Constructing the Judgment Matrix.* The uniform matrix method was proposed to determine the weight between each influencing factor. $a_{ij}$ is the comparison result of the importance between element $i$ and element $j$. Table 1 is the nine important levels and assignments given by Saaty.

*3.2.3. Hierarchical Single Arrangement.* The eigenvector corresponding to the maximum eigenvalue $\lambda_{\max}$ of the judgment matrix is denoted as $W$ after normalization (making the sum of all elements in the vector equal to 1). The element of $W$ is the ranking weight of the same level factor for the relative importance of the previous level factor. This process is called hierarchical single arrangement. The calculation steps are presented as follows:

Step (1): multiplying element of each row in the judgment matrix A, that is, $M_i = \prod_{j=1}^{n} a_{ij}, i = 1, 2 \cdots n$

Step (2): calculating the $n-th$ root of $M_i$, $\bar{w}_i = \sqrt[n]{M_i}$

Step (3): if $\bar{w}_i$ is normalized to $w_i = \bar{w}_i / \sum_{j=1}^{n} \bar{w}_j$, then $w_i$ is the eigenvector

Step (4): calculating the maximum eigenvalue, $\lambda_{\max} \approx \sum_{i=1}^{n} (AW)_i / n w_i$

*3.2.4. Consistency Test.* The consistency test is to determine the allowable range of inconsistency in the judgment matrix

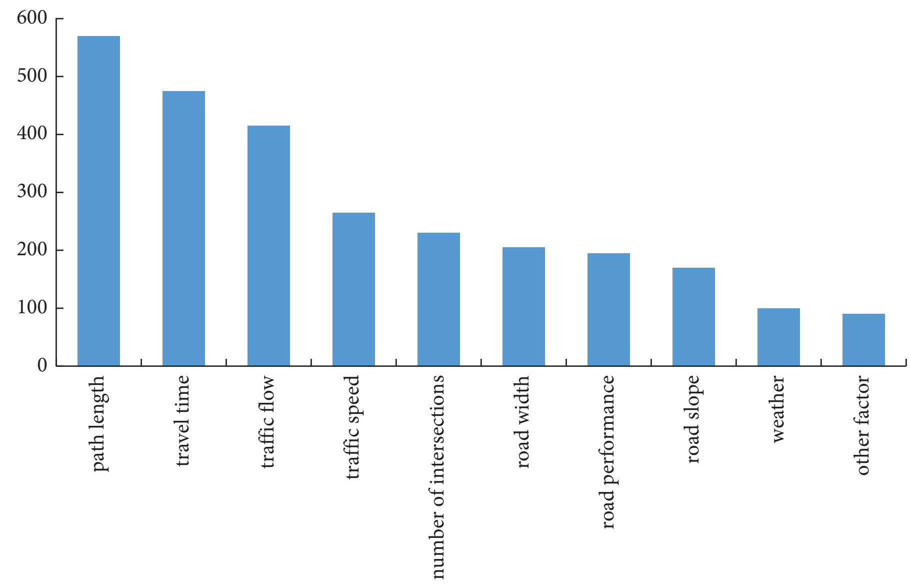


FIGURE 1: Statistical distribution diagram of various influencing factors affecting path optimization.

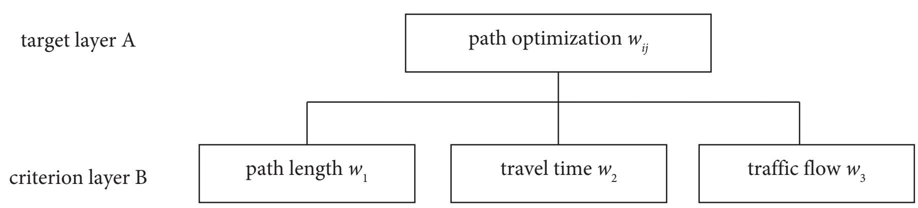


FIGURE 2: The layering diagram of path optimization.

A, which the test standard is indicated in the following equation:

$$CR = \frac{CI}{RI}, \tag{4}$$

where $CR$ is the conformance ratio. When its value is less than 0.1, the judgment matrix passes the consistency test; otherwise, it needs to be corrected. $CI$ is the consistency index, $CI = \lambda_{\max} - n/n - 1$. $RI$ is the random consistency index, determined by the order of the judgment matrix, which is shown in Table 2.

Among the 543 valid questionnaires, 291 questionnaires were selected with the path length, travel time, and traffic flow as the top three influencing factors. The judgment matrix of this paper is determined by 291 questionnaires and the scale method of Table 1. The constructed judgment matrix is shown in Table 3.

The weight of the criterion layer is determined by the eigenvalue method mentioned above.

The maximum eigenvalue is $\lambda_{\max} = 3.0385$. The consistency test result is $CR = CI/RI = 0.0193/0.58 = 0.0333 < 0.1$, indicating that the constructed judgment matrix passes the consistency test. The eigenvalue of the criteria layer is $w_1 = 0.637$, $w_2 = 0.258$, and $w_3 = 0.105$.

*3.3. Quantification of Influencing Factors.* The factors affecting path optimization in this paper are path length, travel time, and traffic flow, but the dimensions of the three influencing factors are inconsistent. In order to apply the influence of different factors on path optimization, dimensionless processing of different influencing factors is required. The extremum method is used to perform dimensionless processing influencing factors [14], and the variables are transformed into (0, 1]. The transformation equation is indicated as follows:

$$x_i' = \frac{x_i}{\max x_i}, \tag{5}$$

where $x_i'$ is the dimensionless value of $x_i$. $\max x_i$ is the maximum value of $x_i$.

The weights of the influencing factors in the criterion layer are obtained through Section 3.2. Then, the comprehensive weight-influencing factor of the path is calculated considering the three factors of path length, travel time, and traffic flow as follows:

$$s_{ij} = w_1 \cdot d_{ij} + w_2 \cdot t_{ij} + w_3 \cdot n_{ij}, \tag{6}$$

where $s_{ij}$ is the comprehensive weight-influencing factor considering path length, travel time, and traffic flow. $d_{ij}$ is the dimensionless value of path length. $t_{ij}$ is the

Table 1: Important scale.

| Important scale | Meaning |
|---|---|
| 1 | The two factors are equally important |
| 3 | The former is slightly more important than the latter |
| 5 | The former is more important than the latter |
| 7 | The former is obviously important than the latter |
| 9 | The former is extremely important than the latter |
| 2, 4, 6, 8 | Intermediate value of two adjacent judgments |
| Reciprocal | If the ratio of the importance between element $i$ and element $j$ is $a_{ij}$, the ratio of element $j$ and element $i$ is $a_{ji} = 1/a_{ij}$ |

Table 2: Average random consistency index.

| Matrix order | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| *RI* | 0 | 0 | 0.58 | 0.90 | 1.12 | 1.24 | 1.32 | 1.41 | 1.45 | 1.49 |

Table 3: The judgment matrix.

| $A$ | $C_1$ | $C_2$ | $C_3$ |
|---|---|---|---|
| $C_1$ | 1 | 3 | 5 |
| $C_2$ | 1/3 | 1 | 3 |
| $C_3$ | 1/5 | 1/3 | 1 |

dimensionless value of travel time. $n_{ij}$ is the dimensionless value of travel flow. $w_1, w_2,$ and$w_3$ are the weights of each influencing factor in the criteria layer, $w_1 = 0.637$, $w_2 = 0.258$, and $w_3 = 0.105$.

## 4. The Improved Ant Colony Algorithm

The classic application of the ant colony algorithm is the TSP problem. In order to make the ant colony algorithm more suitable for dynamic path optimization, the ant colony algorithm is improved.

### 4.1. The Improved Ant Colony Algorithm

*4.1.1. Path Length Conversion.* Based on Section 3.2, path length, travel time, and traffic flow are comprehensively considered, and the comprehensive weight-influencing factors of each influencing factor are taken as path length, which is shown in equation (4).

*4.1.2. Adding Directional Guidance.* In the ant colony algorithm, $\eta_{ij}(t)$ is a heuristic function, representing the expectation between city $i$ and city. Among them, $\eta_{ij}(t) = 1/d_{ij}$ is the reciprocal of the distance between adjacent nodes. The smaller the $d_{ij}$ is, the greater the $p_{ij}^k(t)$ is. The smaller the distance is, the more likely the ant is to select the next node. This definition is applicable to unordered TSP problems, but for ordered path optimization problems, this search method will reduce the search efficiency. The A* algorithm is introduced to improve $\eta_{ij}(t)$. In order to be consistent with the abovementioned, equation (7) is dimensionless according to the method of Section 3.3 as follows:

$$\eta_{ij}(t) = \frac{1}{d_{ij} + d_{jD}}, \tag{7}$$

where $\eta_{ij}(t)$ is the heuristic function, $d_{jD}$ is the dimensionless value of the length between node $j$ and the ending point $D$, and $d_{ij}$ is the dimensionless value of the length between adjacent nodes $i$ and $j$.

The visibility function is improved comprehensively considering equations (1) and (2) as follows:

$$\eta_{ij}(t) = \frac{1}{s_{ij} + d_{jD}}. \tag{8}$$

*4.1.3. Dynamic Optimization.* When the information in the road network changes, the path should be reoptimized according to the changed information. Therefore, when the ant selects the next node, it checks whether the information in the road network changes. If the change occurs, the pheromone concentration needs to be updated, as shown in the following equation:

$$\tau(t+1) = \frac{t_{t+1}}{t_t} \cdot \tau(t), \tag{9}$$

where $\tau(t+1)$ is the pheromone concentration on path $ij$ at time $t+1$, $t_{t+1}$ is the travel time on path $ij$ at time $t+1$, $t_t$ is the travel time on path $ij$ at time $t$, and $\tau(t)$ is the pheromone concentration on path $ij$ at time $t$.

*4.2. Design of the Improved Ant Colony Algorithm.* The improved ant colony algorithm is applied to path optimization.

*4.2.1. Ant Transfer Rule.* The ant moves from node $i$ to node $j$ according to the following equation:

$$j = \begin{cases} \operatorname{argmax}\left\{\left[\tau_{ij}(t)\right]^{\alpha} \cdot \left[\eta_{ij}(t)\right]^{\beta}, & q < q_0, \\ P_{ij}^k(t), & q \geq q_0, \end{cases} \tag{10}$$

where $q$ is a random variable uniformly distributed on [0,1]. $q_0$ is the parameter that controls the movement rule, $q_0 \in [0,1]$. The value of $q_0$ can be divided into three types according to the scale of the road network, which is generally large, medium, and small, and the values are 0.7, 0.5, and 0.2 [15]. $\eta_{ij}$ is shown in equation (8). $p_{ij}^k(t)$ is indicated in the following equation:

Table 4: Constants and variables in ant colony algorithm.

| Symbol | Meaning |
|---|---|
| $n$ | Number of nodes |
| $m$ | Number of ants |
| $\eta_{ij}(t)$ | A heuristic function that represents the expectation between node $i$ and node $j$ |
| $d_{ij}$ | The distance between node $i$ and node $j$ |
| $\tau_{ij}(t)$ | The pheromone concentration between node $i$ and node $j$ at time $t$ |
| $\Delta\tau_{ij}^{k}$ | The pheromone concentration of ant $k$ released between node $i$ and node $j$ |
| Q | Pheromone constant |
| $\alpha$ | Pheromone importance factor, or pheromone factor for short |
| $\beta$ | The importance factor of heuristic function is referred to as heuristic function factor |
| $\rho$ | Pheromone volatile factor, where $0 < \rho < 1$ |
| $p_{ij}^{k}(t)$ | The probability of ant $k$ moving from node $i$ to node $j$ at time $t$ |
| $\text{allow}_k$ | Search table, representing ant $k$ is looking forward to visiting the node |
| $\text{tabu}_k$ | Search tabu table, representing ant $k$ have visited the node |

$$p_{ij}^{k}(t) = \begin{cases} \dfrac{\left[\tau_{ij}(t)\right]^{\alpha} \cdot \left[\eta_{ij}(t)\right]^{\beta}}{\sum_{s\in \text{allow}_k}\left[\tau_{is}(t)\right]^{\alpha} \cdot \left[\eta_{is}(t)\right]^{\beta}}, & j \in \text{allow}_k, \\ 0, & j \notin \text{allow}_k. \end{cases} \tag{11}$$

The variables in equation (11) are shown in Table 4.

It can be seen from equation (8), when $q < q_0$, the ant temporarily ignores the existence of the better next node, and accumulates the pheromone on the path of node $i$ to all the nodes $j$ to be selected. When $q \geq q_0$, the ant will select the next node according to $p_{ij}^{k}(t)$, preventing the ant from selecting the path with large pheromone concentration at the beginning, which is beneficial to the global search and avoids local convergence.

*4.2.2. Pheromone Update.* There are two ways to update the pheromone, namely, local pheromone updates and global pheromone updates. Local pheromone update means that when the ant completes a path search, the pheromone is updated on the path. While global pheromone update means that the pheromone is updated of the optimal path in all paths when all ants complete a path search.

The local pheromone update rule is as follows:

$$\begin{aligned} \tau_{ij}(t+1) &= (1-\rho)\cdot \tau_{ij}(t) + \Delta\tau_{ij}(t), \\ \Delta\tau_{ij}(t) &= \sum_{k=1}^{m} \Delta\tau_{ij}^{k}(t), \end{aligned} \tag{12}$$

where $\Delta\tau_{ij}^{k}$ is the concentration of pheromone left between node $i$ and node $j$ by ant $k$. $\Delta\tau_{ij}$ is the pheromone concentration that all ants increase between node $i$ and node $j$ due to the release of pheromones. The ant cycle model is used for calculating $\Delta\tau_{ij}^{k}$ as follows [16]:

$$\Delta\tau_{ij}^{k} = \begin{cases} \dfrac{Q}{L_k}, & \text{If the ant visits node } i \text{ to node } j, \\ 0, & \text{otherwise}, \end{cases} \tag{13}$$

where $Q$ is the pheromone constant released by the ant during the whole path optimization. $L_k$ is the total length traveled by ant $k$.

The global pheromone update rule is as follows:

$$\begin{aligned} \tau_{ij}(t+1) &= (1-\zeta)\cdot \tau_{ij}(t) + \Delta\tau_{ij}(t), \\ \Delta\tau_{ij}(t) &= \sum_{k=1}^{m} \Delta\tau_{ij}^{k}(t), \\ \Delta\tau_{ij}^{k} &= \begin{cases} \dfrac{Q}{L_k}, & \text{The optimal path of ants in this circle}, \\ 0, & \text{otherwise}, \end{cases} \end{aligned} \tag{14}$$

where $\xi$ is the pheromone volatile factor, $\xi \in (0,1)$. $L_k$ is the sum of the lengths selected by the ants in this circle.

*4.2.3. Dynamic Optimization.* Traffic information on the road network is updated every 5–15 minutes. When the vehicle reaches the next node of the road network, it is checked whether the pheromone on the road has changed according to equation (9). If the pheromone has changed, the path is searched according to the changed pheromone, and the path is dynamically optimized.

The flow of the improved ant colony algorithm is as follows:

Step 1: initializing each parameter, set the number of iterations to $NC = 0$, and place $m$ ants on the starting point.

Step 2: the number of iterations set to $NC = NC + 1$.

Step 3: the ant performs a path search according to equation (10).

Step 4: when an ant reaches the end point, the pheromone is updated to the path searched by the ant according to the local pheromone update rule.

Step 5: repeat Step 2–Step 4. When all the ants have reached the end point, the path that all ants passed is the optimal path.

Step 6: select an optimal path from all paths and perform global pheromone update on the optimal path.

Step 7: if $NC > NC_{\max}$, the search ends and outputs the current optimal path, otherwise return to step 2.

Step 8: check whether the road network has been updated. If updated, the pheromone is updated according to equation (9).

Step 9: if the vehicle has reached the end point at this time, the search is finished, otherwise return to step 2.

## 5. Results and Discussion

Using the improved ant colony algorithm, the path optimization is carried out for the simulated road network and the instance network.

### *5.1. Simulated Road Network*

*5.1.1. Road Network Data.* In order to verify the effectiveness of the improved ant colony algorithm proposed in this paper, some sections of Chaoyang Zhou South Road in Nanchang City were selected as the study area. A road network with 15 nodes is designed, and the road network contains 21 road segments. The road network to be optimized in this paper is shown in Figure 3, where node O is the starting point of the road section, and node D is the ending point of the road section. The goal of path optimization is to find the optimal path from node O to node D. Vehicle arrivals follow the normal distribution. In the road network, the update interval of traffic information is 5 minutes.

The length, the travel time at a certain time, and the traffic flow are shown in Tables 5–7, respectively. The table only shows the results of nondimensionalization according to the abovementioned method.

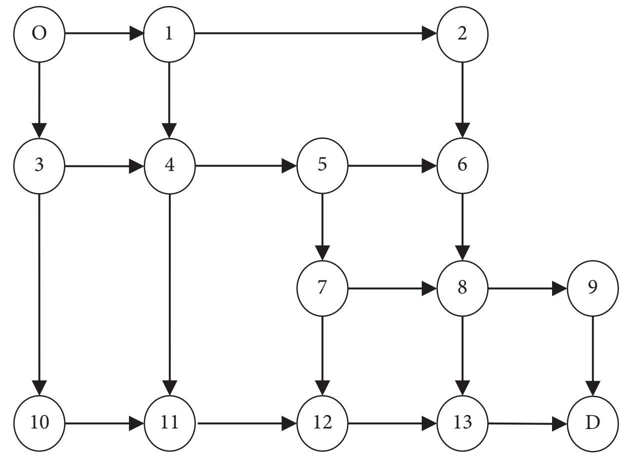


Figure 3: Road network diagram.

Table 5: Table of path length.

| Node-node | Path length (m) |
|---|---|
| O-1 | 0.549 |
| 1–4 | 0.704 |
| 3–10 | 1.000 |
| 5-6 | 0.282 |
| 7-8 | 0.268 |
| 8–13 | 0.394 |
| 11-12 | 0.282 |
| O–3 | 0.718 |
| 2–6 | 0.746 |
| 4-5 | 0.282 |
| 5–7 | 0.423 |
| 7–12 | 0.437 |
| 9-D | 0.423 |
| 12-13 | 0.310 |
| 1-2 | 0.676 |
| 3-4 | 0.563 |
| 4–11 | 0.972 |
| 6–8 | 0.451 |
| 8-9 | 0.282 |
| 10-11 | 0.563 |
| 13-D | 0.282 |

*5.1.2. Parameter Settings.* The parameters in the improved ant colony algorithm are shown in Table 4, and the main parameters are set as follows:

(1) $m$ represents the number of ants. $m$ affects the calculation results of MATLAB. The literature research and simulation results showed that when the number of ants is 1.5 times the number of nodes, the effect is better. In this paper, the number of nodes is 15, so the number of ants is set to 23.

(2) $n$ indicates the number of nodes. $n = 15$.

(3) $\alpha$ denotes the pheromone heuristic factor, which describes the influence of the pheromone released by the ant during the path finding process on the ant path selection. Through literature research and simulation results, it is known that the effect is better when $\alpha$ is 0 to 5, and $\alpha = 1$ selected in this paper.

(4) $\beta$ refers to the expected value heuristic factor, indicating the degree of action expected in the path selection. The larger the $\beta$, the easier to fall into the local optimal solution. The smaller the $\beta$, the smaller the effect of the expected value, the harder to find the optimal solution. The simulation results showed that $\beta$ is 0–5, the effect is better, and this paper takes $\beta = 5$.

(5) $\rho$ is the pheromone volatilization factor, indicating the level of disappearance of the pheromone. $1 - \rho$ is the pheromone residual factor, describing the retention level of the pheromone. Through simulation results, it is shown that $\rho$ is 0.2–0.5; the simulation effect is better, so $\rho$ is set to 0.3 in this paper.

*5.1.3. Results and Analysis.* Using the data in Section 5.1.1 and the parameters determined in Section 5.1.2, the results were inputted into the MATLAB simulation platform to verify the improved ant colony algorithm proposed in this paper.

After the optimized processing of the improved ant colony algorithm, the optimal path is shown in Figure 4, and

Table 6: Table of travel time at a certain time.

| Node-node | Travel time (s) |
|---|---|
| O-1 | 0.659 |
| 1–4 | 0.634 |
| 3–10 | 1.000 |
| 5-6 | 0.254 |
| 7-8 | 0.241 |
| 8–13 | 0.245 |
| 11-12 | 0.338 |
| O–3 | 0.462 |
| 2–6 | 0.987 |
| 4-5 | 0.298 |
| 5–7 | 0.634 |
| 7–12 | 0.357 |
| 9-D | 0.585 |
| 12-13 | 0.254 |
| 1-2 | 0.704 |
| 3-4 | 0.423 |
| 4–11 | 0.921 |
| 6–8 | 0.272 |
| 8-9 | 0.241 |
| 10-11 | 0.441 |
| 13-D | 0.220 |

Table 7: Table of traffic flow.

| Node-node | Traffic flow (vehicle) |
|---|---|
| O-1 | 0.533 |
| 1–4 | 0.615 |
| 3–10 | 0.770 |
| 5-6 | 0.256 |
| 7-8 | 0.304 |
| 8–13 | 0.488 |
| 11-12 | 0.450 |
| O–3 | 0.347 |
| 2–6 | 1.000 |
| 4-5 | 0.254 |
| 5–7 | 0.464 |
| 7–12 | 0.687 |
| 9-D | 0.411 |
| 12-13 | 0.251 |
| 1-2 | 0.507 |
| 3-4 | 0.450 |
| 4–11 | 0.758 |
| 6–8 | 0.303 |
| 8-9 | 0.258 |
| 10-11 | 0.488 |
| 13-D | 0.256 |

the convergence curve is shown in Figure 5. In the improved ant colony algorithm, the comprehensive weight-influencing factors are used for calculation, and after the optimal path is obtained, the optimal path is described in the actual road network.

As can be seen from Figure 4, the optimal path from node O to node D is O-3-4-5-7-12-13-D, and the optimal path length (comprehensive weight-influencing factor) is 2.885.

Meantime, the basic ant colony algorithm is used to calculate the optimal path, which is compared with the

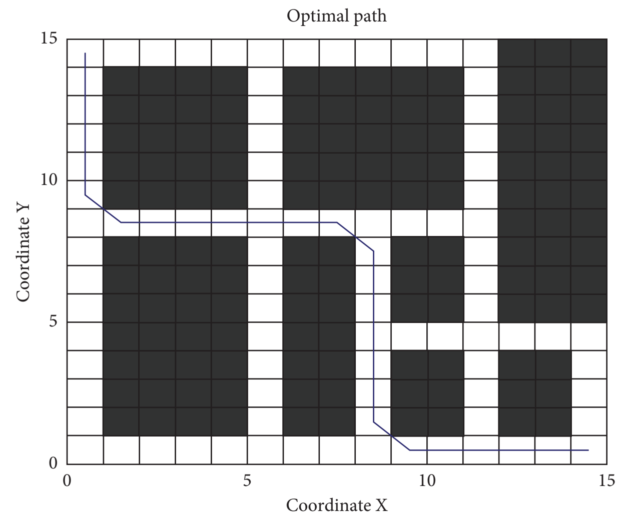


Figure 4: The optimal path of the improved ant colony algorithm.

improved ant colony algorithm proposed in this paper. Figure 6 shows the optimal path of the ant colony algorithm, and Figure 7 shows the convergence curve of the ant colony algorithm.

As indicated in Figure 6, the optimal path from node O to node D obtained by the ant colony algorithm is O-1-4-5-7-8-13-D, and the optimal path length (comprehensive weight-influencing factor) is 2.902.

A comparison of the improved ant colony algorithm, the basic ant colony algorithm, and the spatial shortest distance algorithm is shown in Table 8.

From Figures 4–7 and Table 8, the following conclusions can be drawn:

(1) The length of the optimal path obtained by the improved ant colony algorithm (3.015) is longer than the length obtained by the basic ant colony algorithm (2.092). This is because the improved ant colony algorithm comprehensively considers the influence of path length, travel time, and traffic flow on the optimal path. Therefore, when choosing the optimal path, the road with a shorter travel time and less traffic flow will be considered, which may lead to the selection of the longer path length. However, when the optimal path is simultaneously expressed by the comprehensive weight-influencing factor, the optimal path selected by the basic ant colony algorithms is longer than the optimal path obtained by the improved ant colony algorithm, since the two algorithms do not consider the real-time traffic conditions of the road segment (such as the delay time caused by traffic congestion).

(2) The number of iterations of the improved ant colony algorithm is reduced compared with the basic ant colony algorithm. Because of the directional guidance introduced in the improved ant colony algorithm, the ant's search always points to the ending point, and the convergence speed is accelerated.

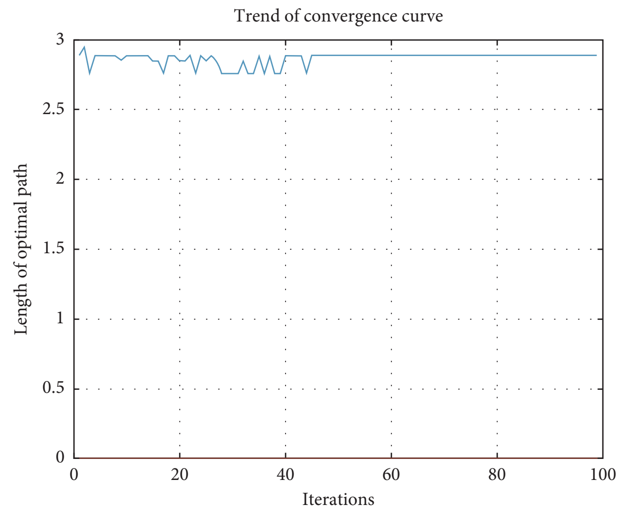


Figure 5: The convergence curve of the improved ant colony algorithm.

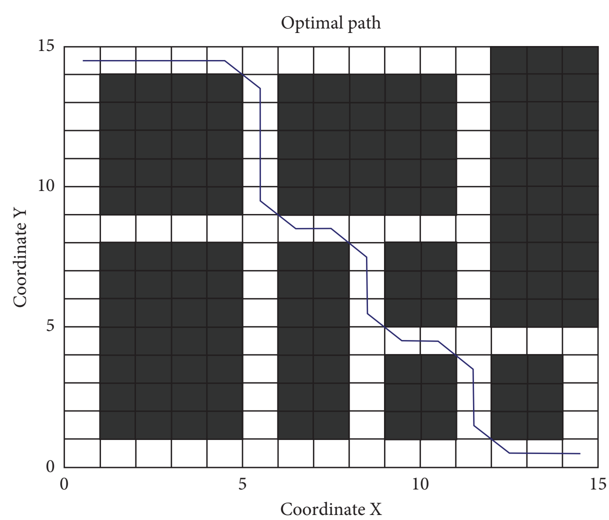


Figure 6: The optimal path of the ant colony algorithm.

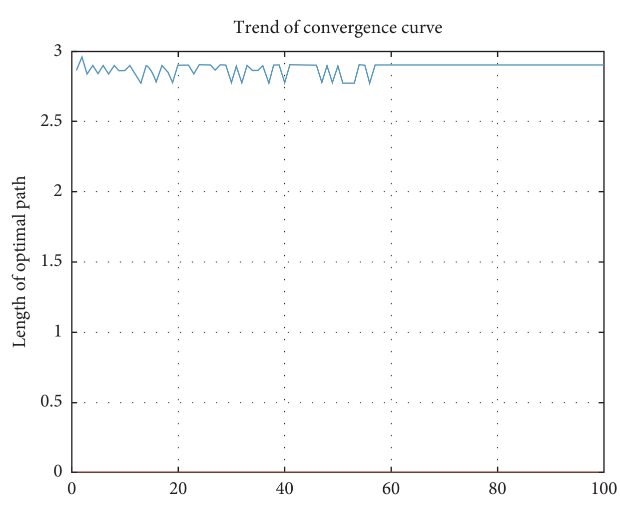


Figure 7: The convergence curve of the ant colony algorithm.

Table 8: Comparison of various algorithms in Simulated Road Network.

| Path optimization algorithm | Optimal path | Path length: Actual length of the path | Path length: Comprehensive weight-influencing factor | Travel time (s) |
|---|---|---|---|---|
| Improved ant colony algorithm | O-3-4-5-7-12-13-D | 3.015 | **2.885** | **376** |
| Ant colony algorithm | O-1-4-5-7-8-13-D | **2.902** | 2.911 | 416.3 |

Bold valuers represent the optimal values of various path optimization algorithms.

Table 9: Comparison of various algorithms in Instance network.

| Path optimization algorithm | Optimal path | Path length: Actual length of the path (m) | Path length: Comprehensive weight-influencing factor | Travel time (s) | Number of iterations |
|---|---|---|---|---|---|
| Improved ant colony algorithm | 1-2-17-7-11-12-16 | 2666 | **4.109** | **377.1** | **18** |
| Ant colony algorithm | 1-5-6-10-11-15-16 | **2662** | 4.240 | 426 | 26 |
| Spatial shortest distance algorithm | 1-5-9-10-11-12-16 | 2680 | 4.243 | 424 | — |

Bold valuers represent the optimal values of various path optimization algorithms.

(3) The travel time of the optimal path obtained by the improved ant colony algorithm is significantly shorter than that of the basic ant colony algorithm and the spatial shortest distance algorithm, indicating that the improved ant colony algorithm improves the accuracy when optimizing the path. Although the length of the optimal path obtained by the improved ant colony algorithm is not the shortest, the improved ant colony algorithm will bypass relatively congested roads while driving and can reach the destination more quickly.

*5.2. Instance Network.* In order to verify the effectiveness of the proposed method, the road network of [17] is selected for verification. The purpose of path optimization is to find the optimal path from node 1 to node 16.

The comparisons of the optimal paths obtained by the improved ant colony algorithm, the basic ant colony algorithm and the space shortest distance algorithm, the length of the path, the travel time, and the number of iterations are shown in Table 9.

It can also be seen from Table 9 that the length of the optimal path obtained by the improved ant colony algorithm is longer than that obtained by the basic ant colony algorithm. However, when the optimal path is simultaneously expressed by the comprehensive weight-influencing factors at the same time, the optimal path length selected by the basic ant colony algorithm and the spatial shortest distance algorithm is obviously longer than the optimal path obtained by the improved ant colony algorithm. The number of iterations of the improved ant colony algorithm is less than that of the basic ant colony algorithm. The travel time of the optimal path obtained by the improved ant colony algorithm is significantly shorter than that of the basic ant colony algorithm and the spatial shortest distance algorithm, indicating that the improved ant colony algorithm has improved accuracy in optimizing the path compared with the basic ant colony algorithm and the spatial shortest distance algorithm. The effectiveness of the improved ant colony algorithm in path optimization is further verified.

## 6. Conclusion

The dynamic path optimization method was studied, and the application of the dynamic path multiobjective programming model and ant colony algorithm in TSP problem were analyzed in this paper. Through the actual investigation and analysis, the section length, travel time, and traffic flow are converted into comprehensive weight-influencing factors by using the AHP. At the same time, directional guidance and dynamic optimization are added. The improved ant colony algorithm is proposed, which is verified by the simulation road network and the example road network. The travel time comparison results of the optimal path showed that the accuracy of the optimal path obtained by the improved ant colony algorithm is improved compared with the basic ant colony algorithm and the space shortest distance algorithm, which verified the effectiveness of the improved ant colony algorithm. Meanwhile, directional guidance is introduced to reduce the number of iterations.

Because of the time and the lack of appropriate data, the paper is verified with simulation data. The author hopes to use real data in future research to verify the accuracy of the model. Besides, in the future research, the author uses PSO, SSO, WOA [18–20], and other methods to establish a dynamic path optimization model.

## Data Availability

The data used to support the findings of the study are available from the corresponding author upon request.

## Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

## Acknowledgments

This study was supported by the Jiangsu University Philosophy and Social Science Research Project (no. 2021SJA0518).

## References

[1] R. Bauer, D. Delling, P. Sanders, D. Schieferdecker, D. Schultes, and D. Wagner, "Combining hierarchical and goal-directedspeed-up techniques for dijkstra's algorithm," *Journal of Experimental Algorithmics*, vol. 15, 2010.

[2] M. Wei and Y. Meng, "Research on the optimal route choice based on improved Dijkstra," in *Proceedings of the Advanced Research & Technology in Industry Applications*, IEEE, Ottawa, ON, September 2014.

[3] W. Pijls and H. Post, "A new bidirectional search algorithm with shortened postprocessing," *European Journal of Operational Research*, vol. 198, no. 2, pp. 363–369, 2009.

[4] U. Atila, I. R. Karas, C. Gologlu, B. Yaman, and I. M. Orak, "Design of a route guidance system with shortest driving time based on genetic algorithm," in *Proceedings of the 10th WSEAS international conference on Applied computer and applied computational science. World Scientific and Engineering Academy and Society (WSEAS)*, pp. 61–66, Beijing China, July 2011.

[5] L. D'Acierno, M. Gallo, and B. Montella, "An Ant Colony Optimisation algorithm for solving the asymmetric traffic assignment problem," *European Journal of Operational Research*, vol. 217, no. 2, pp. 459–469, 2012.

[6] M. Yu, G. Yue, Z. Lu, and X. Pang, "Logistics terminal distribution mode and path optimization based on ant colony algorithm," *Wireless Personal Communications*, vol. 102, 2018.

[7] M. A. Kobayashi, H. Shimizu, and Y. Yonezawa, "Dynamic route search algorithms of a traffic network," in *Proceedings of the 36th SICE Annual Conference. International Session Papers*, IEEE, Tokushima, Japan, July 2002.

[8] G. Che, L. Liu, and Z. Yu, "An improved ant colony optimization algorithm based on particle swarm optimization algorithm for path planning of autonomous underwater vehicle," *Journal of Ambient Intelligence and Humanized Computing*, vol. 11, no. 8, pp. 3349–3354, 2020.

[9] Z. Zhang, L. Zhang, J. Deng, M. Wang, Z. Wang, and D. Cao, "An enabling trajectory planning scheme for lane change collision avoidance on highways," *IEEE Transactions on Intelligent Vehicles*, vol. 12, 2021.

[10] C. Wang, Z. Wang, L. Zhang, and T. Chen, "Post-impact motion planning and tracking control for autonomous vehicles[J]," *Chinese Journal of Mechanical Engineering*, vol. 35, no. 1, pp. 1–18, 2022.

[11] L. Zhang, Z. Zhang, Z. Wang, J. Deng, and D. G. Dorrell, "Chassis coordinated control for full X-by-wire vehicles-A review," *Chinese Journal of Mechanical Engineering*, vol. 34, no. 1, pp. 42–25, 2021.

[12] N. Rivera, J. A. Baier, and C. Hernández, "Incorporating weights into real-time heuristic search," *Artificial Intelligence*, vol. 225, no. 225, pp. 1–23, 2015.

[13] G. K. H. Pang, K. Takabashi, T. Yokota, and H. Takenaga, "Adaptive route selection for dynamic route guidance system based on fuzzy-neural approaches," *IEEE Transactions on Vehicular Technology*, vol. 48, no. 6, pp. 2028–2041, 1999.

[14] C. L. Zong, X. Y. Li, and Y. T. Wang, "A multi-objective programming model of route choice before travel [J]," *JOURNAL OF TRANSPORTATION SYSTEMS ENGINEERING AND INFORMATION TECHNOLOGY*, vol. 5, no. 6, pp. 58–61, 2005.

[15] M. Dorigo and L. M. Gambardella, "Ant colony system: a cooperative learning approach to the traveling salesman problem," *IEEE Transactions on Evolutionary Computation*, vol. 1, no. 1, pp. 53–66, 1997.

[16] Y. C. Chang, V. C. Li, and C. J. Chiang, "An ant colony optimization heuristic for an integrated production and distribution scheduling problem [J]," *Engineering Optimization*, vol. 46, no. 4, p. 18, 2014.

[17] N. Li, *A Research in Dynamic Traffic Assignment and Route Guide System Based on Ant colony Algorithm [D]*, Changsha University of Science & Technology, Hu Nan Sheng, China, 2008.

[18] A. J. Humaidi and H. M. Badir, "Linear and nonlinear active rejection controllers for single-link flexible joint robot manipulator based on PSO tuner," *JOURNAL OF ENGINEERING SCIENCE AND TECHNOLOGY REVIEW*, vol. 13, no. 6, pp. 2272–2278, 2018.

[19] T. Ghanim, A. R. Ajel, and A. J. Humaidi, "Optimal fuzzy logic control for temperature control based on social spider optimization," *IOP Conference Series: Materials Science and Engineering*, vol. 745, no. 1, Article ID 012099, 2020.

[20] A. J. Humaidi, H. M. Badr, and A. H. Hameed, "PSO-based active disturbance rejection control for position control of magnetic levitation system," in *Proceedings of the 2018 5th International Conference on Control, Decision and Information Technologies (CoDIT)*, Thessaloniki, Greece, April 2018.