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MUNICIPAL SOLID WASTE COLLECTION AND TRANSPORTATION ROUTING OPTIMIZATION BASED ON IAC-SFLA

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Highlights:
- IAC-SFLA was successfully applied in municipal solid waste collection and transportation;
- multi-model collection and transportation systems can reduce the cost of waste collection and transportation;
- IAC-SFLA outperformed the basic AC algorithm by reducing 19.76 km and increasing the average loading rate by 4.15%.

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Abstract. In order to realize the efficient collection and low-carbon transport of municipal garbage and accelerate the realize the "dual-carbon" goal for urban transport system, based on the modeling and solving method of vehicle routing problem, the municipal solid waste (MSW) collection and transport routing optimization of an Improved Ant Colony-Shuffled Frog Leaping Algorithm (IAC-SFLA) is proposed. In this study, IAC-SFLA routing Optimization model with the goal of optimization collection distance, average loading rate, number of collections, and average number of stations is constructed. Based on the example data of garbage collection and transport in southern Baohe District, the comparative analysis with single-vehicle models, multiple-vehicle models, and basic ant colony algorithms. The multi-vehicle model of collection and transportation is superior to the single-vehicle model and the improved ant colony algorithm yields a total collection distance that is 19.76 km shorter and an average loading rate that rises by 4.15% from 93.95% to 98.1%. Finally, the improved ant colony algorithm solves for the domestic waste collection and transportation path planning problem in the north district of Baohe. Thus, the effectiveness and application of the proposed algorithm is verified. The research result can provide reference for vehicle routing in the actual collection and transport process, improve collection and transport efficiency, and achieve the goal of energy conservation and emission reduction.

Keywords: municipal solid waste, improved ant colony algorithm, collection and transportation routing planning, vehicle routing problem.

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1. Introduction

With the increasing level of urbanization in our country, the optimization of municipal solid waste vehicle routing has attracted growing attention in academic circles and has presented new characteristics. In addition, recycling and transfer comprise the key connecting parts in front-end domestic waste generation and end treatment, with the cost of domestic waste collection and transportation accounting for approximately 50% of the total cost of waste treatment (Cao et al., 2021). Correspondingly, reasonable planning of urban domestic waste collection and transportation path can not only save operation time, improve collection and transportation efficiency, save fuel cost, and reduce the transportation cost of vehicles, but it can also reduce the environmental pollution of domestic waste, which provides a crucial foundation for ecological and environmental protection (Ganji et al., 2020).

In this study, the state probability transfer function and pheromone update rule in the ant colony algorithm were improved and then fused with the hybrid frog-hopping algorithm to obtain an improved ant colony-hybrid frog-hopping algorithm. This was followed by the planning of the domestic waste collection and transportation path in the Baohe District of Hefei City using MATLAB®, with an aim to solve the problems of long urban domestic waste collection as well as transportation distance and collection based solely on experience.

2. Literature review

The vehicle routing problem was first proposed by Dantzig et al. and has received widespread attention from scholars, resulting in many variants of research on vehicle routing optimization problems, such as capacity constrained vehicle routing problems, vehicle routing optimization problems considering time windows, dynamic vehicle routing problems, and so on (Yesodha & Amudha, 2022). With the increasingly prominent environmental issues, some scholars have begun to study the green vehicle routing problem, using different path optimization strategies to reduce energy consumption and carbon emissions.

Existing algorithms for solving the vehicle path planning problem include exact, metaheuristic, and intelligent algorithms (Dhanya & Kanmani, 2016; Wang et al., 2020c; Wu et al., 2022). Each algorithm for the vehicle path problem has its own advantages and applications. For a collaborative multicenter vehicle routing problem with time windows and dynamic customer demands. A hybrid heuristic algorithm comprising an improved k-medoids clustering algorithm and an extended reference pointbased nondominated genetic algorithm-III, is designed to solve the multi-objective optimization model (Wang et al., 2022b). A truck-drone hybrid routing problem with time-dependent road travel time (TDHRP-TDRTT) to address the truck-drone cooperation issue, and the proposed model and algorithm are of practical significance in reducing operating cost, improving transportation efficiency, and facilitating a smart and sustainable urban logistics distribution system (Wang et al., 2022a). Wang propose an optimization framework for large-scale multi-echelon logistics delivery and pickup networks to solve the GLLRPE for logistics operations sustainability (Wang et al., 2020a). The exact approach can locate the exact solution to a problem, but it requires extensive computation. Moreover, as the size of the problem increases, the solution computation becomes more time-consuming and complex (Bräysy & Gendreau, 2005; Mahato & Singh, 2018). In recent years, metaheuristic algorithm was widely used for optimizing the design of green supply chain networks. For example, cuckoo optimization algorithm, multi-objective invasive weed optimization, multi-objective simulated annealing algorithm, multi-objective gray wolf optimization, and multi-objective invasive weed optimization generate high-quality solutions (Goli et al., 2020, 2022). Compared to the exact approach, the metaheuristic algorithm is faster, but its overall search performance is poor, and it cannot guarantee that the solution obtains all of the problem's solution spaces; thus, "satisfactory solutions" are common (Homberger & Gehring, 2005; Wang et al., 2020b). Conversely, the intelligent algorithm is an approach that has been researched for many years, has a strong global search capability, and can produce high-precision, satisfactory results within a specified time frame (Wang & Li, 2018; Zhou et al., 2022). The Ant Colony Algorithm is an example of an intelligent algorithm that is ideally suited for solving the optimization problem of domestic waste collection and transportation routes (Pellerin et al., 2020). However, its own positive feedback makes it easy to fall into the local optimal solution, thus making it difficult to obtain the global optimum (Chen et al., 2017; Zhu et al., 2020). In addition, it also has the disadvantages of slow solution speed and long search times. Recent research indicates that the frog-hopping algorithm is more applicable to vehicle path problems (Dalavi et al., 2016; Hidalgo-Paniagua et al., 2015). Although the ant colony algorithm solves complex optimization problems with high precision, the search time is long, and the search efficiency is low; conversely, the frog hopping algorithm has better global convergence, particularly in the later stages, but has specific requirements for the initial solution. Hence, it can be seen that improving existing algorithms or using different algorithms to form hybrid algorithms to solve MSW vehicle routing problems is still a hot research direction in the field of algorithms.

In existing research on green vehicle routing problems, there is little comprehensive consideration of the impact of fixed vehicle costs, transportation costs, carbon emission costs, as well as vehicle capacity and time window constraints on transportation costs. Thus, this study takes the example of garbage collection and transportation in Baohe District as the research object, comprehensively considering four factors: collection distance, average loading rate, number of collections, and average number of stations. A green and low-carbon garbage collection and transportation vehicle scheduling and path optimization model is constructed, and an improved ant colony-shuffled frog leaping algorithm is designed to solve the problem and find the optimal collection and transportation plan.

3. Problem statement and mathematical model

3.1. Problem statement

The domestic waste collection route problem is a typical Vehicle Route Problems (VRP), which also belongs to the NP problem (Non-deterministic Polynomial), a multi-drive, multi-loop, multi-vehicle, single-point-to-multiple-collection point, and a waste collection problem with a dynamic road network (Kang & Lee, 2018). Accordingly, the waste collection route comprises a very complex combinatorial optimization problem; thus, the fundamental theory applicable to VRP also applies to it.

In this study, by analyzing the current state of research and combining it with the reality of the study area, the Capacity Vehicle Routing Problem (CVRP) model with capacity constraints is extended by analogy with the generalized VRP problem, as described below (Hiermann et al., 2016):

1. Known conditions: A total of m identical domestic waste collection vehicles parked at v0 (garage) were required to go to n waste collection points in the destination area for domestic waste collection and transportation. The waste collection points include v1, v2, ..., vn; the location coordinates of each waste collection point comprise xi and yi; the volume of waste qi (i = 1, 2, ..., n) at this collection point is known, which finally goes to the terminal transfer station vn+1.

2. The required number of vehicles, K, is dependent on the overall conditions within the collection area, the allocation of a certain number of refuse collection vehicles with a capacity of Q, and the distribution of routes and carriers on the return route to minimize the total distance.

3. Restrictions: The removal vehicle leaves the point of departure (v0) to collect the waste from each collection point in the area. This collection point can only be served by one removal vehicle. The vehicle stops collection when it is full and then returns to the point of departure; the carrying capacity of the transport vehicle must not be exceeded and traffic regulations need to be observed.

3.2. Mathematical model

Generally speaking, the establishment of mathematical models for domestic waste collection and transportation can be divided into three steps (Zhang et al., 2022): (1) defining decision variables based on the actual problem situation, which are typically represented by letters with different subscripts, and defining controllable factors as decision variables; (2) defining the objective function: the objective function of a multi-model for waste collection and transportation is typically to minimize distance, operating costs, and human and material resources; (3) determining Constraints: for different mathematical models, the constraints are often complex and uncertain, and need to be set according to the actual situation.

Let the distance from task i to j be d_{ij} and the distance from the yard to task j be d_{0j}, then the cost per vehicle C_{ij}^k s determined as follows.

1. When i is a garage: $C_{0j}^k = C_0^k + C_1^k \times d_{0j}$, $j = 1,2,\cdots,M$;

2. When i is a task point: $C_{ij}^k = C_1^k \times d_{ij}$, $i \neq 0$, $j = 0,1,\cdots,M$,

where C_0^k – model k marginal cost of adding one vehicle; C_1^k – the cost per unit of travel for model k relative to distance.

First, the decision variables of the mathematical model is defined:

$$y_{iq}^k = \begin{cases} 1 & \text{Task } i \text{ is performed by the } q\text{th vehicle of the } k\text{-model} \\ 0 & \text{otherwise} \end{cases}; \tag{1}$$

$$x_{ijq}^k = \begin{cases} 1 & \text{The } q\text{th vehicle of vehicle type } k \text{ from } i \text{ to } j \\ 0 & \text{otherwise} \end{cases}. \tag{2}$$

Using t_i to denote the start time of task i, i.e. the time when the vehicle arrives at waste collection point i, and ct_i to denote the time (i = 1, 2, ..., M) when task point i completes the collection task (i.e. the waste is transported back to the transfer station), where t_0 = 0 and ct_0 = 0; t_{ij} to denote the travel time of the vehicle from i to j (i, j = 1, 2, ..., M); the time for the vehicle to reach task point j is given by:

$$t_j = \sum_{i=0}^{M}\sum_{k=1}^{K}\sum_{q=1}^{q_k}\left(t_i + t_{ij} + ct_i\right) \times x_{ijq}^k, \quad i,j = 1,2,\cdots,M; \tag{3}$$

$$ET_i \le t_i \le LT_i, \; i = 1,2,\cdots,M; \tag{4}$$

$$x_{ijq}^k = 0 \text{ or } 1, \quad i,j = 0,1,2,\cdots,M; \; \forall k,q; \tag{5}$$

$$y_{iq}^k = 0 \text{ or } 1, \quad i = 1,2,\cdots,M; \; \forall k,q. \tag{6}$$

Equation (3) indicates the time at which the collection vehicle reaches mission point j; Equation (4) represents the optimal service time period specified for the collection point; Equations (5) and (6) represent the corresponding 0–1 variable constraints.

A mathematical model of domestic waste collection is developed as follows (Aliahmadi et al., 2020; Nguyen-Trong et al., 2017):

$$\min z = \sum_{i=0}^{M}\sum_{j=0}^{M}\sum_{k=1}^{K}\sum_{q=1}^{q^k} C_{ij}^k x_{ijq}^k; \tag{7}$$

$$\text{s.t.} \quad \sum_{k=1}^{K}\sum_{q=1}^{q^k} \Delta_i^k y_{iq}^k = 1, \; i = 1,2,\cdots,M; \tag{8}$$

$$\sum_{i=0}^{M} x_{ijq}^k = y_{jq}^k, \; j = 1, 2, \cdots, M, \; \forall k,q; \tag{9}$$

$$\sum_{j=0}^{M} x_{ijq}^k = y_{iq}^k, \; i = 1, 2, \cdots, M, \; \forall k,q; \tag{10}$$

$$\sum_{i=1}^{M} \Delta_i^k \times g_i \times y_{iq}^k \le Q^k, \; \forall k,q; \tag{11}$$

$$\sum_{j=1}^{M} x_{0jq}^k = 1, \; \forall k,q; \tag{12}$$

$$\sum_{i=0}^{M} x_{ihq}^k = \sum_{j=0}^{M} x_{jhq}^k, \; h = 1,2,\cdots,M \, \forall k,q; \tag{13}$$

$$\sum_{i=1}^{M} x_{i0u}^k = 1, \; \forall k,q. \tag{14}$$

Equation (7): z represents the value of the objective function. C_{ij}^k represents the transportation cost of a model k from collection point i to collection point j. It is represented variably depending on the aim of the model built, and in this study, it is represented as the distance of collecting and transportation; Equation (8) indicates that each waste collection point is guaranteed to be collected by only one vehicle of a model that corresponds to its waste generation; Equations (9) and (10) represent the binding relationship between the two variables; Equation (11) indicates that the volume of collection for each vehicle dispatched with a compatible collection point does not exceed the full capacity of that vehicle; Equations (12), (13), and (14) indicate that each vehicle departs from the refuse transfer station and returns to the transfer station after completing the refuse collection task.

Additionally, the number of vehicles assigned to each model during collection is less than the number of each model owned by the garage. The model uses full capacity as a control constraint, i.e., the total amount of household waste loaded by a collection vehicle does not exceed the maximum full capacity of that vehicle, thereby substantially increasing the full capacity of the vehicle and reducing the number of vehicles that must be dispatched, thereby reducing operating costs.

Ultimately, the fundamental constraints on the total collection minimum distance during transport are as follows: 1) all waste generated must be collected and transported to achieve daily output; 2) the total amount of household waste collected on any one collection path must not exceed the full capacity specified for the collection vehicle, or a penalty function will be implemented; and 3) it is guaranteed that all waste is collected at all collection points.

4. Materials and methods

4.1. Study area

The area under study comprises the Baohe District of Hefei City, Anhui Province. Baohe District is situated in the southeast of the main urban area of Hefei City, Anhui Province, with a total regional area of 340 km^2, 70 km^2 of which are covered by Chaohu Lake. According to the seventh census, the resident population of Baohe District in 2020 is 1.21 million, of which 690,000 are urban residents. In 2021, Baohe District achieved a gross regional product of 160.694 billion yuan, a 7.3% increase over the previous year.

The focus of the investigation is the region's municipal solid waste. The Xiaocangfang domestic waste transfer station is located north of Taishan Road and Fanrong Avenue and is responsible for the transfer of all household waste within the Baohe District. Currently, the transfer station has a transfer capacity of 1,300 tons per day, including 200 tons/day of food waste and 1,100 tons/day of other waste. In urban areas, garbage is collected twice daily at 9:00 a.m. and 9:00 p.m. After the collection and transportation is completed, the waste is transported to Longquanshan Landfill and Feidong Energy-saving Incineration Power Plant from the Xiaocangfang Refuse Transfer Station.

Due to the large number and dispersed distribution of front-end domestic waste collection and transportation stations in the district, the waste generation volume of each district varies, and only special vehicles are used to clean and transport domestic waste. While the driving route of the cleaning vehicles relies solely on experience driving, the absence of scientific path selection and optimization is likely to reduce the collection and transportation efficiency of the collection and transportation system and increase the collection and transportation costs. Thus, it is necessary to combine the domestic waste collection and transportation model with path planning algorithms to select a suitable collection and transportation path so as to reduce the system collection and transportation cost and improve the collection and transportation efficiency, provided that the collection and transportation requirements are met.

4.2. Data sources

The data information on road network distribution, road length, and road class needed for this study was obtained from vector data downloaded from the National Road Network Vector Map 2020 of the Open Street Map website, and the road network map of the study area was obtained after cropping as depicted in Figure 1.

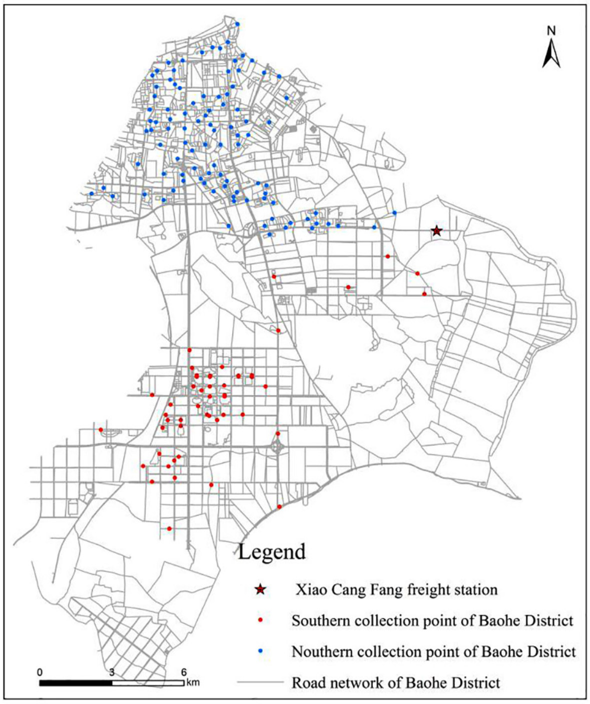

Figure 1. Road network and collection points in study area

As China's waste classification management is still in its infancy, statistics and monitoring of waste generation at each collection point are not yet available. According to the findings of relevant studies, the population is the primary factor influencing the volume of domestic waste generation (Cheng et al., 2020; Zhao et al., 2022), so the waste generation was estimated based on the population of the selected domestic waste collection points in the Baohe District. According to the Hefei City Statistical Yearbook 2021, the average household population in Baohe District in 2020 was 2.86 people, and the total number of households in each district was determined by checking the total number of households in each district on the websites of Anjuke and Chain Home. Correspondingly, the average daily per capita domestic waste removal volume in China was obtained as 1.12 kg per person (Wang et al., 2017), based on the data obtained from the Research Report on the Assessment of Urban Domestic Waste Management in China by the National Institute of Development and Strategy, Renmin University, China, from which the total waste collection volume of each recycling point was derived.

4.3. Ant colony algorithm

In his Ph.D. dissertation published in 1991, Italian scholar M. Dorigo introduced a new method of ant colony optimization (ant colony algorithm) based on the colony behavior of real ants in nature and applied it to solve a series of combinatorial optimization problems (Dorigo et al., 1996). Extensive observation and study by entomologists have revealed that ants are capable of figuring out the shortest route from the nest to the food source without any initial guidance and that they can respond by creating new path choices in response to environmental changes (Zhang & Xiong, 2018). Ant colony algorithm is easy to combine with other algorithms, and by making reasonable improvements to its mathematical model, it can effectively solve many problems. Many scholars have combined it with other heuristic intelligent optimization methods and achieved good results. By utilizing a design approach that complements each other's strengths, optimization solutions can be enriched and better solutions can be sought.

The basic algorithm for an ant colony consists of two processes. The first process is state transfer; accordingly, the probability function for state transfer in the ant colony algorithm is determined by the distance between nodes and the pheromone concentration (Luo et al., 2020). Thus, at time *t*, after city *i*, the state transfer probability of ant *k* choosing the next city *j* is given by the following equations:

$$P_{ij}^{k}(t)=\begin{cases}\dfrac{\tau_{ij}^{\alpha}(t)\eta_{ij}^{\beta}(t)}{\sum_{s\in allowed_k}\tau_{is}^{\alpha}(t)\eta_{is}^{\beta}(t)}, & j\in allowed_k\\ 0 & \text{otherwise}\end{cases};\quad (15)$$

$$\eta_{ij}=\frac{1}{d_{ij}};\quad (16)$$

$$d_{ij}=\sqrt{\left(x_i-x_j\right)^2+\left(y_i-y_j\right)^2},\quad (17)$$

where $allowed_k = \{0, 1, ..., n-1\}$ denotes the city that ant *k* is allowed to choose next; $\eta_{ij}(t)$ denotes the visibility of edge (*i*, *j*), reflecting the degree of heuristic for transferring from city *i* to city *j*, and is a heuristic function defined according to its own fitness ($\eta_{ij}=1/d_{ij}$); α is the pheromone heuristic factor; β is the expectation heuristic factor; $taub_k$ denotes the taboo table of the set of cities that the ant has finished visiting; and d_{ij} is the node *i* to node *j* Euclidean distance.

The second process is pheromone updating, and after *n* seconds, the ant completes a cycle in which the quantity of pheromone on each path is adjusted in accordance with Equation (18) (Chen et al., 2017; He et al., 2021).

$$\begin{cases}\tau_{ij}(t+1)=\rho\times\tau_{ij}(t)+\Delta\tau_{ij}(t,t+1)\\ \Delta\tau_{ij}(t,t+1)=\sum_{k=1}^{m}\Delta\tau_{ij}^{k}(t,t+1)\end{cases},\quad (18)$$

where $\Delta\tau_{ij}^{k}(t,t+1)$ presents the number of pheromones left on path (*i*, *j*) by the k^{th} ant at time (*t*, *t* + 1), which depends on the performance of the ants, the path length, and the density of the pheromones. Additionally $\Delta\tau_{ij}^{k}(t,t+1)$, presents the increment of pheromones on path (*i*, *j*) in the current cycle; (1 – ρ) prevents the tracks from accumulating continuously on the path and is generally set to 0 < ρ < 1.

4.4. Shuffled frog leaping algorithm

Based on guided search, Eusuff and Lansey (2003) proposed a Shuffled Frog Leaping Algorithm (SFLA) inspired by frog group foraging. The algorithm simulates the coevolution of subpopulations of a group of frogs as they search for the most food locations, and it combines deterministic and stochastic methods with more efficient computational power and global search performance. It combines deterministic and stochastic methods, providing more efficient computing power and global search performance.

The algorithm divides a group of frogs with the same structure into multiple populations, searches for feasible solutions locally based on specific strategies for the frogs in the population, and then searches for the global optimal solution via global information exchange. The combination of global information exchange and local optimal search, thus, enables the algorithm to escape the local extremum and accelerates global optimal search (Duan et al., 2018). The process is described below:

First a population of frogs (*p*) is randomly generated, with each frog representing a solution $x_i = [x_{i1}, x_{i2}, ..., x_{is}]$ containing *s* variables. The frogs within the population are then ranked in descending order of individual fitness and then grouped to form a matrix of *p* = *r* × *c subpopulations*, which contains *c* subpopulations of *r* frogs each. The solutions with the best and worst fitness in each population are denoted by X_b, X_w, respectively, and the solution with the highest global fitness among all populations is denoted by X_g. When performing a local search for each colony, it is necessary to perform a cyclic update of X_w in the colony using the following equations.

$$D_j=rand\times\left(X_b-X_w\right);\quad (19)$$

$$X_w^{'}=X_w+D_j,\ D_j\in\left[D_{min},D_{max}\right],\quad (20)$$

where D_j is the distance moved on component *j*; *rand* is a random number between 0 and 1; and D_{min}, D_{max} are the minimum and maximum steps allowed for frog position change.

If the resultant solution X'_w is superior to the initial solution X_w, update the solution in the original population; if no improvement is observed, X_b is replaced with X_g. Subsequently, Equations (19)–(20) are repeated. If there is still no improvement, a new solution is randomly generated to replace the original X_w. This update procedure is repeated until the specified number of iterations is completed. When the local depth search of all populations is complete, the frogs of all populations are reordered and divided into populations, followed by another local depth search, and so on, until the termination condition is met.

4.5. Fusion of improved ant colony algorithm and shuffled frog leaping algorithm

4.5.1. Improved ant colony algorithm

1. Improvement of the state probability transfer function

To address the deficiencies of the conventional ant colony algorithms, the state transfer probability formula presented in this paper is first enhanced. Based on the transfer probability used by the traditional ant colony algorithm in node selection, pseudo-random rules are introduced to ensure the initial convergence speed of the algorithm (Reed et al., 2014). When the ant selects the next node j, it first makes a selection according to Equation (21).

$$j = \arg \max_{s \in allowed_k} \left\{ \left(\tau_{is}\right)^{\alpha} \times \left(\eta_{sD}\right)^{\beta} \right\}, \text{ if } q \le q_0, \quad (21)$$

where q represents a random number in the interval (0, 1); q_0 is a design parameter whose value decreases with increasing number of iterations; η_{jD} is the inverse of the distance from node j to the target D; and α and β denote the relative importance of the pheromone and distance expectations.

If q is less than or equal to q_0, then the node $j = \arg \max_{s \in allowed_k} \left\{ \left(\tau_{is}\right)^{\alpha} \times \left(\eta_{sD}\right)^{\beta} \right\}$. Correspondingly, the candidate node j will be selected based on the maximum pheromone concentration and the highest path node expectation in any selectable node $s \in allowed_{gi}$; when q is larger than q_0, node j is selected using the probability formula $P_{ij}^{k}(t)$ or any candidate; subsequently, the roulette wheel is used to decide the next node.

2. Dynamic global pheromone improvements

The traditional ant colony algorithm only takes into account the effect of pheromone concentration on the path and visibility between the current node and the next node. This method can effectively solve the node selection problem in the early stages of the algorithm, but leads the algorithm to fall into local optimum in the middle and late stages. Correspondingly, the probability function is improved by analyzing the calculation results, as shown in Equation (22) (Deng et al., 2020).

$$P_{ij}^{k}(t) = \begin{cases} \dfrac{\left(\tau_{ij}\right)^{\alpha} \left(\eta_{jD}\right)^{\beta} H^{-1}}{\sum_{s \in allowed_k} \left(\tau_{is}\right)^{\alpha} \left(\eta_{js}\right)^{\beta} H^{-1}}, & s \in allowed_k \\ 0, & \text{others} \end{cases}, \quad (22)$$

where H denotes the cumulative number of times node s has been visited. Clearly, the transfer probability $P_{ij}^{k}(t)$ is inversely proportional to H, which helps to increase the diversity of solutions.

In ant initialization algorithms, a fresh pheromone increment is generally set, which is plainly irrational since the increase in pheromone needed by the algorithm fluctuates between various iterations. To avoid getting stuck in a local optimization situation, a dynamic pheromone update algorithm is used to speed up the convergence of the algorithm, as seen in Equation (23).

$$Q_{(t)} = Q_0 + \lambda t, \quad (23)$$

where Q_0 is the initial value of the pheromone and λ is the pheromone update mechanism.

4.5.2. Algorithm fusion

Reason for fusion: The ant colony algorithm solves complex optimization problems with high accuracy, but the search time is long and the search efficiency is not high. Although the global convergence of the frog hopping algorithm is better, particularly the search efficiency at the later stage, but there is a requirement for the initial solution. Thus, the combination of the two algorithms can achieve optimal results.

The specific steps are as follows:

1. Pheromone Q, the number of iterations N, and other control parameters were initialized.
2. The next node j was then determined by the state transformation equations by Equations (21) and (22), and the previous position was initialized to i. In addition, position j was placed in a forbidden table corresponding to ant k until all ants K had completed their search operations.
3. The value of the objective function for each ant was recorded.
4. Based on the calculation results of the ant colony algorithm, the size of each objective function was ranked. The path with priority M was selected as the initial M frogs for the hybrid frog hopping algorithm. Meanwhile, the fitness of each frog was calculated using various objective functions, and the values of each objective function were ranked according to the outcomes of the ant colony algorithm. The paths with M priorities were used to initialize M frogs for the hybrid frog jump. In addition, the fitness level of each frog was determined by analyzing each objective function.
5. Subgrouping M frogs: They were divided into m subgroups of n frogs each, based on fitness values.
6. In various subpopulations, the worst frog learned from the best. If the fitness increased after learning, the poorest frog obtained more information from the best overall; subsequently, the next iteration was initiated; if the fitness value did not improve after learning, it was updated according to Equation (23) and proceeded to the next step.
7. Typically, $in \leftarrow in+1$; if $in < m$ (m is the number of subgroups), the protocol was initiated back from step (6). Conversely, the local search was deemed complete and the next step was initiated.

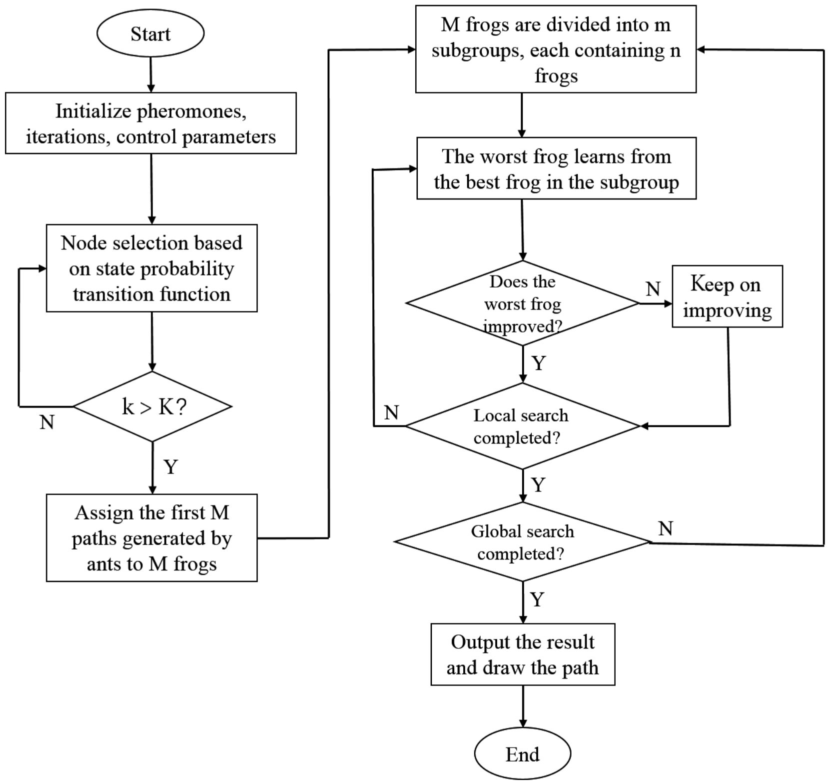

Figure 2. Ant colony-shuffled frog leaping algorithm flow chart

8. Global search: g←G+1; if $G < G_{max}$, the protocol was initiated back from step (5); conversely, the global optimal frog was obtained as the output. Subsequently, the next step was initiated.
9. The as-generated final path was then optimized using the simplified operator to obtain the optimal result as the output. The flow chart of the improved algorithm is shown in Figure 2.

5. Results and discussion

5.1. Algorithm validation: southern Baohe District

5.1.1. Algorithm parameter setting

In this study, an improved ant colony-shuffled Frog Leaping Algorithm was used to solve the path planning problem of domestic waste collection and transportation in the Baohe District, and the example was simulated using MATLAB® (version R2019a). The values of the algorithm parameters directly affect the efficacy of the algorithm's solution and the superiority of the optimal solution; therefore, prior to conducting the example experiments, in order to determine a reasonable combination of parameters to ensure the efficacy of the example and the reliability and efficacy of the algorithm, the algorithm parameters were set by consulting relevant literature and by testing multiple parameter combination schemes through simulation: the initial number of iterations of the algorithm Nc = 1, the pheromone heuristic factor $\alpha = 0.67$, expectation heuristic factor $\beta = 0.343$, decay coefficient of pheromone trajectory $\rho = 0.67$, total pheromone value Q = 3, number of ants m = 10, the maximum number of iterations NCmax = 80, number of frog population groupnum = 4, number of iterations outside the group gc = 4, number of iterations inside the group lc = 5, and number of frogs N = 20.

5.1.2. OD matrix distance analysis

Through survey and research, it is known that there are 135 dwelling quarters in the south of Baohe District. Thus, in this study, "quarters" is extended as a household trash collecting station. At the same time, due to the dense streets and road distribution characteristics, many garbage collection points are located close to each other or on the same road, while the location of the starting point (Xiaocangfang garbage transfer station) as a garbage collection vehicle is relatively far away. Thus, in order to facilitate the study and be more realistic, 50 different neighborhoods were selected as the study objects according to different areas, different side roads, distance, and superposition of domestic waste volume, etc. The precise distribution is depicted in Figure 3, and the coordinates of the collection points and the domestic waste output of the corresponding points are shown in Table 1.

In order to make the domestic waste collection and transportation vehicles drive more in line with the actual situation, the new OD distance analysis, in the loading position was selected with the help of ArcGIS network analysis tools. In addition, the distribution of domestic waste collection points in the south of Baohe District for the

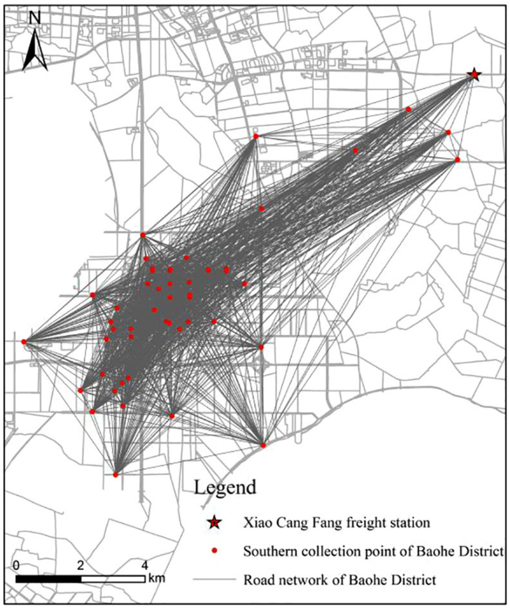

Figure 3. Analysis of OD distance between collection points and nodes in the south of Baohe District

loading starting point was solved and the data was organized to obtain the actual distance cost matrix between the two pairs of points in order to load when the vehicle is in motion. The results are shown in Figure 3.

5.1.3. Algorithm implementation

In order to increase the reliability of the results, the research process for different models to solve the vehicle path planning problem on MATLAB® code is solved five times. After comparing the collection distance five times, the number of collection, the average loading rate, and the number of stations, the optimal one operation result is selected.

Case 1: The vehicle path planning problem is solved for single model collection mode when the load of domestic waste collection vehicles is 5 t and 8 t, respectively, using the improved ant colony-shuffled frog hopping algorithm.

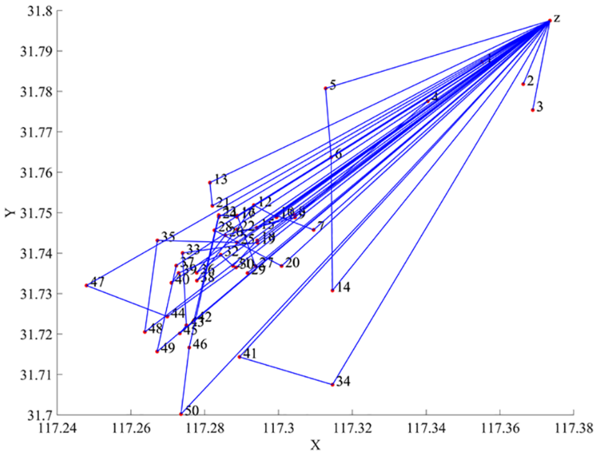

Figure 4. Route planning of single-type bicycle (5 t) in southern Baohe District

Table 1. Coordinates of the MSW collection points and quantity in southern Baohe District

Grade	x_i	y_i	$g_i(t)$
Z	117.373552	31.797494	0
1	117.3551875	31.78727937	0.86
2	117.3663054	31.7817819	2.98
3	117.3688812	31.77538763	3.00
4	117.3404518	31.77757364	1.59
5	117.3127509	31.78074578	2.57
6	117.3142584	31.76372043	1.11
7	117.309501	31.74574595	1.99
8	117.3044228	31.74943532	2.05
9	117.3044428	31.74882525	1.43
10	117.2993938	31.74930329	3.00
11	117.2994439	31.74887318	1.00
12	117.2933053	31.75186176	2.00
13	117.281408	31.75743857	2.00
14	117.3146101	31.73075523	1.22
15	117.2940845	31.74631025	2.47
16	117.2888343	31.74928763	1.58
17	117.2887346	31.74895773	2.01
18	117.2942447	31.74314976	1.12
19	117.2942548	31.74260967	0.99
20	117.3008219	31.73681966	3.06
21	117.2820672	31.75170701	3.00
22	117.2887151	31.74584747	0.98
23	117.2838042	31.74940445	0.96
24	117.2838242	31.74892439	1.58
25	117.2887155	31.74261719	1.04
26	117.2855515	31.74441165	0.57
27	117.2937861	31.73677961	1.51
28	117.2826369	31.74565572	1.88
29	117.2916007	31.73506245	1.01
30	117.2884968	31.736457	2.46
31	117.2876783	31.73682812	0.41
32	117.2843444	31.73958288	0.45
33	117.2739924	31.74003504	2.35
34	117.3146209	31.7074712	2.03
35	117.2671708	31.74315048	1.62
36	117.2778277	31.73512136	1.37
37	117.2722946	31.73691582	1.34
38	117.2778678	31.73320116	0.98
39	117.272954	31.73507505	0.58
40	117.2709866	31.73266611	2.44
41	117.2894377	31.71433356	2.87
42	117.2770794	31.72336034	2.03
43	117.2750323	31.72217189	1.06
44	117.2698589	31.72432613	1.43
45	117.2732548	31.72016309	0.54
46	117.2757917	31.71666065	2.66
47	117.247964	31.73200349	1.09
48	117.2637772	31.72051058	2.31
49	117.2671033	31.71566759	3.06
50	117.2735654	31.70020014	0.64

The results are shown in Figure 4, Figure 5, Table 2, and Table 3. The horizontal coordinate X indicates longitude; the vertical coordinate Y indicates latitude; the numbers (red dots) indicate waste collection points; Z indicates the small barn domestic waste transfer station; and the blue line indicates the route of the domestic waste collection vehicle. The same representation is used in Figures 5 to 7.

Case 2: A multi-vehicle collection model was developed, using a combination of four different loadings of 5 t, 6 t, 8 t, and 12 t domestic waste collection vehicles to solve the vehicle path planning problem in the south area of the Baohe District, based on the basic ant colony algorithm for the solution; the results are shown in Figure 6 and Table 4.

Table 2. Route planning of 5 t MSW collection and transportation vehicle in southern Baohe District

N	Driving route	Loading rate	Number of sites
1	Z→48→35→25→Z	0.994	3
2	Z→36→26→9→4→Z	0.992	4
3	Z→41→34→Z	0.980	2
4	Z→40→39→32→31→18→Z	1	5
5	Z→29→27→16→1→Z	0.992	4
6	Z→28→20→Z	0.988	2
7	Z→38→22→12→11→Z	0.992	4
8	Z→14→6→5→Z	0.980	3
9	Z→10→7→Z	0.998	2
10	Z→50→46→24→Z	0.976	3
11	Z→49→37→Z	0.880	2
12	Z→45→43→33→19→Z	0.988	4
13	Z→21→13→Z	1	2
14	Z→2→Z	0.596	1
15	Z→15→8→Z	0.904	2
16	Z→47→44→30→Z	0.996	3
17	Z→3→Z	0.600	1
18	Z→42→23→17→Z	1	3
		Total distance:	459.27 km

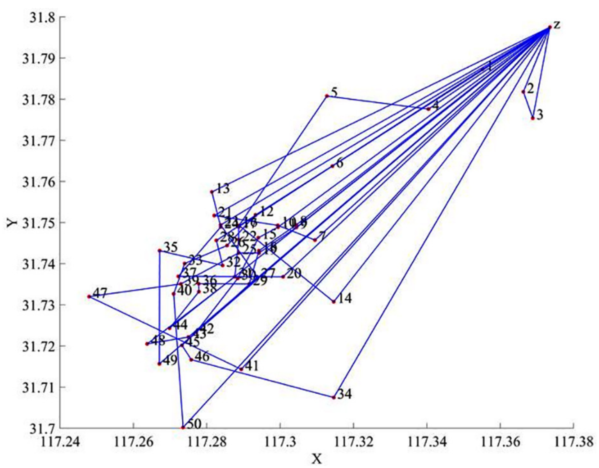

Figure 5. Route planning of single-type bicycle (8 t) in southern Baohe District

Table 3. Route planning of 8 t MSW collection and transportation vehicle in southern Baohe District

N	Driving route	Loading rate	Number of sites
1	Z→42→30→15→11→Z	0.995	4
2	Z→34→46→45→27→23→Z	0.962	5
3	Z→49→35→32→28→1→Z	0.983	5
4	Z→21→10→7→Z	0.998	3
5	Z→44→38→36→29→18→8→Z	0.995	6
6	Z→14→16→5→4→Z	0.870	4
7	Z→41→47→39→25→19→9→Z	1	6
8	Z→50→40→33→26→12→Z	1	5
9	Z→13→24→37→20→Z	0.997	4
10	Z→3→2→Z	0.748	2
11	Z→43→48→31→22→17→6→Z	0.985	6
		Total distance:	315.28 km

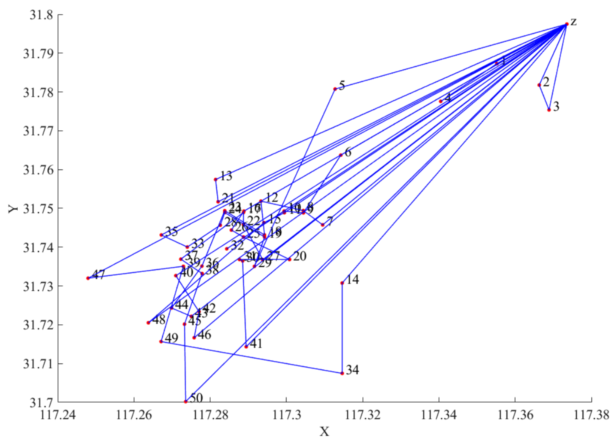

Figure 6. Results of the basic ant colony algorithm for multi-vehicle in the south area

Table 4. South multi-vehicle basic ant colony algorithm path planning table

N	Driving route	Loading rate	Sites number	Types
1	Z→4→1→Z	0.94	2	5 t
2	Z→21→13→Z	1	2	5 t
3	Z→48→15→11→Z	0.963	3	6 t
4	Z→32→10→9→6→Z	0.998	4	6 t
5	Z→3→2→Z	0.997	2	6 t
6	Z→47→39→49→34→14→Z	0.997	5	8 t
7	Z→50→45→38→37→17→22→27→Z	1	7	8 t
8	Z→42→46→40→Z	0.891	3	8 t
9	Z→35→33→28→24→19→29→5→Z	0.999	7	12 t
10	Z→41→30→31→20→25→26→16→Z	1	7	12 t
11	Z→43→44→36→23→18→12→8→7→Z	0.998	8	12 t
		Total distance: 300.74 km		

Case 3: A multi-vehicle collection and a transportation model was developed, using a combination of four different loadings of 5 t, 6 t, 8 t, and 12 t domestic waste collection vehicles to solve the vehicle path planning problem in the south area of the Baohe District, based an improved ant colony-shuffled frog hopping algorithm; the results are shown in Figure 7 and Table 5.

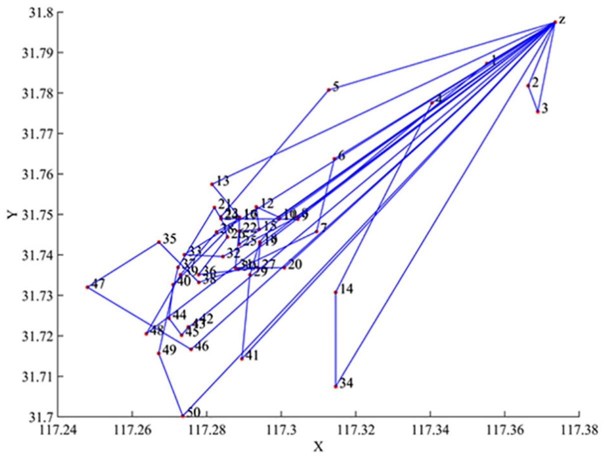

Figure 7. Route planning diagram of multi-vehicle in southern Baohe District

Table 5. Route planning table of multi-vehicle in southern Baohe District

N	Driving route	Loading rate	Sites number	Types
1	Z→34→14→4→Z	0.968	3	5 t
2	Z→33→32→8→Z	0.970	3	5 t
3	Z→41→29→18→11→Z	1	4	6 t
4	Z→3→2→Z	0.997	2	6 t
5	Z→48→39→28→17→25→Z	0.978	5	8 t
6	Z→19→27→36→26→23→5→Z	0.996	6	8 t
7	Z→20→31→22→15→12→10→Z	0.993	6	12 t
8	Z→42→43→45→44→40→16→13→Z	0.923	7	12 t
9	Z→50→49→37→21→24→9→1→Z	0.993	7	12 t
10	Z→46→47→35→38→30→7→6→Z	0.993	7	12 t
		Total distance: 280.98 km		

As seen from the table, the larger the load capacity of the vehicle, the longer the corresponding driving route. Additionally, the corresponding loading rate and the number of stops will be relatively high. This is because the larger the load capacity of the vehicle, the larger the amount of waste it can carry, and thus the more collection points the vehicle can pass through and the longer the collection path.

5.1.4. Comparative analysis of model and algorithm

In order to compare the differences between the two modes of single-vehicle type and multi-vehicle type collection, as well as the basic and improved ant colony algorithms, the results of the solved algorithms were compared and analyzed in terms of collection distance, average loading rate, number of collections, and average number of stations, respectively, as shown in Table 6.

Table 6. Comparison of results of different consignments in southern Baohe District

Cases		Distance (km)	Average loading rate (%)	Number of pick-ups and deliveries	Average number of sites
1	5 t type	459.27	93.64	18	2.7
	8 t type	315.28	95.77	11	4.5
2	multi-model	300.74	93.95	11	4.5
3	multi-model	280.98	98.10	10	5.0

As shown in Tables 2–6, a comparative analysis with different single-vehicle models, multiple-vehicle models, and basic ant colony algorithms is presented:

1. Comparison between single-vehicle models

As seen from Table 6, Case 1, when the single-vehicle type used was changed from 5 t to 8 t, the distance traveled by the vehicle in the collection was also reduced from 459.27 km to 315.28 km. In addition, the number of vehicle collections was reduced from 18 to 11, and the average loading rate and the average number of stops were increased from 93.64% to 95.77% and 2.7 to 4.5, respectively. It can therefore be concluded that when only a single vehicle type is selected for use in the collection, the higher the vehicle load capacity, the shorter the distance traveled throughout the collection process, with a concomitant increase in the average vehicle loading rate, along with a concomitant decrease in the number of collections and an increase in the average number of stops per collection route.

2. Single-vehicle versus multi-vehicle model

As shown in Table 5, when using the combination of multiple vehicle types for collection and transportation, the southern Baohe District needs to use the models with 5 t, 6 t, and 8 t to collect 2 times and the model with 12 t to collect 4 times respectively. Thus, the total number of collection and transportation is 10 times. Moreover, from the comparison of Case 1 and Case 2 in Table 6, it can be found that when using the combination of multiple vehicle types for collection and transportation, the total distance was reduced to 280.98 km. In addition, there was a reduction of 34.3 km and a reduction in the number of collection trips. Moreover, the average loading rate increased from 95.77% to 98.1%, with an increase of 2.33 percentage points. Conversely, the average number of stops increased to 5. Therefore, it can be concluded that the collection mode with multiple vehicle types performs better than the collection mode with a single vehicle type in transportation. In the multi-model collection mode, vehicles traveled a shorter total distance, completed fewer collection trips, had a higher average vehicle loading rate, and passed through a greater number of stops. When multi-vehicle modes minimize the distance traversed by the vehicles, they save collecting time and are less likely to incur time penalty fees, resulting in a lower relative total cost.

3. Comparison of basic and improved ant colony algorithms

From the comparison of Case 2 and Case 3 in the table, it can be found that the total collection distance obtained by solving using the improved ant colony algorithm was 19.76 km shorter than the result of the basic ant colony algorithm, and the average loading rate increased from 93.95% to 98.1%, with an increase of 4.15%. In addition, the number of stations on each collection path also increased, and the total number of collections decreased once. In conclusion, the improved ant colony algorithm outperforms the basic ant colony algorithm in every respect.

5.2. Algorithm application: northern Baohe District

In the example study in the south district of Baohe, it was determined that the multi-vehicle model of collection and transportation is superior to the single-vehicle model in terms of vehicle travel distance and average loading rate and that the improved ant colony algorithm solves better than the basic ant colony algorithm; consequently, for the domestic waste collection and transportation path planning problem in the north district of Baohe, the multi-vehicle model was chosen.

Figure 8 displays the results of the distribution of domestic waste collection points and OD distance analysis in the area for the 99 living communities that were selected for this study in the same manner as described in section 5.1.

Using a multi-vehicle collection model, the vehicle path planning problem for northern Baohe District was solved using a combination of four vehicle types with different loads of 5 t, 6 t, 8 t, and 12 t, as well as an improved ant colony-hybrid frog hopping algorithm; the results are depicted in Figure 9 and Table 7.

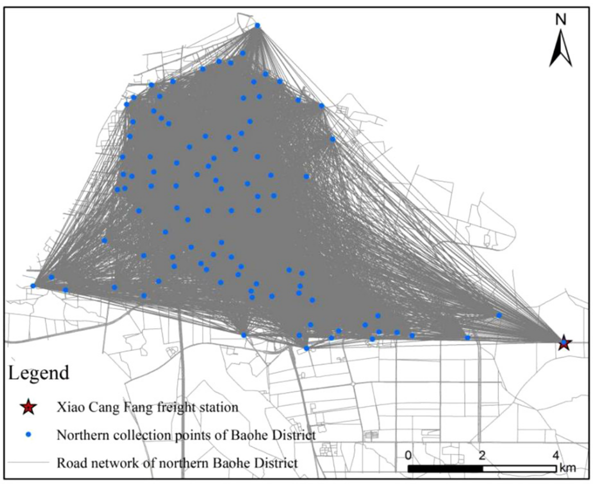

Figure 8. Analysis of OD distance between collection points and nodes in northern Baohe District

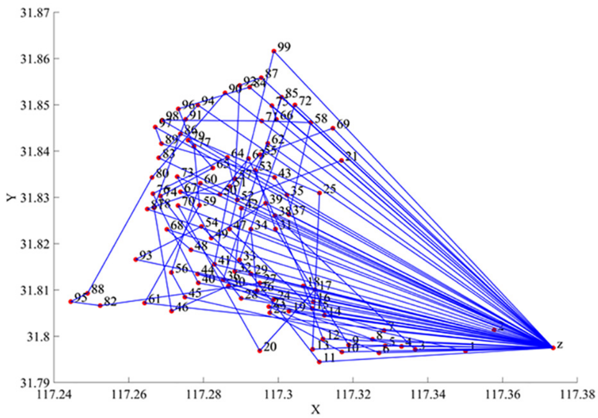

Figure 9. Route planning of multi-vehicle in the northern area

After five runs, the program's results were recorded, and the best one was chosen to produce Table 7 by comparing the collection distance, number of collections, average loading rate, and number of stations for each run. The best solution to the domestic waste collection and transportation path planning problem in the northern district of Baohe was found after compilation and summarization, as shown in Table 8. When the multi-vehicle model was used to collect household waste in the northern part of the Baohe District, as shown in Table 8, the total collection distance was 714.83 km, the average vehicle loading rate for all routes was 95.56%, and there were 18 collections, with 6 collection vehicles from the 5 t model, 6 from the 6 t model, 8 from the 8 t model, and 9 from the 12 t model being used. However, the final number of vehicles required for the collection process is not the number of vehicles for each model. For instance, if there are 6 of the 5 t vehicles that are required, only 1 of the 5 t collection vehicles can be used to complete 6 collections, or 2 of the 5 t vehicles can be used to 3 collections each, and so on.

Table 7. Route planning of multi-vehicle in northern Baohe District

N	Driving route	Loading rate	Site number	Types
1	Z→2→Z	0.616	1	5 t
2	Z→72→33→11→Z	0.906	3	5 t
3	Z→18→12→Z	0.98	2	5 t
4	Z→23→6→Z	0.998	2	5 t
5	Z→44→7→Z	0.962	2	5 t
6	Z→75→66→Z	0.994	2	5 t
7	Z→70→20→17→Z	0.995	3	6 t
8	Z→19→1→Z	0.997	2	6 t
9	Z→73→49→39→Z	0.957	3	6 t
10	Z→38→3→Z	0.985	2	6 t
11	Z→42→32→Z	0.983	2	6 t
12	Z→68→48→Z	0.993	2	6 t
13	Z→93→54→29→Z	0.918	3	8 t
14	Z→41→51→55→69→Z	0.961	4	8 t
15	Z→60→56→45→4→Z	0.968	4	8 t

End of Table 7

N	Driving route	Loading rate	Site number	Types
16	Z→81→57→92→87→Z	0.973	4	8 t
17	Z→34→26→Z	0.688	2	8 t
18	Z→85→36→24→22→10→Z	0.968	5	8 t
19	Z→99→47→15→Z	0.983	3	8 t
20	Z→62→53→31→9→Z	0.991	4	8 t
21	Z→79→65→74→28→Z	0.995	4	12 t
22	Z→83→86→25→86→13→5→Z	0.989	6	12 t
23	Z→40→76→64→52→21→Z	0.983	5	12 t
24	Z→61→59→77→96→84→Z	0.997	5	12 t
25	Z→94→91→78→46→30→8→Z	0.996	6	12 t
26	Z→97→89→43→35→14→Z	0.988	5	12 t
27	Z→90→80→88→95→82→27→Z	0.996	6	12 t
28	Z→98→71→58→37→Z	0.987	4	12 t
29	Z→67→50→63→16→Z	0.966	4	12 t
		Total distance: 714.83 km		

Table 8. Results of multi-vehicle routing planning in the north area of Baohe District

Total distance	Average loading rate	Number of pick-ups and deliveries	5 t type	6 t type	8 t type	12 t type
714.83 km	95.56%	18	6	6	8	9

5.3. Management insights

Taking into account the domestic waste collection route planning for the southern and northern districts of Baohe, the results of the domestic waste collection route planning for the entire district of Baohe District can be obtained based on the collection distance, average loading rate, number of collection trips, and use of various types of vehicles, as shown in Table 9. In Baohe District, we can see that the average loading rate is 96.83% and that the total collection path distance for household waste is 995.81 km. The collection of household waste in the district must be completed 28 times, 8 times for vehicles carrying 5 t and 6 t, 10 times for vehicles carrying 8 t, and 13 times for vehicles carrying 12 t. The management insights of this study can be summarized as follows:

1. The participation of IAC-SFLA reduce the transportation distances of vehicles. By optimizing the allocation of transportation resources, the utilization rate of vehicles can be improved, thereby reducing the number of vehicles. Therefore, it can save costs or resources and create higher profits for enterprises.

2. The participation of IAC-SFLA increase the average loading rate. Using multiple vehicle models for transportation will improve the utilization rate of transportation equipment, thereby improving transportation efficiency and service quality. Therefore, dynamically adjusting vehicle models and optimizing vehicle scheduling schemes can significantly improve the average loading rate, thereby reducing operating costs and environmental pollution.

3. The government and enterprises should strengthen cooperation. The government should encourage cross city, multi vehicle collaboration, and design resource saving and environmentally friendly transportation networks. Enterprises should use artificial intelligence and big data resource sharing platforms to reduce operating costs, improve cooperation efficiency, and promote the sustainable development of vehicle transportation networks.

Table 9. Summary of MSW collection and transportation route planning scheme in Baohe District

	Distance	Average loading rate	Number of pick-ups and deliveries	5 t type	6 t type	8 t type	12 t type
South	280.98 km	98.10%	10	2	2	2	4
North	714.83 km	95.56%	18	6	6	8	9
Total	995.81 km	96.83%	28	8	8	10	13

6. Conclusions

An improved ant colony-hybrid frog-jumping algorithm was used to solve the path-planning problem for urban household waste collection with capacity constraints for single and multi-model vehicles, and multiple perspectives were used to compare and contrast the various solutions. The conclusions are as follows:

1. Multi vehicle transportation is better than single vehicle transportation

In the homegrown waste assortment and transportation course arranging issue in the south region of Baohe, when contrasted and the single-vehicle assortment and transportation model, the assortment distance is decreased to 280.98 km, which is 34.3 km less contrasted and the single-vehicle model, and the quantity of assortments is diminished by 1 time; The average loading rate rises by 2.33 percentage points, from 95.77% to 98.1%; and there were now an average of 5 stations. Consequently, in the metropolitan waste assortment course arranging issue, the assortment model with numerous vehicles outflanks the single vehicle assortment model as far as assortment distance, normal stacking rate, number of assortments, and a normal number of stations.

2. The fusion algorithm is superior to a single algorithm

When compared to the basic ant colony algorithm for solving the domestic waste collection path planning problem in the south district of Baohe, the improved ant colony algorithm yields a total collection distance that is 19.76 km shorter and an average loading rate that rises by 4.15% from 93.95% to 98.1%; The total number of collections decreases by one, but there is an increase in the number of stations on each collection path. As a result, the improved ant colony algorithm performs better than the basic algorithm in every way.

3. The participation of IAC-SFLA increase the average loading rate and reduce the transportation distances of vehicles

The average loading rate for domestic waste is 96.83%, and the total collection and transportation path distance for the district of Baohe is 995.81 km. In order to complete the collection and transportation of domestic waste throughout the entire district, 28 times are required–8 times for vehicles weighing 5 t and 6 t, 10 times for vehicles weighing 8 t, and 13 times for vehicles weighing 12 t. It is demonstrated that the fusion of the improved and shuffled Frog Leaping Algorithms can be used to solve the domestic waste collection path planning problem, making the improved ant colony-shuffled Frog Leaping Algorithm feasible and generalizable.

Future studies will be focused on planning the collection and transportation routes of rural household waste. In order to accelerate the convergence speed of the algorithm, we suggest studying other optimization algorithms and comparing them with the algorithm in this paper.

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Conflict of interest

The authors declare no conflict of interests.

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