

Research on garbage truck path planning method based on improved ant colony algorithm Paper

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Abstract. The current garbage truck path planning algorithm has the problems of not considering the capacity constraints, high computational complexity, and difficult to obtain the optimal solution. We propose a path planning method based on the improved ant colony algorithm. Firstly, this method adds the capacity constraint to the calculation process of the algorithm, and updates the capacity residual value when the ant explores. Then, by changing the update coefficient of the local pheromone to increase the pioneering of the algorithm, it is easy to obtain the optimal solution. By updating the global pheromone on the optimal path, it provides positive feedback and speeds up the optimization. Finally, the global pheromone is dynamically adjusted. This adjustment is to reduce the computational complexity, so that the algorithm can correct the iterative results in time and find the optimal path faster. Experiments show that the proposed algorithm can effectively solve the problem of collecting and transporting garbage trucks. It has the advantages of fast convergence speed and strong optimization ability of garbage truck path planning under capacity constraints. It is a feasible solution to garbage collection point garbage collection path planning method.

Keywords: Garbage truck path planning, ant colony algorithm, pheromone update, capacity constraint.

1. Introduction

With the development of the economy and the acceleration of the process of smart garbage collection sites, the domestic garbage at garbage collection sites has grown rapidly, and the total amount of garbage is still growing at a relatively high rate every year, and the cleaning pressure is also increasing. Therefore, it has become a key problem to be solved to collect and transport the domestic garbage in time to keep it clean and tidy[1]. In order to improve various environmental problems caused by domestic waste in garbage collection sites, various stages of collection, transportation and transfer in garbage collection should be comprehensively considered, and the recycling path should be optimized, so as to improve the environment of garbage collection sites and improve people's health. standard of living.

By analyzing the path planning problem of garbage trucks, this paper proposes an improved ant colony optimization algorithm, establishes a path planning mathematical model under capacity constraints, improves the basic ant colony algorithm, introduces capacity constraints, and introduces negative information by introducing capacity constraints. The pheromone is updated locally to prevent all ants from converging to the suboptimal solution in advance or quickly, avoiding falling into local optimum, and increasing the pioneeringness of the algorithm. The global dynamic pheromone update is used to improve the speed of the algorithm and obtain the optimal path. The method verifies each optimal path by inserting the roulette operation and the 3-opt optimization algorithm, and updates the optimal result to improve the performance of the algorithm[2].

Ant colony algorithm was first proposed by Dorigo and Stutzle (2004), which was inspired by the foraging behavior of ants in real life. The path planning problem was proposed by Professor DANTIZG in 1959 and belongs to the NP-hard problem. Since then, the solution of path planning problems has been a hot research topic[3]. Ma Liang et al. were the first group of scholars to study the ant colony algorithm, and brought the ant colony algorithm into the combinatorial optimization problem, and made important contributions to the subsequent research on the path planning

problem[4]. However, it is used in the planning of garbage collection vehicles for garbage collection, without considering the actual environmental constraints such as capacity constraints. Many researchers have proposed new methods to improve the original ant colony algorithm, especially applying other algorithms to the ant colony algorithm to solve the problem of garbage truck path planning, but it is prone to the problem of premature convergence to a suboptimal solution. When using the ant colony algorithm to solve the problem, it is rarely improved for the new solution generation strategy. This paper can combine the ant colony algorithm and the tabu algorithm on the basis of previous research to improve the operation efficiency of the algorithm[5].

In this paper, the improved ant colony algorithm is used to solve the local optimal problem and the problem of high computational complexity, easy search and low efficiency in ant colony algorithm[6]. In the ant colony algorithm, after one ant completes a route construction, before the following ants start experimenting to build their solution, the pheromone is updated, at which time the route will be improved by applying heuristics. In this paper, the heuristic algorithms 2-opt and 3-opt are applied to each optimal solution obtained, respectively, and the current path is modified by removing two edges, reversing one of the resulting paths, and then reconnecting the paths with two new edges, Make optimal route improvements[7].

Aiming at the problem of falling into local optimality, the roulette algorithm is introduced into the ant colony optimization algorithm for local optimization, and in order to increase the pioneering ability of the algorithm, this paper selects 2-opt search as the local search method after all vehicle pairs are selected. strategy to improve the performance of ant colony algorithm[8].

Aiming at the problem that the pheromone concentration or too low causes the calculation time to be long, on the basis of the traditional ant colony algorithm, the release concentration variable of the pheromone is added, and an additional pheromone is added for each update, which can increase the positive feedback and speed up the ant colony. The convergence rate of the algorithm.

Aiming at the problem that the actual capacity of garbage trucks is limited, this paper adds a capacity-limiting variable C for garbage transport vehicles.

In the basic ant colony algorithm, the original pheromone update method will cause the distribution of pheromone to not well reflect the change of the current optimal path, which will have a great impact on the solution process of the algorithm. This paper uses the pheromone update method combining local pheromone update and global pheromone update, and global pheromone update adds a new mode of dynamic update[9].

This paper makes the following contributions: (1)By introducing capacity constraints, the actual influencing factors to be faced by the path planning algorithm when the garbage truck is recycled are considered more comprehensively, and the results are more suitable for the actual operating environment.(2)On the basis of the improved ant colony algorithm, negative feedback is added to improve the update method of pheromone, and local pheromone update is used to prevent all ants from converging to suboptimal solutions in advance, and reduce the generation of local optimal solutions.(3)The traditional ant colony algorithm is optimized and improved, artificial pheromone is added for optimization, and additional pheromone is manually released when the pheromone trajectory is modified on the path to enhance the positive feedback result, accelerate the convergence speed of the ant colony, and obtain the optimal solution.(4)2 - opt calculation for each optimal solution, and update the calculated optimal path result. Do not number your paper: All manuscripts must be in English, also the table and figure texts, otherwise we cannot publish your paper. Please keep a second copy of your manuscript in your office. When receiving the paper, we assume that the corresponding authors grant us the copyright to use the paper for the book or journal in question.

2. Related work

Regarding path planning algorithms, there are search-based path planning, such as Floyd algorithm, A * algorithm, Dijkstra algorithm, and probability-based path planning, such as RRT algorithm, RRT* algorithm, Informed RRT* algorithm, and intelligent algorithm-based algorithm. path planning,

such as genetic algorithm and ant colony algorithm[10]. The most common modern optimization algorithms are genetic algorithm, ant colony algorithm, particle swarm algorithm, fish swarm algorithm and simulated annealing algorithm. Many traditional optimization algorithms belong to the category of convex optimization, and have a unique and clear global optimal point; while the vast majority of intelligent optimization algorithms are aimed at multi-extremum problems, how to prevent falling into local optimum and find the global optimum as much as possible is to adopt intelligent The root cause of the optimization algorithm: For single-extremum problems, traditional algorithms are good enough most of the time, while intelligent algorithms have no advantage; for multi-extremum problems, intelligent optimization algorithms can jump out of local optimum and converge to There is a good balance between a point, so as to find the global optimum, but sometimes the local optimum is acceptable, so the traditional algorithm also has a large application space and the possibility of improvement for special structures. This paper presents a hybrid ant colony algorithm that improves the ant colony algorithm[11].

Previous research on VRP has focused on a single algorithm. Huang et al. proposed an improved discrete bat algorithm[12]. and Cai et al. proposed an empire competition algorithm with a split mechanism to solve, which is different from the existing empire competition algorithm, particle swarm algorithm, genetic algorithm, cuckoo Compared with the search algorithm, the proposed algorithm has higher solution efficiency [13]. Li et al. proposed an improved tabu search algorithm to solve the vehicle routing problem with capacity constraints, and gave two methods that act on the local optimal solution. The improved algorithm overcomes the defect that the standard tabu search algorithm relies heavily on the initial solution, reduces the possibility of the algorithm falling into local optimum during the search process, and improves the search quality and efficiency of the algorithm. Efficiency [14]. Guo et al. studied the discrete whale algorithm for solving the vehicle routing problem with capacity constraints, which redefines the prey operation of the basic whale algorithm. And introduce random exchange search, 2-opt, 3-opt optimization methods to optimize the optimal solution obtained in each iteration process, and expand the algorithm search space algorithm [15]. This paper studies the solution to the path planning problem of improved ant colony algorithm under capacity constraints.

3. Problem Definition

It is known that there are a certain number of garbage sorting and recycling points in a certain area, and the amount of garbage provided by each station and the location coordinates of the station are given. These vehicles start from the transit warehouse and collect garbage at different recycling points along the way. Each car has the same upper limit of delivery capacity, each collection point has real-time cargo volume data, each collection point can only be serviced by one vehicle, all vehicles depart from the warehouse and return to the warehouse, a vehicle cannot be in the same non- The warehouse node stops many times, all cars cannot be overloaded, and the sum of the garbage supply of all nodes on a path cannot exceed the maximum capacity of a car.

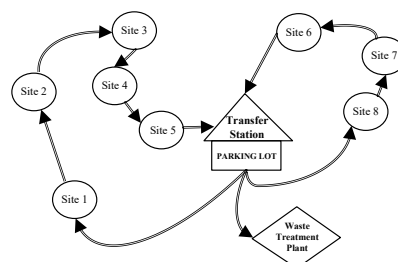


Fig 1. Flowchart of garbage removal and transportation Model establishment

4. Model establishment

4.1 Description of basic symbols

The garbage truck path planning problem is described as the problem of m vehicles starting from the transfer station O to visit n garbage collection sites for recycling. Let d_i be the amount of garbage that needs to be recycled at garbage collection site i , C_{ij} is the path length of the vehicle from garbage collection point i to garbage collection point j , b is the load capacity of the garbage truck body, and G_k is the set of garbage collection point numbers for vehicle k .

4.2 Constraints

The purpose of solving the garbage truck routing problem is to minimize the total cost of removal. The lowest total cost refers to: first, the shortest total path for vehicles; second, the number of garbage trucks dispatched is the least; third, the total working distance of each garbage truck is as uniform as possible.

4.3 Mathematical model

$$x_{ij} = \begin{cases} 1, & \text{Vehicle } k \text{ goes from} \\ & \text{site } i \text{ to the next site } j \\ 0, & \text{other} \end{cases} \quad (1)$$

$$y_k = \begin{cases} 1, & \text{Vehicle } k \text{ is used} \\ 0, & \text{Vehicle } k \text{ is not in use} \end{cases} \quad (2)$$

$$s = \sum_{k=1}^m y^k \quad (3)$$

$$L_k = \sum_{\substack{i \neq j \\ i, j \in G_k}} c_{ij} \quad (4)$$

$$J_1 = \min \sum_{k=1}^m \sum_{\substack{i, j=0 \\ i \neq j}}^n c_{ij} x_{ij}^k \quad (5)$$

$$J_2 = \min \sum_{k=1}^m y^k \quad (6)$$

$$J = a_1 J_1 + a_2 J_2 \quad (7)$$

The following constraints should be met:

$$\sum_{j=1}^n x_{0j}^k = \sum_{j=1}^n x_{j0}^k = 1, k \in (1, 2, 3 \dots, m) \quad (8)$$

$$\sum_{k=1}^m \sum_{\substack{j=0 \\ j \neq i}}^n x_{ij}^k = 1, i \in (1, 2, 3 \dots, n) \quad (9)$$

$$\sum_{k=1}^m \sum_{\substack{i=0 \\ i \neq j}}^n x_{ij}^k = 1, j \in (1, 2, 3 \dots, n) \quad (10)$$

$$\sum_{k=1}^m d_i \sum_{\substack{j=0 \\ j \neq i}}^n x_{ij}^k \leq b, k \in (1, 2, 3 \dots, m) \quad (11)$$

Equation (8) indicates that all vehicles start from the same parking lot, and return to the parking lot after completing their tasks, and the path taken by each vehicle forms a closed loop; Equations (9) and (10) indicate that the vehicle must Garbage collection points serve and can only serve once; Equation (11) indicates that when each vehicle collects garbage, its own capacity cannot be lower than the total supply of serviced garbage collection points.

5. Methods

Ant colony algorithm is a probabilistic algorithm used to find optimal paths. It was proposed by Marco Dorigo in his doctoral dissertation in 1992 and was inspired by the behavior of ants to find paths in their search for food. Ant colony algorithm is a self-organizing, systematic and positive feedback algorithm that adopts distributed computing. In the algorithm, ants choose the path according to the concentration of pheromone. In this paper, the transition probability $p(t)$ of randomly selecting garbage collection sites in garbage trucks is as follows:

$$p_{ij}^k(t) = \begin{cases} \frac{\tau_{ij}^\alpha(t)\eta_{ij}^\beta(t)}{\sum_{j \in N_i^k(t)} \tau_{ij}^\alpha(t)\eta_{ij}^\beta(t)}, \\ 0, j \in N_i^k(t) \end{cases} \quad (12)$$

Among them: τ_{ij} represents the pheromone concentration on the edge (i, j) , η_{ij} represents the attractiveness of transferring from one garbage collection site to another. Here $\eta_{ij} = \frac{1}{d_{ij}}$ is set, d_{ij} represents the distance between the garbage collection site i and the site j , and N is the set of optional sites. α represents the relative importance of pheromone τ_{ij} in the ant's movement. When $\alpha = 0$, the movement of the ants is determined by the attraction degree η_{ij} , that is, the garbage collection site that the ant will choose only considers the distance between the two garbage collection site. β represents the relative importance of η_{ij} in the movement of ants. When $\beta = 0$, the movement of ants is determined by the concentration of pheromone τ_{ij} , which will cause the path to fall into the local optimum and cannot converge to the global optimum.

It can be seen from the above that the main influencing factor for the ant colony to select the next garbage collection site is the pheromone concentration between garbage collection sites. Too low pheromone concentration will cause a relatively long computing time, and too high pheromone concentration will lead to accelerated convergence, so the global optimal solution cannot be obtained. Therefore, this paper optimizes the algorithm to improve the performance of the algorithm.

In the traditional ant colony algorithm, the original pheromone update method will cause the distribution of pheromone to not fully reflect the change of the current optimal path, which will have a great impact on the solution process of the algorithm. Aiming at the problems existing in the pheromone update process of the ant colony algorithm, this paper uses a pheromone update method that combines local pheromone update and global pheromone update. In addition, a new mode of dynamic update is added to the global pheromone update method.

5.1 Local update

In the process of constructing the optimal path, every time the ant passes an edge (i, j) , it will update the pheromone on this edge according to the following pheromone update formula: $\tau_{ij}(t + 1) = (1 - \rho_1)\tau_{ij}(t) + \rho_1\tau_0$ (12). where ρ_1 denotes the locally updated volatility coefficient, and $\rho_1 \in (0, 1)$. τ_0 represents the initial value of the pheromone, which is a small positive constant. Let $\tau_0 = \frac{1}{n_G L}$, n_G represent the number of nodes, and L represent the length of the generated path.

The purpose of introducing the local update of pheromone is to make the ants volatilize part of the pheromone on this path when they pass through the path segment (i, j) , reduce the probability that other ants also choose this edge, and can explore other paths more, which greatly enhances the pioneering ability of the algorithm.

5.2 Global dynamic update

After one iteration is completed, the pheromone on the optimal path obtained by this iteration is globally updated as follows:

$$\tau_{ij}(t + 1) = (1 - \rho)\tau_{ij}(t) + \rho\Delta\tau_{ij} \quad (13)$$

$$\Delta\tau_{ij} = \frac{L_2 - L_1}{L_2} \quad (14)$$

Among them, ρ represents the globally updated pheromone volatilization coefficient, and $\rho \in (0, 1)$. $\Delta\tau_{ij}$ represents the increase in pheromone. L_1 represents the optimal path length obtained in x iterations. L_2 represents the length of the optimal path in all iteration results after $x - 1$ iterations. The purpose of the pheromone update strategy on the optimal path is to provide positive feedback information of pheromone for the optimization work in the iterative process, which enables the algorithm to find the optimal path better and faster in the subsequent iterations.

Formula (13) and (14) can dynamically adjust the global pheromone on the optimal path obtained by the current iteration according to the condition of the optimal path obtained in each iteration. After x iterations, an optimal path is obtained, which is shorter than $x - 1$ iterations. That is, the difference between L_2 and L_1 is positive, indicating that the optimal path found in the current iteration is better than the one found before, but the pheromone concentration on this path is not high at this time. According to formula (14), the larger the difference between L_2 and L_1 , the larger $\Delta\tau_{ij}$ will be, and the faster the pheromone concentration will accumulate in the subsequent iterations. Conversely, the smaller the difference between L_2 and L_1 , the smaller $\Delta\tau_{ij}$ will be, and the slower the accumulation of pheromone concentration will be in subsequent iterations. If, after x iterations, the optimal path obtained by the algorithm is longer than L_2 , that is, the difference between L_2 and L_1 is negative, it means that the optimal path found in the current iteration is not as good as the previously found path. According to Equation (14), the greater the difference between L_2 and L_1 , the greater $\Delta\tau_{ij}$ will be, and the pheromone concentration will volatilize faster in subsequent iterations. The smaller the difference between L_2 and L_1 , the smaller $\Delta\tau_{ij}$ will be, and the slower the pheromone concentration will be volatilized in subsequent iterations. This dynamic adjustment is to allow the algorithm to correct the results obtained iteratively in time, and to guide the algorithm to find the optimal path faster.

5.3 2-opt

In order to increase the pioneeringness of the algorithm, this paper selects 2-opt as the local search strategy after all vehicle-to-path selections are completed. This heuristic is applied separately to each vehicle route established by the ants. Starting from a feasible path, it modifies the current path by removing two edges, reverses one of the resulting paths, and then reconnects the paths with two new edges. This paper implements 2-opt for each vehicle route by using the best-improvement stopping rule.

6. Algorithm steps

According to the improved algorithm described above, the specific flow of the algorithm is as follows:

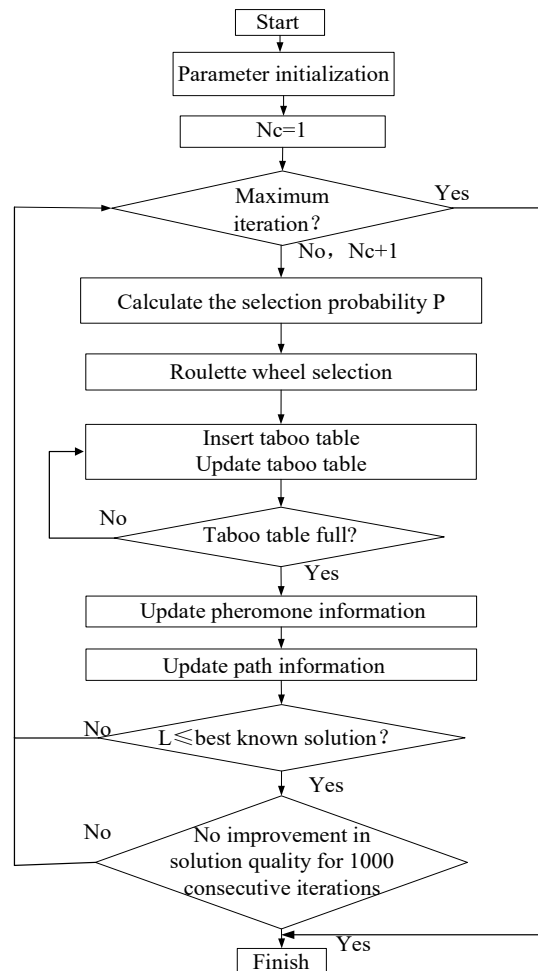


Fig 2. Improved ant colony algorithm flowchart

7. Result

The experimental hardware platform of the algorithm in this paper: the CPU is AMD Ryzen 7 5700G@3.80GHz, the memory is 16GB RAM, the operating system is 64-bit Windows 11, the development tool is Visual Studio Code, and the programming language is Python. The experiment adopts a set of simulated data of 49 garbage collection sites and 1 garbage transfer site. Among them, the parameters of the algorithm in this paper are set as follows: the number of populations is $N=50$, the number of iterations is $Max_Nc=500$, the vehicle load is $C=7000kg$, the number of vehicles is 4, $\alpha=2$, $\beta=5$.

This paper compares the calculation results of the improved ant colony algorithm with the basic ant colony algorithm and genetic algorithm. The same experiment is carried out in 10 groups, and the result is the average of the 10 groups of experimental data. The final results are shown in Table 1.

Table 1. Comparison of calculation results

Algorithm	GA	ACA	Our method
20	2304.55	2500.67	2059.59
50	2233.63	2287.43	1973.34
100	2114.17	2178.66	1953.57
200	2077.44	2070.76	1953.57

300	2001.44	2032.54	1953.57
500	2001.44	2021.33	1953.57

Comparing the algorithm convergence value after 500 iterations, the final result of this method is significantly smaller than the other two methods. From the comparison results, it can be concluded that the other two methods are still trapped in the local minimum at 500 iterations and cannot converge to better results than the method in this paper. It can be concluded that the search ability of the improved ant colony algorithm is greatly improved, and it is not easy to fall into the local optimum.

Generally, a larger number of iterations is more likely to obtain a high-quality solution, but it often consumes more computing time, so the convergence speed of the algorithm is equally important. When the number of iterations is 50, the result of GA is 2304.55, the result of ACA is 2500.67, and the result of our algorithm is 2059.59. When the number of iterations is 100, the algorithm in this paper converges to the optimal value. While GA converges to the local optimum at 300 iterations, AGA does not converge at 500 iterations. It can be seen from the table that the improved ant colony algorithm has a significant improvement in the convergence speed compared with the other two methods, which saves the running time of the algorithm.

In the above experiments, the optimal vehicle path planning of the algorithm in this paper is shown in Table 2 and Figure 3 below:

Table 2. The optimal solution of the algorithm in this paper

Number of vehicles	Total distance	Vehicle Information		
		Vehicle number	Vehicle path	Load capacity
4	1953.57	1	20→18→29→23→8→35→19→22→21→7→6→40→44	6600
		2	36→15→49→43→50→46→2→31→12→39→10→4→32→26→24	6730
		3	34→42→11→47→27→37→41→33→13→25→28→38→14	6690
		4	16→45→48→30→3→9→5→17	4800

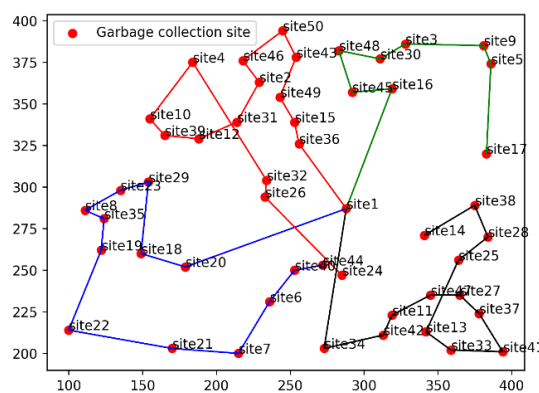


Fig 3. Optimal path graph under improved ant colony algorithm

It can be seen from Table 2 and Figure 1 that four garbage trucks are planned to depart from garbage transfer stations to complete the garbage collection at 49 garbage collection sites. The vehicles on the four paths all meet the capacity constraints, and the full load rate of the other vehicles is over 94% except for the last vehicle that is not fully loaded. There are no routes such as detours

and repetitions, which conforms to the principle of least vehicles and shortest paths in the problem of garbage truck path planning, and can meet actual requirements.

8. Summary

Aiming at the low solution efficiency of basic ant colony algorithm, low quality of feasible solutions, and easy to fall into local optimal solution, after fully considering the mathematical model and solution of general vehicle routing optimization problem, a new method with wheel is proposed. The improved ant colony algorithm combining the gambling operation and the 2-opt optimization operation, the algorithm performs a secondary calculation on the probability of the selected path during the operation process, which expands the global search range; The local search ability improves the quality of understanding; the results of the simulation experiments show that compared with the results obtained by the basic ACO algorithm and the genetic algorithm, the improved ant colony algorithm has great advantages in performance and solution quality, and can be more Solve the vehicle routing optimization problem with capacity constraints well, and save the cost better.

Acknowledgment

This work was supported by Foundation of School-enterprise Cooperation Practice Education Base Project of Hefei University in 2019 and Provincial Teaching Demonstration Course Project of Hefei University in 2020 hosted by Juanjuan Gu.

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