Research on optimal vehicle path algorithm based on improved ant colony algorithm

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ABSTRACT

At present, vehicle routing optimization has become the key to improving logistics efficiency and reducing costs. This article proposes an improved ant colony algorithm to address the limitations of traditional ant colony algorithms in the optimal path problem for vehicles. The core of this study is to improve the pheromone update model of ant colony algorithm and validate it by constructing an experimental environment. The improved ant colony algorithm proposed in this article has significant performance improvements in solving vehicle path optimization problems, and is feasible and superior in practical applications, especially in terms of search efficiency. This algorithm provides a new perspective for future research directions.

Keywords: Vehicle path optimization problem, improve ant colony algorithm, intelligent transportation

1. INTRODUCTION

Vehicle routing problem is one of the important research topics in intelligent transportation applications in recent years. Reasonably allocating and optimizing logistics vehicles can reduce vehicle expenses, improve the transportation efficiency of logistics vehicles, and increase user satisfaction and economic benefits for enterprises[1]. Therefore, how to optimize the vehicle routing problem has important theoretical and economic significance.

Dorigo[2] first proposed the concept of ant colony algorithm and explained that the inspiration for this algorithm comes from the behavior of ants discovering paths while searching for food. Huang et al.[3] combines K-means algorithm with heuristic algorithm to solve the optimal delivery path for vehicles. Li et al.[4] simulated a semi open time window delivery model in rural logistics distribution, expanding the scope of ant colony algorithm solutions., On the basis of establishing a logistics path optimization model, Wu et al.[5] considered multiple distribution centers, effectively reducing costs while ensuring customer satisfaction. Li et al.[6] recompiled the pheromone volatilization mechanism of ant colony algorithm, applied variable neighborhood search, and proposed an improved ant colony algorithm, which improved the initial solution and solving process.; Zhu et al.[7] addresses the shortcomings of traditional ant colony algorithms in solving indoor evacuation problems, such as slow convergence speed and susceptibility to local optima. The dynamic parameters of the fire scene are introduced into the ant colony algorithm to improve its path selection strategy, heuristic function, and pheromone update strategy, in order to solve for a better evacuation path for the entire evacuation population; Yang et al.[8] studies the optimization problem of logistics paths, aiming to effectively reduce the distance of logistics distribution, achieve high efficiency and low cost in completing distribution tasks, and propose an improved ant colony algorithm by optimizing the heuristic function of the basic ant colony algorithm. Zhao et al.[9] adopts two methods, local optimization and global optimization, to expand the pheromone update method of traditional ant colony algorithm to the optimal solution search range, and extends the function definition range of the heuristic factor to the initial node. Chen et al.[10] proposes an improved ant colony optimization algorithm that utilizes global information of the working environment to establish a target attraction function, increasing the probability of ant colony selecting the optimal path to reach the target point and shortening the iteration time of the algorithm; Liu et al.[11] improved the pheromone update method based on the standard ant colony algorithm, and added the nearest neighbor algorithm and local optimal search strategy to solve the ant path selection problem in the early stage of the algorithm. At the same time, the dynamic pheromone update method was used

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to optimize and improve the standard ant colony algorithm, making it tend towards global convergence. The experiment showed that the performance of the algorithm was effectively improved;

This study addresses the limitations of traditional classical ant colony algorithms and improves the updating method of pheromone concentration by optimizing the total amount of pheromones to enhance global search capabilities, in order to better meet the requirements of solving the optimal path problem in transportation systems. In this case, this article proposes an improved method based on ant colony algorithm to construct an optimal transportation path optimization model.

2. ENVIRONMENTAL MODELING

The essence of the optimal transportation path optimization problem is a scientifically reasonable logistics transportation path, such as minimizing transportation time, shortest path, and lowest distribution cost, while satisfying constraints to a certain extent, such as the maximum load capacity of vehicles and the completion time of transportation. The optimal path optimization problem for logistics transportation can be described by a directed graph F=(M, N), where the user and transportation point are denoted as $M = \{m_0, m_1, m_2, \dots m_n\}$; The directed arc between the user and the transportation point is expressed as $P = \{(m_x, m_y)|m_x, m_y, x \neq y\}$.

For a weighted directed graph G (V, {E}), where V is the set of vertices, E is the set of arcs, c (v, w) is the weight of the arc, and $P_{st} = (v_0=v_s, v_1=, ..., v_n=v_t)$ is a path from vs to v_t in V, the optimal path problem can be expressed as the following mathematical model:

L_{min} (P_{st})

$$\text{s.t.} \begin{cases} T(P_{st}) = \sum_{i=0}^{n-1} c(v_i, v_{i+1}) \\ c(v_i, v_{i+1}) \geq 0 \\ i = 0, \cdots, n-1 \\ 0 \leq s \leq t \leq n \end{cases} \tag{1}$$

The analysis indicates that the optimal path optimization problem in transportation is fundamentally a combinatorial optimization problem. The Ant Colony Algorithm is inspired by the foraging behavior of ants. Despite their limited vision, ants can efficiently locate the shortest path from a food source to their nest. Research has shown that ants communicate through pheromones deposited on the paths they traverse. Paths with higher concentrations of pheromones are more attractive to ants, leading them to prefer these routes. Additionally, as ants traverse a path, they release more pheromones, reinforcing its attractiveness. This process creates a positive feedback loop. Over time, this mechanism results in the convergence towards an optimal path, ultimately identifying the shortest route from the nest to the food source.

3. TRADITIONAL ANT COLONY ALGORITHM AND MODEL

Ants release pheromones on the path between their nest and food, and initially choose the next feasible path with equal probability regardless of the length of the path. Later, as the number of iterations increased, ants would choose routes with higher pheromone concentrations when moving, resulting in an increasing number of ants on shorter routes and a decreasing number on longer routes. Therefore, through these pheromones, ants can find the shortest path from their nest to food.

Assuming m is the number of ants and $\rho_{ij}(t)$ is the concentration of pheromones on path (i, j) at time t. All ants start from the starting point of path planning, and each ant calculates the transition probability based on the concentration of pheromones on adjacent paths at node i when choosing its path. The transition probability of ant k (k=1, 2, 3, ..., n) from node i to node j at time t is:

$$P_{ij}^k(t) = \begin{cases} \left([\varphi_{ij}(t)]\right)^{\alpha} \cdot [\sigma_{ij}(t)]^{\beta} / (\sum_{s \subseteq A_k} [\rho_{ij}(t)]^{\alpha} \cdot [\sigma_{ij}(t)]^{\beta}, & j \in A_k \\ 0, & other \end{cases} \tag{2}$$

In equation (2), $P_{ij}^k(t)$ represents the transition probability of ant k between road nodes i and j at time t; $[\sigma_{ij}(t)]^{\beta}$ represents the heuristic function; $[\varphi_{ij}(t)]^{\alpha}$ represents the pheromone concentration of the corresponding path between ant and road nodes i and j, $A_k = \{N - t_k\}$ represents the set of road nodes that ant A_k wants to access, σ_{ij} represents the expected degree of transition from node i to node j, usually $\sigma_{ij} = 1/d_{ij}$, where d_{ij} represents the distance from node i to node j.

After ants complete a search for all nodes, they need to update the concentration of pheromones. Using the Ant-Cycle model, the concentration of pheromones on the path (i,j) at time $t+\Delta t$ is:

$$\varphi_{ij}(t + \Delta t) = (1 - \rho) \cdot \varphi_{ij}(t) + \Delta\varphi_{ij}(t) \tag{3}$$

$$\Delta\varphi_{ij}(t) = \sum_{k=1}^{m} \Delta\varphi_{ij}^{k}(t) \tag{4}$$

$$\Delta\varphi_{ij}(t) = \begin{cases} \dfrac{Q}{L_n}, & \text{Ant n passes through (i, j)} \\ 0, & \text{Ant n has not passed through (i, j)} \end{cases} \tag{5}$$

4. IMPROVED ANT COLONY ALGORITHM BASED ON PHEROMONE UPDATE METHOD

4.1 Principle of limiting pheromone concentration

We set the minimum value φ_{min} and maximum value φ_{max} of pheromone concentration on each path, with the pheromone concentration on each path limited to between $[\varphi_{min}, \varphi_{max}]$. In the improved ant colony algorithm, the lower limit of pheromone concentration is set to φ_{min}. Although the probability of choosing these paths is very small, it will not be zero, which avoids the phenomenon of ants stagnating and enables them to conduct higher-level searches; Due to the fact that in classical ant colony algorithms, the capacity of the road network is not taken into account when searching for the optimal path, congestion may occur. The improved ant colony algorithm considers that each path in the actual transportation network has a maximum carrying capacity, so the upper limit of pheromone strength is set to φ_{max}.

4.2 Improvement of pheromone local update algorithm

In the actual transportation network, there is a phenomenon that the passing time on a certain road increase with the increase of traffic flow. The use of pheromone local update method can make the edges with higher pheromone concentration less attractive to the ants behind, thus making the ants have stronger exploration ability for the unselected edges. Moreover, experiments have shown that local update rules can effectively prevent ants from converging to the same path. Therefore, in this paper, the pheromone update method during ant walking is set as the local update principle. Using a smoothing mechanism, when ants pass through path (i,j), the concentration of pheromones on path (i,j) is updated as follows:

$$\varphi_{ij}(t + 1) = \begin{cases} (1 - \delta)\varphi_{ij}(t) + \delta\varphi_0, & \varphi_{min} \leq \varphi_{ij} \leq \varphi_m \\ (1 - \delta)\varphi_{ij}(t), & \varphi_m \leq \varphi_{ij} \leq \varphi_{max} \end{cases} \tag{6}$$

In equation (6), δ is a parameter on [0,1], $\varphi_0 = {}^1\!/_{nL_{best}}$ is an empirical observation value, which is a very small number, n is the number of nodes in the network, L_{best} is the shortest path length in this cycle, and φ_m is the critical value, which is determined according to the specific experimental situation.

4.3 Improvement of pheromone update model

The factors that affect the optimal path selection for vehicle transportation processes include transportation time, cost, and road smoothness. To quickly obtain the optimal solution, a mathematical model based on multiple constraint conditions is constructed for path selection based on transportation time, transportation cost, and road smoothness factors. It is combined with ant colony algorithm to achieve path updating and dynamic selection with multiple constraint conditions as the carrier, guiding logistics transportation selection towards the optimal path.

4.3.1 Transportation time elements

$$I_1(j) = \begin{cases} {T_j}\!\big/\!{T_{jmax}}, & T_j \leq T_{jmax} \\ 0, & otherwise \end{cases} \tag{7}$$

T_{jmax} is the maximum expected time limit allowed in transportation; T_j represents the specific time required for logistics transportation, and $T_j \leq T_{jmax}$ and $I_1(j)$ represent the transportation time elements, whose values are the ratio between the specific time at transportation node j and the expected longest time. The larger the value, the longer the actual transportation time.

4.3.2 Elements of transportation costs

$$I_2(j) = \begin{cases} V_j / V_{jmax}, & V_j \leq V_{jmax} \\ 0, & otherwise \end{cases} \tag{8}$$

A is the transportation cost element, whose value is the ratio between the cost required for transportation at node j and the estimated maximum cost. The larger its value, the higher the actual transportation cost. V_j represents the cost required for transportation at node j, and V_{jmax} is the estimated maximum cost. Among them：

$$V_j = abtasion_j + Toll_j + Fuel_y, \ V_j \leq V_{jmax} \tag{9}$$

A is the cost of road transportation losses, $Toll_j$ is the cost of tolls, and $Fuel_y$ is the cost of fuel.

4.3.3 Smooth road elements

$$I_3(j) = \begin{cases} Q_j / O_{jmax}, & Q_j \leq Q_{jmax} \\ 0, & otherwise \end{cases} \tag{10}$$

$I_3(j)$ is the factor of average road smoothness, which refers to the ratio between the smoothness of the transportation path at node j and the minimum tolerance of road smoothness. The larger the value, the smoother the selected path of the transportation vehicle; Q_j is the smoothness of the transportation path at node j, and Q_{jmax} is the minimum tolerance for road smoothness.

In summary, the constraint function is:

$$I(j) = \beta I_1(y) + \gamma I_2(y) + \delta I_3(y) \tag{11}$$

Among them, β, γ, and δ are the actual proportions of time, cost, and road smoothness consumed by vehicle transportation at node j.

5. EXPERIMENTAL SIMULATION AND RESULTS

5.1 Problem description

Suppose there is a transportation center with 20 customers who need to transport goods, numbered 1-20. The transportation center location (numbered 0, coordinates (4, 35)) needs to transport goods to these customers every day. The transportation center can dispatch 4 vehicles per day. For the convenience of testing, map the coordinates of the transportation center and the positions of 20 customers onto the XOY plane, as shown in Figure 1. The location coordinates of each customer and the daily volume of goods transported are shown in Table 1.
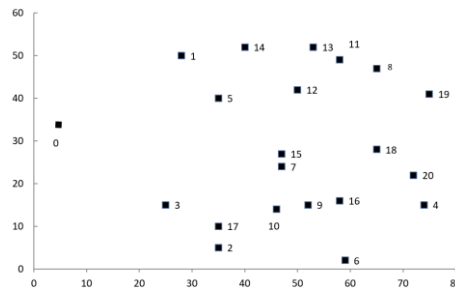

Figure 1. Coordinate diagram of chain stores and warehouses.

Table 1. Location coordinates of chain stores and daily supply demand.

No.	x	y	No.	x	y	No.	x	y	No.	x	y
1	28	50	6	59	2	11	58	49	16	58	16
2	35	5	7	47	24	12	50	42	17	35	10

| No.	x	y	No.	x	y	No.	x	y	No.	x	y
3	25	15	8	65	47	13	53	52	18	65	28
4	74	15	9	52	15	14	40	52	19	75	41
5	35	40	10	46	14	15	47	27	20	72	22

5.2 Simulation results and analysis

For this case, traditional ant colony algorithm (AC), adaptive transfer ant colony algorithm (AAC), and the improved ant colony algorithm proposed in this paper were used for simulation calculations. Table 2 presents the distribution costs, convergence generations, and running time results of three ant colony algorithms based on this case, which were run 10 times.

Table 2 The running results of three ant colony algorithms.

Number of experiments	AC			AAC			This article's algorithm		
	Delivery cost	Convergent algebra	Running time	Delivery cost	Convergent algebra	Running time	Delivery cost	Convergent algebra	Running time
1	520.6	37	22.2	518.4	31	17.9	513	36	21.1
2	520.2	33	22.9	517.9	30	20.5	514.5	30	19
3	520.5	34	24.6	518	36	18.9	513.6	32	22.2
4	520.2	56	21.2	518.1	32	28.3	513	31	19.3
5	520.6	34	22.4	518.4	48	21.4	514.4	30	17.3
6	519.9	37	19.6	518.5	35	20.3	514.5	32	18
7	521	37	20.7	519.5	32	21.9	514.3	37	17.1
8	520.9	33	20.5	518.4	33	25.3	513	28	21.1
9	519.9	37	26.4	518.9	31	19.6	513	35	16.9
10	521	33	24.3	518.7	30	19.9	513	36	18.1
Worst value	521	56	26.4	519.5	48	28.3	514.5	37	22.2
Best value	519.9	33	19.6	517.9	30	17.9	513	28	16.9
Average value	520.4	37.1	22.48	518.48	33.8	21.4	513.63	32.7	19.01

From Table 2, it can be seen that the delivery cost of the AC algorithm is concentrated around 520, with no significant breakthrough. The minimum convergence algebra is 33 and the maximum is 56, with significant variation and instability; The delivery cost of AAC algorithm is mainly concentrated around 518, with no significant changes and no obvious regularity in convergence algebra. Compared with the previous two ant colony algorithms, this paper improves the ant colony algorithm to make substantial progress and breakthroughs in delivery cost, breaking through the constraint of 515 and converging to 513 with a 50% probability. The optimal convergence algebra is also the lowest at 28. In addition, compared with the running time of the three algorithms, our algorithm outperforms the first two ant colony algorithms in terms of optimal value, worst value, and average value. Below are the delivery costs, optimal delivery plans, and convergence algebras for three algorithms, as shown in Figures 2-4.
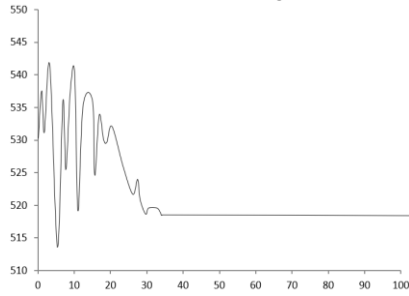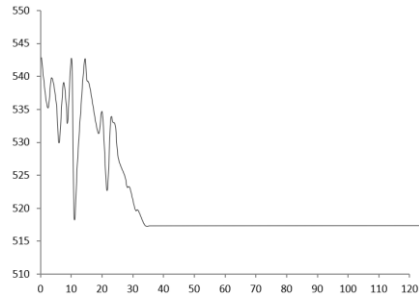
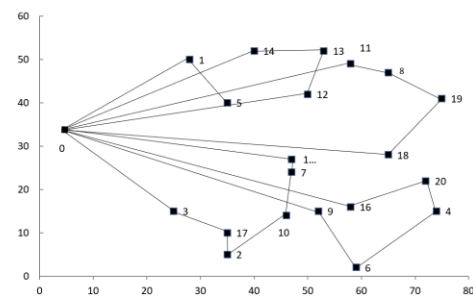(a) Delivery cost of AC algorithm
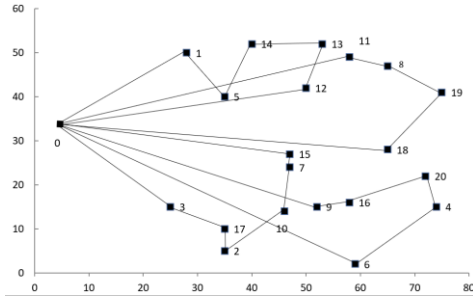
(b) Optimal delivery plan of AC algorithm

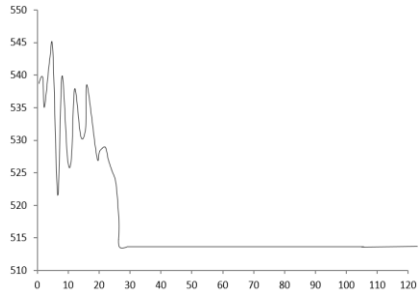Figure 2. AC algorithm planned delivery plan and delivery cost.

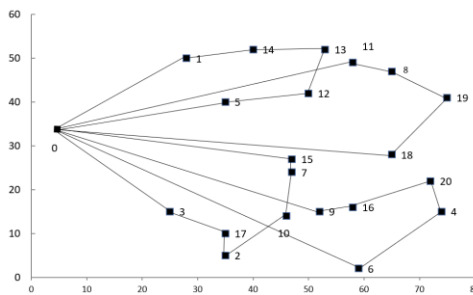(a) The delivery cost of AAC algorithm

(b) The optimal delivery plan of AAC algorithm

Figure 3. Distribution plan and cost planned by AAC Algorithm.

(a) The delivery cost of this algorithm

(b) The optimal delivery plan of this algorithm

Figure 4. The distribution plan and cost of the algorithm planning in this article

By comparing Figures 2-4, it can be seen that the AC algorithm found the optimal path in the 34th generation, with one route being 0-1-5-14-13-12-0. After completing branches 1 and 5, it goes to branch 14, which obviously violates the axiom of "the shortest line segment between two points". Therefore, this route is definitely not optimal. After a long period of turbulent search, the AC algorithm finally converged at 520. The AAC algorithm drew the optimal path in the 31st generation and finally converged at 518. Although the vehicle route was optimized, there were still intersecting routes, indicating that there is still room for improvement. The optimal path of the improved ant colony algorithm in this article was completed in the 29th generation and finally converged at 513. Compared with the AC algorithm and AAC algorithm, it shortened the convergence algebra by 17.24% and 6.89% respectively, and reduced the delivery cost by 1.37% and 0.97% respectively. This article improves the ant colony algorithm to ensure that there are no detours or intersecting paths in the vehicle route, making it the optimal path. In summary, the algorithm proposed in this article has significantly improved time efficiency and delivery costs compared to traditional ant colony algorithms, and is more efficient in solving optimal path planning problems in transportation networks.

6. CONCLUSION

The vehicle transportation path selection problem significantly affects enterprise transportation costs, time, and efficiency. This article modifies the traditional ant colony algorithm by limiting pheromone concentration on paths and incorporating constraints based on transportation time, cost, and average road smoothness factors. These enhancements aim to improve the algorithm's global optimization capability, ultimately leading to shorter delivery paths, reduced costs, and enhanced efficiency.

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