Routing optimization method of waste transportation vehicle using biological evolutionary algorithm under the perspective of low carbon and environmental protection

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Abstract

Reasonably and effectively formulating the best route for urban waste transportation vehicle is particularly important for realizing low carbon and environmental protection of Green China construction concept. However, the current path planning method has shortcomings such as local optimization. In order to solve this problem, this paper aims at low carbon and environmental protection construction needs and proposes a routing optimization method of waste transportation vehicles based on improved ant colony algorithm. Firstly, the mathematical model of Vehicle Routing Problem (VRP) is constructed by considering transportation distance and carbon emissions cost. Then, network parameters in traditional ant colony algorithm are combined and optimized to realize self-adaptive update in the whole cycle. Furthermore, the neighborhood algorithm is used to iteratively optimize improved algorithm to avoid the defects of local optimization when solving VRP problem. Finally, the simulation results based on an actual dataset in North China show that the proposed method can achieve efficient and accurate optimal routing optimization for complex samples, and its solution stability index P_{best} is 0.87 and the average deviation V_{ar} is 0.011, the lowest distribution cost after optimization is about 3,080 yuan, which are better than the comparison methods.

Keywords: Ant colony algorithm, Carbon emission, Neighborhood algorithm, Parameter optimization, Pheromone update, Routing optimization

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1. Introduction

With the rapid development of social economy and acceleration of urbanization, the amount of various types for waste has increased sharply [1-3]. According to incomplete statistics, the total amount of domestic waste in China's cities and towns ranks first in the world. In recent years, with the acceleration of my country's urbanization process and the improvement of people's living standards, urban domestic waste is still increasing at an annual rate of 5 to 8% [4].

At present, on the one hand, the amount of waste is huge, on the other hand, there are phenomena such as backward transportation management methods and high equipment operation costs in the process of waste collection and transportation [5, 6]. This will lead to excessive waste of resources and low work efficiency problems in the current waste transportation links.

According to statistics, 80–85% of waste disposal system cost is attributed to the transportation system [7]. At the same time, the carbon dioxide emissions of my country's transportation industry are showing an increasing trend, and transportation energy consumption accounts for about 9% of the total energy consumption of whole society [8]. With the transfer of waste treatment facilities to the outer suburbs and expansion of main urban area, the coverage of entire waste collection and transportation system is getting larger and larger. Therefore, scientific and reasonable planning of waste collection and transportation routes is an important guarantee for the realization for concept of "low energy consumption, low pollution and low emissions", which is particularly urgent.

In recent years, the academic research on waste collection path is mainly based on the corresponding analysis of Traveling Salesman Problem (TSP) and the Chinese Postman Problem (CPP) [9, 10]. But in fact, we can divide waste collection and transportation routes into two

aspects: waste collection routes and waste transfer routes. If focusing on the two aspects of modeling ideas and solving goals, the waste collection routing problem should belong to the category of Vehicle Routing Problem (VRP) [11, 12].

At present, some researchers have discussed this based on intelligent algorithms. Reference [13] established cost-oriented urban distribution optimization model, adopted an improved genetic algorithm and designed successive correction operators on both sides to improve the solution quality and efficiency of algorithm. Reference [14] established mixed integer programming model and designed a joint optimization genetic algorithm to solve the model. It used the proposed joint optimization genetic algorithm and two-stage genetic algorithm for simulation calculation and analysis. Reference [15] proposed a hybrid method based on sine cosine algorithm and paper swarm algorithm to solve the problem of heterogeneous vehicle routing. Reference [16] was based on the gray wolf spatial integer coding and solution of routing before grouping. It proposed an adaptive genetic gray wolf optimization algorithm to solve VRP with capacity constraints. However, it should be noted that the current routing optimization methods based on intelligent algorithms generally have the problems of weak adaptive ability and weak global optimization convergence ability [17]. This make the problem of searching for the best path in complex space often lose the optimal solution, and it will cause network to diverge in severe cases.

Aiming at the problems existing in current VRP planning method, this paper proposes a routing optimization method for waste transportation vehicles that meets the needs of low carbon environmental protection based on improved ant colony algorithm. The innovative points of proposed method are:

1 1) In order to further improve the optimization characteristics of the best route for waste
2 vehicle transportation, this paper optimizes the network parameters based on traditional ant
3 colony algorithm, which improves the global convergence and solution efficiency of the ant
4 colony algorithm.

5 2) The pheromone setting method in the network is improved to realize the full-period self-
6 adaptive update of network parameters and avoids losing the global optimal solution.

7 The remaining content of this paper is arranged as follows: Section 2 describes and models
8 VRP problem accordingly. Section 3 describes the corresponding improvement content of ant
9 colony algorithm. Section 4 is the simulation verification of proposed method based on actual
10 sample dataset. Section 5 is the conclusion of this paper.

12 **2. Problem Description and Model Construction**

13 **2.1. Problem Description**

14 Waste management requires not only government investment and management, but also
15 residents' awareness of environmental protection. The government needs to increase waste
16 collection facilities in each community under its jurisdiction and arrange waste vehicles to
17 recycle waste in each community in time.

18 In an area, the process of waste collection can be described as follows: multiple waste
19 vehicles depart from parking lot at the same time and begin to collect waste in various
20 communities. Each community must be served and can only be served once (assuming that the
21 amount of waste generated in each community is less than or equal to the maximum load
22 capacity of waste vehicles). When the waste vehicle reaches or is close to the maximum load, it

will first drive to transfer stations, unload the waste and then return to the depot. The goal of solving the problem is to find a shortest path that minimizes the total distance traveled by all waste vehicles. Fig. 1 is a simple schematic diagram of waste collection path.

Fig. 1. Schematic diagram of waste vehicle path.

As can be seen in Fig. 1, there are a total of 7 communities, and 2 waste vehicles can be used to complete the waste collection work in the community. Each waste vehicle departs from parking lot and starts to serve the community. After the waste collection volume reaches or approaches the maximum load capacity, waste vehicles go to the transfer station (treatment plant) to unload waste. Finally it returns to the parking lot.

In order to better describe the mathematical model of problem, the model elements are elaborated accordingly. The components of waste collection path problem include: parking lot, waste vehicle, waste, community, transfer station (processing plant), constraint conditions and objective function.

2.1.1. Depot

The parking lot is similar to logistics distribution center. It is the starting point and ending point of the waste vehicle's driving process. According to the number of parking lots, it can be divided

1 into single parking lot and multiple parking lot. However, considering the actual situation,
2 usually a parking lot in an area can park required waste vehicles. So this paper studies the
3 situation of bicycle yard.

4 5 2.1.2. Waste vehicle

6 Waste vehicle is a tool for transporting waste, which can be divided into single vehicle type and
7 multiple vehicle types. The difference of model often determines the difference in maximum
8 load. The maximum load capacity refers to the upper limit of waste vehicle loading capacity. The
9 type of waste loaded is divided into solid and non-solid. The load condition refers to full load or
10 partial load. The number of vehicles refers to the number of waste vehicles, which are divided
11 into single vehicles and multiple vehicles according to their differences. The maximum mileage
12 limit refers to whether to consider the restriction of waste vehicle mileage [18]. This paper
13 mainly studies the problem of recycling path of community domestic waste. Most domestic
14 waste is solid waste, so a waste vehicle loaded with solid waste is selected for research.
15 Considering comprehensively, multiple waste vehicles of the same model (the same maximum
16 load) are used for waste collection. The waste vehicles are fully loaded and mileage limit is not
17 considered.

18 19 2.1.3. Waste

20 Waste is similar to goods in logistics transportation, with attributes such as weight and collection
21 location. These two attributes are the basis for waste vehicles to choose the driving route.

2.1.4. Community

Each community is a service object corresponding to a waste collection location, and must be served once.

2.1.5. Transfer station (processing plant)

Taking into account the actual situation of community waste treatment by county, this element may be a transfer station or a treatment plant. According to their different numbers, it can be divided into single transfer station (treatment plant) and multiple transfer station (treatment plant). In order to reduce the complexity of solving the problem, this paper conducts research on the premise of a single transfer station (processing plant).

2.1.6. Constraint conditions

Waste vehicles must meet the following constraints when reclaiming waste: (1) Each waste vehicle must start from the yard; (2) The loading capacity is close to but not exceeding its own maximum load; (3) It must be transported before returning to the yard. The station (treatment plant) unloads the waste; (4) Every community must be served and only served once.

The time for waste collection by waste vehicles is arranged by the government every day, and it will not be shifted by the will of a certain community. There is no strong internal relationship between service and time, and the time window constraint has no practical significance in solving this problem. Thus, this paper does not consider the time window limitation.

2.1.7. Objective function

The commonly used objective functions for solving VRP problems are: (1) The total mileage of vehicles is the shortest; (2) The time-consuming is the least; (3) The cost is the least. This paper uses objective function (1) when solving the waste collection path problem, that is, the sum of all waste vehicles has the shortest mileage.

2.2. Model Construction

The routing optimization problem of waste transportation vehicles can be represented by an undirected graph $G = (V, E)$ [19]. For ease of expression, the following symbols are introduced: point set $V = \{1, 2, \dots, n\}$ of parking lot, community, transfer station (processing plant), where point $i=1$ represents parking lot, point $i=n$ represents transfer station (processing plant), the remaining points represent communities, and the number of communities is $n-2$. The element in edge set E is d_{ij} , which represents the distance between point i and point j . The point may be a parking lot, a community or a transfer station (processing plant). The waste discharge of each community is $w_i (i = 2, 3, \dots, n-1)$. There are $r (k = 1, 2, \dots, r)$ waste vehicles for waste collection in these $n-2$ communities. Each vehicle has the same model, and the maximum load capacity is W and $W \geq w_i (i = 2, 3, \dots, n-1)$. Define the following variables:

$$x_{ij}^k = \begin{cases} 1, & \text{the garbage truck } k \text{ runs from } i \text{ to } j \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

The goal of solving the problem is to find an optimal path so that the total mileage Z of all waste vehicles is taken to the minimum.

$$Z = \min \sum_{k=1}^r \sum_{i,j=1, i \neq j}^n d_{ij} x_{ij}^k \quad (2)$$

1 The constraints that the model should meet are as follows:

$$2 \quad x_{nj}^k = \begin{cases} 1, & j = 1 \\ 0, & \text{otherwise} \end{cases}, k \in \{1, 2, \dots, r\}, j \in V \quad (3)$$

$$3 \quad x_{i1}^k = \begin{cases} 1, & i = n \\ 0, & \text{otherwise} \end{cases}, k \in \{1, 2, \dots, r\}, i \in V \quad (4)$$

$$4 \quad \sum_{j=2}^{n-1} x_{1j}^k = \sum_{j=2}^{n-1} x_{in}^k = 1, k \in \{1, 2, \dots, r\} \quad (5)$$

$$5 \quad \sum_{k=1}^r \sum_{i,j=2,i \neq j}^n x_{ij}^k = 1, i \in \{2, 3, \dots, n-1\} \quad (6)$$

$$6 \quad \sum_{k=1}^r \sum_{i=1,i \neq j}^{n-1} x_{ij}^k = 1, j \in \{2, 3, \dots, n-1\} \quad (7)$$

$$7 \quad \sum_{i=2}^{n-1} \sum_{j=2,i \neq j}^{n-1} w_i x_{ij}^k \leq W, k \in \{1, 2, \dots, r\} \quad (8)$$

8 In the above constraints, Eq. (3) indicates that waste vehicles must and can only return to the
 9 depot after arriving at transfer station (processing plant). Eq. (4) means that waste vehicles must
 10 arrive at the transfer station (processing plant) to unload the waste before returning to the parking
 11 lot. Eq. (5) means that every waste vehicle must depart from the parking lot and drive to transfer
 12 station (processing plant) after completing tasks. From the first two constraints, the driving route
 13 of each waste vehicle can be obtained as: parking lot-each community node-transfer station
 14 (processing plant)-parking lot. Eq. (6) and (7) indicate that every community can be served and
 15 can only be served once. Eq. (8) indicates that the total amount of waste collected by each waste
 16 vehicle in the community must not exceed its own maximum load.

17 However, a large amount of carbon emissions will be generated in the process of waste
 18 transportation, which will not only pollute the environment, but also increase the transportation

cost of responsible department. Therefore, we also introduce carbon emissions into the routing optimization analysis.

The cost of carbon emissions mainly refers to the cost of carbon emissions generated in the transportation of waste vehicles. Carbon emissions are the product of fuel consumption and CO2 emission coefficient. The fuel consumption of vehicles is related to the load capacity and driving distance of vehicles. The relationship between the fuel consumption per unit distance of a transport vehicle and the load capacity can be expressed as:

$$\kappa(w_i) = \rho_0 + \frac{\rho^* - \rho_0}{W} w_i \quad (9)$$

Among them, ρ_0 represents the fuel consumption per unit distance when the transport vehicle is empty; ρ^* represents the fuel consumption per unit distance when the transport vehicle is fully loaded; W represents the full load capacity of vehicles.

Then, the target formula of routing optimization problem of waste transportation vehicles from the perspective of low carbon environmental protection is rewritten as:

$$\begin{aligned} G &= \min \xi \varepsilon \kappa(w_i) Z \\ &= \min \sum_{k=1}^r \sum_{i,j=1, i \neq j}^n \xi \varepsilon d_{ij} x_{ij}^k \kappa(w_i) \end{aligned} \quad (10)$$

where ξ represents the carbon tax; ε represents the carbon emission coefficient.

The community waste collection routing problem belongs to the category of VRP problem, which is similar to Capacitated VRP (CVRP) [20, 21]. Compared with the CVRP model, the biggest difference in the mathematical model of this paper is that each waste vehicle must drive to the transfer station (treatment plant) to unload waste before returning to the depot, and then return from the transfer station (treatment plant) to depot.

3. Routing Optimization of Waste Transportation Vehicles Based on Improved Ant Colony Algorithm

Ant colony algorithm has a certain memory function, which can continuously transfer from an old state to a new state when solving combinatorial optimization problems. But there are defects of local optimization and low search ability [22, 23]. For this reason, this paper improves traditional ant colony algorithm to realize the model solution of waste transportation vehicle routing optimization.

3.1. Mathematical Model of Ant Colony Algorithm

Before ant colony algorithm completes an iteration, the ants can only visit each node once, and return to the initial node after visiting all nodes. Ants secrete pheromone along the path they traveled. The amount and time of pheromone secretion are determined by algorithm.

Assuming that the number of communities to be visited is n , the size of ant colony is m , and the distance between nodes i and j is d_{ij} , then $d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$, where x_i , x_j , y_i and y_j represent the horizontal and vertical coordinates of nodes i and j respectively or latitude and longitude coordinates. At the beginning of each iteration, m ants will be randomly placed in these n nodes, making the starting point of ants random. In order to prevent the same ant from accessing the same node multiple times in one iteration, we set up a taboo table to record nodes that each ant has visited. $tabu_k$ records the names and order of the nodes that ant k have visited. $\tau_{ij}(t)$ represents the pheromone concentration on the path $\langle i, j \rangle$ at time t . At the initial time (at time $t=0$), the pheromone concentration on all paths is set to the same constant. The probability

that ant k moves from current node i to node j at time t is represented by $p_{ij}^k(t)$. We call this state transition rule a random proportional rule, and its formula is as follows:

$$p_{ij}^k(t) = \begin{cases} \frac{[\tau_{ij}(t)]^\alpha [\eta_{ij}]^\beta}{\sum_{s \in allowed_k} [\tau_{is}(t)]^\alpha [\eta_{is}]^\beta} & j \in allowed_k \\ 0 & otherwise \end{cases} \quad (11)$$

where the heuristic factor η_{ij} represents the visibility of path $\langle i, j \rangle$, which reflects the heuristic degree of ants moving from node i to j , usually its value is:

$$\eta_{ij} = \frac{1}{d_{ij}} \quad (12)$$

Parameter α and parameter β respectively reflect the relative importance of pheromone concentration and heuristic information on the path when ants choose the path. The value of α affects the ant's choice of repeated paths. The larger the value, the greater the ant's ability to walk, which will make the algorithm prone to stagnation. The node numbers that ants have not yet visited are stored in $allowed_k$, and the calculation formula is as follows.

$$allowed_k = \{1, 2, \dots, n\} - tabu_k \quad (13)$$

When ant k selects an accessible node c according to the random ratio strategy and arrives, we need to update the taboo table, that is, add the number of node c to $tabu_k$. If $|tabu_k| < n$, then ant k continues to select the next node and visit according to the random ratio strategy. After repeating the above process, until $tabu_k$ contains all the communities. At this time, ant k returns to the starting point and adds starting community node to the end of $tabu_k$. When m ants have completed their visit tasks, calculate the total distance traveled by each ant according to the visit

order of each ant in the taboo table, and update pheromone on the path according to the following formula.

$$\tau_{ij}(t+1) = (1-\delta)\tau_{ij}(t) + \sum_{k=1}^m \Delta\tau_{ij}^k \quad (14)$$

where δ represents the pheromone volatilization coefficient, which simulates the volatilization of pheromone secreted by ants in nature over time. The value range of δ is $(0,1)$. If the value is too large, the pheromone on the path will volatilize too fast, which will increase the possibility of re-selecting the previously searched path, thereby greatly reducing the understanding space and weakening the ability of algorithm to search globally. If the value is too small, although the possibility of searching for global optimal solution is increased, it also weakens the convergence of algorithm. $\Delta\tau_{ij}^k$ represents the number of pheromone left by ant k on the path $\langle i, j \rangle$ in this iteration.

3.2. Algorithm Design

3.2.1. Parameter selection optimization

In the realization of ant colony algorithm, there are many parameters that need to be initialized. Pheromone and heuristic function, information quantity-heuristic function product, and cooperative behavior between ants will seriously affect the convergence of algorithm [24]. At the same time, the parameters of ant colony algorithm are also key factors affecting the efficiency of its solution performance. Pheromone residual factor, information heuristic factor, expected heuristic factor, pheromone intensity, number of ants, etc. are all very important parameters. The selection method and selection principle directly affect the global convergence and solution

1 efficiency of ant colony algorithm. The choice of different parameters can have a vital impact on
2 the performance of ant colony algorithm.

3.2.1.1. The influence of parameter α on the performance of ant colony algorithm

5 The information heuristic factor α reflects the relative importance of the amount of information
6 accumulated by ants in the process of movement in guiding the search of ant colony. The larger
7 the value, the more likely the ants will choose the path they have walked before, and the
8 randomness of the search will be weakened. When the value of the information heuristic factor
9 α is too small, the search of the ant colony is likely to fall into the local optimum prematurely.

Fig. 2. Sensitivity analysis of parameter α .

12 It can be seen from Fig. 2 that when the value of α is 1.5-4.5, the comprehensive
13 solution performance of ant colony algorithm is better.

3.2.1.2. The influence of parameter β on the performance of ant colony algorithm

16 The expected heuristic factor β reflects the relative importance of heuristic information in
17 guiding ant colony search process, and its size reflects the strength of a priori and deterministic
18 factors in the ant colony optimization process. The larger the value is, the more likely the ant will

choose the local shortest path at a certain local point. Although the convergence speed of algorithm is accelerated at this time, the randomness of ant colony's search for the optimal path is weakened, and it is easy to fall into the local optimal solution.

Fig. 3. Sensitivity analysis of parameter β .

It can be seen from Fig. 3 that when the parameter β is 2-6, the comprehensive solution performance of ant colony algorithm is better.

3.2.1.3. The influence of parameter δ on the performance of ant colony algorithm

The size of the pheromone volatilization factor δ is directly related to the global search ability of ant colony algorithm and its convergence speed. The pheromone residual factor $(1-\delta)$ reflects the strength of individual interaction between ants. Due to the existence of the parameter δ , when the scale of the problem to be dealt with is relatively large, the amount of information on the path that has never been searched will be reduced to close to 0, thus affecting the global search ability of algorithm.

Fig. 4. Sensitivity analysis of parameter δ .

It can be seen from Fig. 4 that under the same conditions of other initialization parameters, when the pheromone residual factor is between 2 and 4, the convergence performance and convergence speed of ant colony algorithm are better, and the calculation performance is also relatively stable.

3.2.1.4. The influence of parameter τ on the performance of ant colony algorithm

The pheromone intensity τ is the total amount of pheromone released on the path that the ant circulates for a week. Its role is to make full use of the global information feedback on the directed graph, so that the algorithm can search for the global optimal solution of problem at a reasonable evolution speed under the action of positive feedback mechanism. When the Q value is large, although the convergence speed of ant colony algorithm is very fast, the global search ability of algorithm will deteriorate at this time, it is easy to fall into the local optimal solution, and calculation performance becomes very unstable.

It can be known from experience that the model used in this paper is ant week model, and the total amount of information has no obvious effect on the performance of ant colony algorithm of ant week model. Generally take $\tau=100$. When the size of city becomes larger, the

value of τ should be relatively increased, otherwise the total amount of information remains unchanged. When the scale of the city is larger, the amount of information volatilized to each path becomes smaller, and it is not easy to find the global optimal solution.

The model used in this paper is ant week model, and the total amount of information has no obvious effect on the performance of ant colony algorithm of ant week model. Based on the experimental analysis of parameter selection law for ant colony algorithm, the specific steps of effective method for selecting the optimal combination parameters of ant colony algorithm are as follows:

(1) Determine the number of ants, that is, the proposed selection strategy of city size/number of ants ≈ 2 to determine the total number of ants;

(2) Coarse parameter adjustment, that is, to adjust the information heuristic factor α , expected heuristic factor β , and pheromone intensity τ with a large value range to obtain a more ideal solution;

(3) Parameter fine-tuning, that is, adjusting the pheromone volatilization factor δ with a smaller value range.

3.2.2. Pheromone update strategy

When m ants have completed a cycle, that is, when all ants have constructed a feasible path R , compare it with the global optimal path R^* , where $R^* = \min(R_k \mid k = 1, 2, \dots, m)$.

Fig. 5. Global pheromone update process.

In order to make each ant's iterative transportation scheme produce positive and negative feedback on the increase and decrease of pheromone, according to the rule of Fig. 5, the pheromone on all ants R in each iteration is updated globally:

(1) The pheromone update formula is:

$$\tau_{ij}^{new} = \theta^2 \tau_{ij}^{old} \quad \forall (i, j) \in R \quad (15)$$

(2) The pheromone update formula is:

$$\tau_{ij}^{new} = \theta \tau_{ij}^{old} \quad \forall (i, j) \in R \quad (16)$$

(3) The pheromone update formula is:

$$\tau_{ij}^{new} = \max(\theta \tau_{ij}^{old} + \Delta \tau_{ij}^*, \tau_{ij}^{old}) \quad (17)$$

$$\Delta \tau_{ij}^* = \frac{Q}{L^*} \quad (i, j) \in R \quad (18)$$

Q is a constant, which represents the total amount of pheromone released by the ant to complete a search; L^* is the optimal path length explored by the ant. θ is the degree of pheromone retention. In the early stage of algorithm, the diversity of understanding can take a relatively

large value. In the middle and late stages, for the rapid convergence of the optimal solution, the pheromone is more concentrated, and it can be smaller.

In order to avoid falling into a local optimal solution in the early stage, MMAS can be used for reference to limit the pheromone within a certain range to avoid losing the possibility of exploring new paths. which is

$$\tau_{ij} = \begin{cases} \tau_{\max} & \text{if } \tau_{ij} \geq \tau_{\max} \\ \frac{\tau_{\max}}{3} & \text{if } \tau_{ij} \geq \tau_{\min} \end{cases} \quad (19)$$

$$\tau_{ij} \in [\tau_{\min}, \tau_{\max}] \quad (20)$$

3.2.3. Optimize the optimal solution using neighborhood algorithm

In order to improve the convergence speed of algorithm, neighborhood algorithm is used to optimize the feasible solution produced by each iteration of ant colony algorithm [25]. There are three ways to find the neighborhood solution: insertion, reversal and exchange. In this paper, the exchange method is used to find the neighborhood solution, that is, the solution produced by each iteration of ant colony algorithm is first obtained. Then randomly select different delivery points to exchange the positions of the two in the path where the solution is obtained, perform random perturbation and recalculate to obtain a new solution. If the new solution is better than the original solution, the solution is updated, otherwise it remains unchanged. Repeat the above operations until the optimal solution is obtained when the maximum number of iterations is reached.

3.3. Algorithm Flow

Step 1: Define the initial value of each algorithm parameter. The pheromone value on the road section between any two points is initially $\tau_{\max}$, and $NC_{\max}$ is set as the maximum number of iterations of algorithm.

Step 2: Put m ants in the parking lot, and put the point in the current solution, using the method of constructing the solution in order.

Step 3: Calculate the transition probability, and require all constraints to be met at the same time, select another demand point in addition to the current solution set, and then place it in the current solution. If the next node that satisfies the constraint conditions is not found, return to the parking lot.

Step 4: Cycle Step 3 until m ants have visited all points, and get the corresponding loop that starts from the parking lot and meets the constraints. The several loops of each ant are equivalent to the distribution path formed by several transportation vehicles issued by vehicle site, and the shortest path R^* is calculated and saved.

Step 5: Perform global update and adjust θ according to the method described in this paper. The adjustment rules are:

$$\theta_i = \begin{cases} 0.95\theta_{i-1} & \text{if } 0.95\theta_{i-1} \geq \theta_{\min} \\ \theta_{\min} & \text{otherwise} \end{cases} \quad (21)$$

Step 6: Judge whether the number of iterations reaches the maximum value, if yes, terminate the transportation, otherwise clear the taboo table and go to Step 2.

4. Case Study and Verification

The verification and simulation of the proposed method are all carried out on a high-performance computer, so that the comparison method also runs in a unified simulation environment. The experimental hardware and software configurations are shown in Table 1. The experimental codes of the routing optimization method based on improved biological evolution algorithm are all realized by Matlab language.

Table 1. Experimental Simulation Scenarios

Software environment	Operating system	Windows10
	Program editor	Matlab2016a
Hardware environment	CPU	3.2GHz Intel Core i5-6500 CPU
	GPU	GeForce GTX 1050Max-Q
	Running memory	8 GB

4.1. Network Parameters and Application Cases

In the improved ant colony routing optimization proposed method, the chromosome coding uniformly adopts the natural number coding method. The parameter settings involved in ant colony algorithm: $m=30$, $\alpha=2.5$, $\beta=3$ and $\delta=3$; the number of iterations is 300 as the termination condition.

The experimental example uses an actual dataset in a certain area of North China, which governs 31 villages and uses a waste vehicle with a maximum load of 7,000 kg. Table 2 shows the serial number, name, coordinates and daily waste output of 1 depot, 31 villages, and a waste treatment plant.

1 **Table 2.** Actual Sample Dataset of a Certain Area

No.	Name	Waste output (kg)
1	Parking lot	0
2	Linglong goushang Village	828
3	Shanqian Village	517
4	Hengzhang Jiangjia Village	925
5	Lugezhuang Village	967
6	Mu Lin Zhuang Village	840
7	Shengjia Village	879
8	Wangjia Village	872
9	Qianhuayuan Village	696
10	Houhuayuan Village	585
11	Panjiaji Village	828
12	Oujiakuang Village	853
13	Lugezhuang Village	515
14	Lujia village	638
15	Linglong Taishang Village	523
16	Dajiangjia Village	912
17	Xiaojiangjia Village	548
18	Linglong Gaojia Village	848
19	Fengjia Village	658
20	Liujia Village	776
21	Zhaizi Village	517
22	Dongzhuangtou Village	719
23	Xizhuangtou Village	669
24	Dongtuanbu Village	883
25	Xituanbu Village	792
26	Huwangzhuang Village	593
27	Longquanzhuang Village	769
28	Gaojiatuan Village	824
29	Guanjiahe Village	775
30	Kuang Lujia village	591
31	Lijia village	628
32	Yuquanzhuang Village	857
33	Transfer station	0

2

3 **4.2. Case Analysis**

1 In order to verify the feasibility and engineering applicability of the proposed method, we choose
2 reference [13], reference [14] and reference [16] as the comparison method, and our proposed
3 method is analyzed separately under a unified experimental scenario.

4 Fig. S1 is a schematic diagram of the optimal path proposed in this paper based on
5 improved ant colony algorithm. When the simulation experiment is about the 40th iteration, the
6 best path of waste transportation vehicles is:

7 Waste vehicle No. 1: 1-19-20-21-25-24-22-23-28-29-33-1

8 Waste vehicle No. 2: 1-2-3-9-10-12-17-16-15-18-31-33-1

9 Waste vehicle No. 3: 1-4-5-6-7-8-11-14-13-33-1

10 Waste vehicle No. 4: 1-26-27-30-32-33-1

11 The best path of garbage transportation vehicles and the lowest cost is shown in Figure S2. It can
12 be seen from Figure S2 that when the number of iterations reaches 40, the improved ant colony
13 algorithm can converge quickly, the proposed model tends to be stable, and the minimum cost of
14 distribution after optimization is about 3,080 yuan.

15 At the same time, we also analyze the cost of carbon emissions. The carbon emissions under
16 different methods are shown in Fig.S3.

17 Fig. S3 shows the carbon emissions under different methods. It can be seen from Fig. S3
18 that the proposed method in this paper achieves effective convergence in about 40 iterations, and
19 the cost is roughly controlled at 3,080 yuan. Compared with reference [13] and reference [14],
20 carbon emission costs are reduced by 100 and 70 yuan, respectively, and the convergence speed
21 of comparison algorithm is significantly slower than our proposed method. However, within the
22 specified number of iterations-300 times, the problem is still effectively solved, and it is still in a

divergent state in the reference [16]. The reason is that this paper improves the pheromone update strategy, which can realize the self-adaptive update of pheromone in the whole cycle of solution. This limit avoids the routing optimization problem being vulnerable to the risk of local optimization and realizes the optimization analysis of waste vehicle transportation path.

In addition, in order to more intuitively quantify the analysis performance of various methods, this paper presents the optimal path problem analysis capabilities under different methods in the form of Tab. S1. In Tab. S1, G_{best} is the optimal value found, G_{avg} is the average value, P_{best} is the probability of finding the optimal solution, and V_{ar} is the average deviation.

As shown in Tab. S1, when the waste vehicle transportation path is optimally solved, as the solution performance stability index, the value of our proposed method is 0.87, which is an improvement of 0.08 compared to the reference [14]. The average deviation value of the indicators analyzed in this paper is 0.011, which is 0.03 lower than that in the reference [14]. This shows that the proposed method can effectively analyze complex path analysis problems under the same experimental conditions. The comparison of indicators GB and G illustrates this phenomenon. The indicator values obtained by the proposed method are significantly lower than the comparison method.

In summary, this paper proposes a path analysis method for waste vehicle transportation based on improved biological evolutionary algorithm. This method is oriented to low carbon and environmentally-friendly transportation requirements, which can realize efficient and accurate optimal routing optimization analysis.

5. Conclusions

Aiming at the low efficiency of current VRP problem analysis, this paper considers the concept of low carbon environmental protection and proposes a new method for optimizing waste transportation vehicles based on improved ant colony algorithm. This method improves pheromone by combining and optimizing network parameters, and realizes the full-cycle adaptive update of algorithm. Moreover, it introduces neighborhood algorithm to iteratively optimize the biological evolution algorithm, which further improves the solution performance of VRP algorithm. Experimental results show that the proposed method can achieve optimal solution of complex paths, and it has better execution efficiency than other methods. The future research direction will make VRP problem more concrete and study the routing optimization method of waste transportation vehicles under fuzzy demands. In addition, due to the high timeliness requirements of waste transportation, the driving time in the distribution process will generally be affected by factors such as weather conditions, road conditions, emergency time and vehicle status. Therefore, the uncertainty of these factors can be more considered in the future research on waste transportation.

Author Contributions

The main idea of this paper is proposed by F.L.S. (engineer). All the work of the article was completed by F.L.S. himself.

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