Optimization of Garbage Collection and Transportation Paths Based on Hybrid Element Heuristic Algorithm in Low-Carbon Perspective: The Case of Wuhan City

Yalong Wang ,Zhongning Fu, Jinling Shi, Zhiyue Ou

***Abstract*—To address the issue of urban "garbage siege" and promote low-carbon garbage collection and transportation, this study constructs a garbage collection and transportation optimization model that integrates vehicle capacity and time window constraints, aiming at minimizing fixed costs, operating costs and carbon emission costs. The study introduces the carbon tax mechanism and analyzes the effects of vehicle weight and load on fuel consumption and carbon emissions. Aiming at the NP-hard nature of the problem and the dynamic characteristics of carbon emission, a variety of large-neighborhood search operators for destruction and repair solutions are designed, and the destruction-repair large-neighborhood search operators are integrated into the improved genetic algorithm in order to enhance the algorithm's global search capability, and to improve the efficiency and accuracy of the solution. Meanwhile, a sensitivity analysis of the carbon tax price was conducted to explore its impact on cost-effectiveness. The empirical analysis is based on the waste collection and transportation data of a transfer station in Wuhan City, Hubei Province, to verify the effectiveness of the model and algorithm. The results show that, with the proposed optimization strategy, the waste collection distance is reduced by 7.3% compared with the pre-optimization period, and the carbon emission cost and collection cost are reduced by 1.28% and 1.33%, respectively. This work provides a scientific framework for optimizing urban waste logistics, offering significant economic and environmental benefits.**

Index Terms*—*waste collection and transportation optimization, low carbon-based transportation, hybrid meta-heuristic algorithm, carbon tax.

Manuscript received August 19, 2024, revised March 22, 2025.

This research was supported by The Major Special Projects of Science and Technology in Gansu Province, (No. 25ZDFA010), The National Natural Science Foundation Regional Science Foundation Project(No. 71961016), The Natural Science Foundation of Gansu Province, China(No. 20JR10RA245), Project supported by the National Natural Science Foundation, China(No. 51468035).

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I. INTRODUCTION

WITH the rapid development of China's economy and urbanization at the beginning of the 21st century, municipal solid waste production has shown a significant growth trend, with an annual output of more than 100 million tons. This growth has led to the phenomenon of "garbage surrounding the city," which has gradually become a major factor threatening the health of citizens and severely restricting the sustainable development of cities. The Chinese government has implemented several waste separation policies to address this challenge and promote resource conservation and environmental protection. However, the implementation of waste separation has been inconsistent across the country, especially in remote areas, where irrational mixing of waste collection and transportation is still prevalent, reducing the efficiency of resource recycling and exacerbating the problem of environmental pollution. In addition, the waste collection and transportation cost has accounted for more than half of the total management cost above, highlighting the urgency of optimizing vehicle routes and staffing.

The sorted garbage collection path problem, essentially the Vehicle Routing Problem (VRP), was first proposed by Dantzig et al. (1959). This problem encompasses various constraints, including vehicle capacity and time constraints[1]. To address these challenges, researchers both domestically and internationally have conducted extensive studies on methods to optimize path selection, aiming to enhance operational efficiency and cost-effectiveness by incorporating environmental and economic considerations.

Ahkamiraad et al. (2018) modeled the vehicle routing challenge with capacity and scheduling constraints, utilizing multiple intersecting bins and incorporating hybrid genetic and particle swarm algorithms for its solution[2]. Lahyani et al. (2019) introduced an adaptive large-neighborhood search strategy, integrating a local optimization approach within a hybrid meta-heuristic framework to enhance problem-solving efficiency. They demonstrated the effectiveness of this methodology through computational experiments[3]. Hu et al. (2018) designed a strategy combining an improved genetic algorithm for global search and simulated annealing for local optimization to solve the problem based on the demand-splittable problem to minimize the total distance with vehicle capacity constraints[4]. Matijević et al. (2024) used a mixed integer programming model to solve the asymmetric vehicle path problem. Path optimization is performed by meta-heuristic algorithms such as Multi-Start Local Search (MLS), Greedy Random Adaptive Search Procedure (GRASP), and Generalized Variable Neighborhood Search (GVNS). The results show that GVNS performs well in improving the efficiency and quality of the solution and can effectively deal with complex transportation optimization requirements[5]. Rizkiani et al. (2024) investigated the vehicle path problem for multiple trips and simultaneous deliveries and pickups of buckets of water. The model was solved using a forbidden search algorithm combining Saving Matrix and Nearest Neighbor, and the results showed a significant cost reduction. In addition, through sensitivity analysis, the study evaluates the specific impact of different operations on the cost, thus enhancing the robustness and adaptability of the model[6].

With increasing environmental protection awareness, the green vehicle path problem has received extensive attention from scholars, intending to save energy and reduce emissions through rational scheduling and different path optimization strategies. Xiao et al. (2017) addressed the constraints of urban subregions and vehicle types, formulating a path optimization model that minimizes carbon output and transportation costs, and introduced a variable domain search algorithm for solving the model[7]. Zhou et al. (2023) examined the impact of incident speed and real-time load variations on carbon emissions, and developed a dual-objective green vehicle path model that incorporates time-dependent and simultaneous delivery constraints, alongside a hybrid algorithm based on NSGA-II and extensive neighborhood search techniques for model resolution[8]. Cui et al. (2023) considered the problem of non-mixing of some goods in the distribution process and classified three types of priority delivery: non-priority pickup and delivery, non-priority pickup, and delivery according to customer demand. They established the green VRP model of priority delivery with the minimum total cost and developed a hybrid heuristic approach to address the challenge[9]. Zhai et al. (2024) introduced a snow-melt heuristic algorithm to optimize the green low-carbon logistics path, which improved the convergence speed and reduced the local optimum problem. The cost is reduced, and a well-designed objective function minimizes environmental impact. The efficiency and practicality of the algorithm were validated using simulation-based assessments[10]. Jabir et al. (2017) developed an integer linear programming model integrating economic and environmental objectives to optimize green logistics paths, resulting in a dual optimization of costs and environmental impacts[11]. Peng et al. (2021) addressed the passenger route optimization problem using a Genetic Algorithm (GA) and Monte Carlo simulation, incorporating constraints such as travel cost, number of interchanges, and the goal of minimizing the total travel time[12]. Mu et al. (2022) optimized the multi-warehouse green vehicle path problem with an improved adaptive large neighborhood search algorithm (ALNS), with a special introduction of the destruction operator to reduce carbon emissions. The algorithm was shown to significantly improve the computational efficiency and accuracy through simulation experiments[13].

MCVRP, a combinatorial optimization problem derived from VRP, is particularly difficult to solve. Ilon et al. (2017) proposed a two-stage task path optimization algorithm that generates tasks in the first stage, assigns characters in the second stage. They enhanced a genetic approach to optimize the assignment problem and validate the algorithm's efficiency[14]. Reed et al. (2014) applied the ant colony optimization method to the multi-compartment vehicle routing problem, solving the vehicle path optimization challenge with capacity constraints for household waste collection, and suggested that k-means clustering significantly enhances solution efficiency[15]. Akhtar et al. (2017) introduced an enhanced backtracking search algorithm that employs the bright bin concept to identify the optimal waste collection routing solution for the capacitated VRP[16]. Liu et al. (2024) developed an optimization model aimed at reducing vehicle, energy, and cooling costs for the multi-compartment electric vehicle routing problem (MCEVRP-PP). The model utilizes an innovative hybrid ant colony optimization (HACO) technique, which notably improves path planning flexibility, lowers operational costs, and boosts vehicle utilization efficiency[17]. Li et al. (2023) clustered waste nodes based on the spatiotemporal distribution pattern, introduced a carbon tax system to evaluate carbon emissions, and developed a low-carbon waste management model aimed at minimizing overall costs. They also designed an enhanced ACO algorithm to solve the model[18]. Xiao et al. (2023) introduced a multi-cycle and multi-compartment vehicle routing model for waste sorting and collection. The goal of this model is to minimize total costs while considering factors such as timeliness and the multi-compartment nature of the vehicles. They employed an enhanced adaptive large neighborhood search (ALNS) method, structured in two stages, to solve the problem[19]. Rattanawai et al. (2024) optimized the waste collection routes for the northern Thailand region of Khao Kho and proposed a differential evolutionary approach to address the model[20].

The Multi-Compartment Vehicle Routing Problem with Time Windows (MCVRPTW) extends the classical Multi-Compartment Vehicle Routing Problem (MCVRP) by incorporating time window constraints. Zhou et al. (2021) analyzed the effect of vehicle load on carbon emissions and developed a green waste collection and transportation optimization model to determine the shortest route while minimizing emissions. Additionally, they introduced an enhanced DMBSO approach to refine the model's performance, verifying its robustness and applicability[21]. Shen et al. (2024) proposed a two-layer optimization model to address the siting and routing challenges in medical waste management and transportation, utilizing simulated annealing and an improved harmonic search algorithm. The model integrates the reliability assessment of loading and travel time, effectively improving the system's safety and efficiency[22]. (Peña D et al., 2024) integrated battery range and load limitations into a waste collection optimization model and developed an energy consumption model that combined route height, vehicle speed, and collection operations. By optimizing the routes with a genetic algorithm, the model significantly improves efficiency in applications in New York City and Puerto Real[23].

The Flexible Multi-Cabin Vehicle Routing Problem with Time Windows (FMCVRPTW) extends the MCVRPTW, adapting it to the specific requirements of waste collection and transportation in China. This study develops an optimization model using mixed integer linear programming, leveraging waste collection and transportation data from a transfer station in Wuhan, Hubei Province. The model aims to minimize operational costs and carbon emissions, while also addressing the complexities of municipal solid waste management and the NP-hard nature of the problem. It combines an enhanced genetic algorithm with an adaptive neighborhood search strategy, improving solution efficiency. The integrated carbon tax mechanism examines the impact of vehicle loads on energy consumption and carbon emissions, with the goal of reducing fuel use and CO2 output. The model's performance was tested in practical scenarios, showing that the proposed approach can significantly lower both operating costs and carbon emissions.

In contrast, the visualization results of the vehicle scheduling optimization scheme show the effectiveness and adaptability of the designed algorithm. This research supports constructing a "double carbon target" and "garbage-free city." It provides complete garbage collection and transportation solutions for sustainable urban development and environmental protection.

The main contributions of this paper are as follows:

(1) We examine the components of each optimization objective, establish an FMCVRPTW model, and introduce a carbon tax mechanism to promote low-carbon operation.

(2) A hybrid technique combining genetic algorithms and adaptive neighborhood search (GA-ALNS) is applied to tackle the optimization task. The results demonstrate a significant improvement in solution efficiency and quality. Solomon's standard case test confirmed the superiority of the GA-ALNS in optimizing waste collection and transportation.

(3) An empirical analysis using Wuhan as an example shows that the optimized system effectively reduces operation cost, driving distance, and carbon emissions, which has significant economic and environmental benefits.

II. Problem Description and Model

A. Problem Description

The low-carbon collection path optimization problem for garbage vehicles with flexible compartments can be described as follows: a garbage transfer station is known to have a collection vehicle, S, responsible for collecting domestic garbage in a particular area. In a time cycle, one or more vehicles with flexible compartments (Vehicles, with adjustable compartments) Vehicles are assigned to each drop-off point to collect various types of waste, while both the transfer station and drop-off locations are bound by specific time windows. After collecting waste from all points, vehicles return to the transfer station, ensuring compliance with capacity and scheduling requirements. In this context, a waste collection optimization model with flexible compartments is developed to minimize vehicle operating costs, fixed expenses, and carbon emissions.

B. Problem Assumptions

Considering the complexity of the actual situation and the solvability of the model, the following key assumptions are made to simplify the problem and ensure the rationality of the model:

1) There is only one garbage transfer station in the region responsible for all the garbage drop-off points.

2) All the garbage collection vehicles start and end at the garbage transfer station, i.e., they start from the garbage transfer station, visit each garbage drop-off point, and return.

3) Each vehicle travels at a constant speed with no road irregularities.

4) The waste equivalent generated at the drop-off points is always less than their maximum capacity limit and does not exceed the maximum vehicle load limit.

5) Multiple drop-off points can be visited by one vehicle, but each can be visited by only one vehicle.

6) The bulkhead adjustment time of the refuse collection vehicle is fixed and negligible.

C. Symbols Definition

A detailed description of the sets and variables involved is required before constructing the FMCVRPTW model. The relevant definitions are given below.

Sets

- N: the set of garbage drop-off points and waste transfer stations, N = {0,1,2,3,..n,n+1}, where 0 denotes the waste transfer station and n+1 denotes the virtual waste transfer station returned after each visit to the garbage drop-off point
- I: the set of garbage drop-off points, I = {1,2,3,..n}
- K: the set of vehicles
- E: the number of times each vehicle travels, E={1,2,..e}
- D: the set of four garbage, D = {1,2,3,4}

Parameters

- f_k: fixed costs for vehicle k (*CNY*)
- η: time taken to load unit volume of waste (*min/kg*)
- t_{ij}: time consumed by a vehicle driving away from node i to reach node j (*min*)
- Q: maximum vehicle weight (*kg*)
- ε : CO_2 emission factors (*kg/L*)
- P: unit fuel price (*CNY/L*)
- μ : carbon emissions per unit of waste collected and transported, per unit of distance traveled (*kg/km*)
- u^l_{ike}: type l waste loading at trip e when vehicle k leaves node i (*kg*)
- q^d_j: current quantity of garbage awaiting transportation at drop-off point j (*kg*)
- w_{ike}: the moment when vehicle k reaches node i in the e^{th} trip (*min*)
- $\gamma(u^l_{ike})$: fuel consumption per unit distance for category l waste loads as the waste collection vehicle drives away from node i and during the drive towards node j (*L/km*)

Decisionvariables

- x_{ijke}: If vehicle k drives from node i to node j for the e^{th} time, x_{ijke} =1; otherwise $x_{ijke} =0$.
- G_k: The k^{th} garbage collection vehicle is in service,then G_k =1; otherwise G_k =0.

D. Optimization Objective Definition

In this section, we examine the optimization goals. One of the primary objectives is to minimize fixed costs, which encompass vehicle maintenance, depreciation, and employee wages, irrespective of distance and time. The total cost is defined as:

$$\mathrm{E}_1 = f_k \sum_{k=1}^{K} G_k \tag{1}$$

The second objective function is the transportation cost of the garbage collection vehicle, which is mainly related to fuel consumption and transportation distance. The fuel consumption per unit collection distance of the garbage collection vehicle is mainly related to the garbage's loaded weight at the time of collection[24], so the fuel consumption when the vehicle's loaded weight is X is defined in equation (2). The total transportation cost is shown in equation (3).

$$\gamma(X) = \frac{\gamma_1 - \gamma_0}{Q} * X + \gamma_0 \tag{2}$$

Where: γ_1 and γ_0 are the fuel consumption per unit collection distance for fully loaded and unloaded refuse collection vehicles, respectively; X is the vehicle's load capacity.

$$E2 = \sum_{k\in K}\sum_{e\in E}\sum_{(i,j)\in A} p * \gamma(u_{ike}^{l}) * d_{ij} * x_{ijke} \tag{3}$$

Where: p is the current fuel price, is the fuel usage per distance for the k^{th} collection vehicle performing its e^{th} trip from node i to load class l unit weight of waste.

The main objective is to minimize carbon emission cost. A vehicle's carbon output is closely linked to its fuel consumption and fuel type. To estimate a vehicle's carbon emissions during operation, a carbon emission factor is introduced to convert fuel consumption directly into carbon output, thus facilitating the conversion from fuel usage to carbon emissions:

$$H_1 = \gamma\left(u_{ike}^{l}\right) * \varepsilon * d_{ij} \tag{4}$$

Emissions of CO_2 from waste decay during collection and transportation are also related to transportation distance and loading capacity.

$$H_2 = \mu * u_{ike}^{l} * d_{ij} \tag{5}$$

Therefore, from equation (4) and equation (5), the total carbon emission cost is:

$$E_3 = C_c * \sum_{(i,j)\in A}\sum_{k\in K}\sum_{e\in E}\left(\gamma\left(u_{ike}^{l}\right) * \varepsilon + \mu * u_{ike}^{l}\right) * d_{ij} * x_{ijke} \tag{6}$$

Where: C_c is the price per unit of carbon tax; ε is the carbon emission factor; μ is the CO_2 emission per unit of waste decay per unit distance traveled by the vehicle.

The objective function for the FMCVRPTW model is defined in equation (7).

$$E = E_1 + E_2 + E_3 \tag{7}$$

E. Mathematical Model

Based on the hypothetical situation, a mathematical model is developed to minimize the total costs, including vehicle fixed costs, operating expenses, and carbon emissions.

Minimize E

Constraints:

$$\sum_{i\in I} x_{0ike} = x_{in+1ke}, \forall k \in K, e \in E \tag{8}$$

$$\sum_{i\in I} x_{0ike} = 1, \forall k \in K, e \in E \tag{9}$$

$$\sum_{i\in I} x_{in+1ke} = 1, \forall k \in K, e \in E \tag{10}$$

$$\sum_{i,j\in N, i\neq j} x_{ijke} - \sum_{j,h\in N, j\neq h} x_{jhke} = 0, \forall k \in K, e \in E \tag{11}$$

$$\sum_{k\in K}\sum_{e\in E}\sum_{j\in N\setminus\{0\}} x_{ijke} = 1, \forall i \in I \tag{12}$$

$$\sum_{i,j\in N, i\neq j\setminus\{0\}}\sum_{e\in E} x_{ijke} \le |S| - 1, \forall k \in K, 1 \le |S| \le I \tag{13}$$

$$\left(u_{ike}^{l} + q_j^{l}\right) * x_{ijke} = u_{jke}^{l}, \forall i \in N, j \in N\setminus\{0\}, k \in K, e \in E, l \in L \tag{14}$$

$$u_{ike} \le Q, \forall i \in N, k \in K, e \in E, l \in L \tag{15}$$

$$\sum_{l\in L} u_{ike}^{l} \le Q, \forall i \in N, k \in K, e \in E, l \in L \tag{16}$$

$$a_i \le w_{ike} \le b_i, \forall i \in N, k \in K, e \in E \tag{17}$$

$$w_{ike} + \eta * \sum_{i\in L} q_i^{l} + t_{ij} - w_{jke} \le \left(1 - x_{ijke}\right) * M, \forall i, j \in N, k \in K, e \in E \tag{18}$$

Equation (7) represents the objective function, aiming to minimize the total collection cost. Equation (8) states that each vehicle trip must depart from the waste transfer station and eventually return. Equations (9)-(10) indicate that each vehicle trip departs from the waste transfer station to a certain waste drop-off point and eventually returns to the waste from a specific drop-off point transfer station. Equation (11) defines the vehicle flow balance, where the number of vehicles visiting a node matches the number of vehicles departing from it. Equation (12) denotes that each waste drop-off point is visited only once; Equation (13) denotes the elimination of the sub-loop, where |S| is the set of waste drop-off points. Equation (14) denotes that the amount of garbage loaded by each vehicle leaving point j on each trip is the sum of the amount loaded when leaving point i and the current amount of garbage transported at node j. Equation (15) shows that the amount of waste per vehicle trip will not exceed its maximum capacity. Equation (16) shows that the total garbage loaded onto the vehicle will not exceed its maximum capacity for any trip from a collection point. Equation (17) indicates that the vehicle's arrival at each node is subject to meeting the scheduling constraints to reach each node before the deadline. Equation (18) defines the continuity of the travel time for refuse collection vehicle k, where the time to reach point j equals the time of arrival at point i, the time spent loading refuse at point *i*, and the travel time between points *i* and *j*, with *M* being an integer tending to positive infinity.

III. Hybrid Genetic Adaptive Large Neighborhood Search Algorithm

A. Outline of GA-ALNS

To tackle the distinct characteristics of the waste collection model, particularly the complexity of the solution space, this paper proposes a hybrid algorithm combining genetic algorithms (GA) with adaptive large neighborhood search (ALNS) to solve the problem. The algorithm takes advantage of the strengths of both GA and ALNS, with GA serving as the central component of the framework, guiding the search during the initial stages of each evolutionary cycle. The solution space is systematically explored through key genetic operations such as selection, crossover, and mutation, with the individual exhibiting the highest fitness being selected for further iterations.

This process not only promotes the maintenance of population diversity but also provides a favorable starting point for subsequent searches; then, the highest fitness individuals obtained in the genetic algorithm are used as the initial solution for the adaptive extensive neighborhood search; finally, the "individual replacement" strategy is carried out, and the improved solution of the ALNS algorithm is used to replace the lower fitness individuals in the population in the GA. Ultimately, the enhanced solution from the ALNS algorithm replaces the less suitable individuals within the genetic algorithm, creating a new population. This process not only boosts the overall quality of the current population but also strengthens the algorithm’s ability to escape local optima, continuing to iterate until it converges to the optimal solution or reaches the predefined maximum iteration limit.

The hybrid genetic adaptive large neighborhood search algorithm (GA-ALNS) developed in this study, leverages the strengths of both algorithms., aiming to make full use of the complementary advantages of the two methods in global and local search to achieve more efficient and accurate optimization results. GA-ALNS is designed to introduce an advanced adaptive mechanism to select the best-performing operator in each generation for solution transformation by dynamically updating the operator weights. This strategy optimizes the decision path in the search process and significantly improves the quality of the solution. The specific algorithm flow is shown in Fig. 1.

B. Chromosome Code

For the waste collection path optimization problem, the chromosome is encoded using real number coding to reflect the waste collection network's structural characteristics accurately. In the proposed coding strategy, 0 represents the garbage transfer station, while the consecutive integer sequences 1, 2, ..., n-1, and n represent the individual trash drop-off points, respectively. For example, the chromosome "013502460" represents that the refuse transfer station sends two vehicles to six drop-off points to collect refuse, forming two refuse collection routes. Route 1: 0-1-3-5-0; Route 2: 0-2-4-6-0. When the number of refuse transfer stations is n, and the number of vehicles used is k, the length of the chromosome is n+k+1.

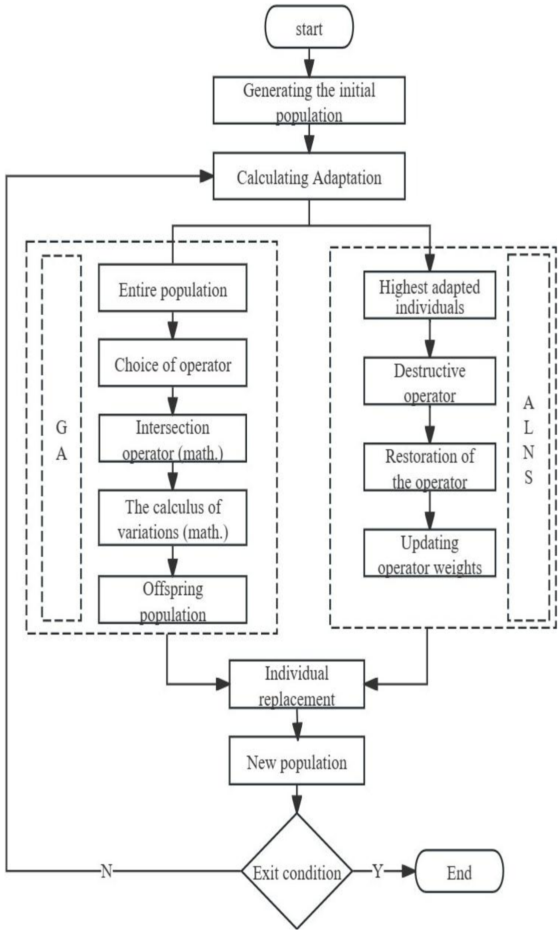

Fig. 1. Flow of hybrid Genetic Adaptive Large Neighborhood Search Algorithm (GA-ALNS)

C. Population Initialization and Adaptation

In the research and application of GA, population initialization is one of the key factors determining the efficiency and accuracy of the algorithm, which, as the starting point of the algorithm's evolutionary process, significantly impacts the subsequent iteration process. Reasonably determining the population size is an important step in realizing the optimization of the algorithm, which is directly related to the algorithm's convergence speed and computational accuracy. Generally speaking, the standard population size is set in the range of 30 to 150. Too large a size may lead to an excessive computational burden. At the same time, a size that is too small may lead to insufficient search capability, which will negatively impact the algorithm's computational efficiency. The random function generation method is employed to efficiently create the initial population, reducing both population generation time and computational complexity. This approach is applied here to form an initial population of 100 individuals, striking a balance between population size and optimization performance.

Genetic algorithms evaluate the quality of individuals using a fitness function. A higher fitness value indicates a better individual, while a lower fitness score corresponds to lower quality, leading to gradual elimination in subsequent algorithm iterations. Fitness is also utilized to handle the model's constraints, with violations addressed through a penalty function approach. Key constraints include vehicle load, time windows at collection points, and carbon emission costs. These constraints are incorporated into the objective function via a specific penalty function, resulting in an objective function that integrates the constraints. As indicated in equation (7), to ensure the load weight constraint is met, M is chosen as a sufficiently large positive number, making the objective function value of any chromosome that violates the constraint extremely large. The fitness function is based on the inverse of the objective function, as demonstrated in equation (19).:

$$fit(i) = 1/E_i \tag{19}$$

Where: $fit(i)$ is the fitness value of individual i and E_i is the objective function value of individual $\boldsymbol{i}$.

D. Elite Retention Strategy

This study employs an elite retention strategy to preserve the high-quality genes of the parent generation, preventing them from being disrupted by subsequent crossover and mutation operations, i.e., the fitness is sorted in descending order to preserve the first 1/3 of the excellent individuals in each generation, which reduces the risk of the excellent solutions being lost due to the random operations, thus enhancing the algorithm solving efficiency.

E. Crossover

We use the step-crossover operator to randomly select the garbage collection vehicle's complete subpath containing the parent individuals' start and endpoints. The left shift operation is executed on the sub-paths of the two selected individuals so that they are placed at the forefront of their respective individuals. Then, the exchange and fusion of genetic information is realized, i.e., the gene sequences after the sub-paths of one individual are copied to the other. The genes that recur are deleted to form two new individuals. The specific operation is shown in Fig. 2. After the crossover operation is completed, the newly generated individuals also need to be evaluated, i.e., the fitness is ranked in descending order to ensure that the individual with the highest fitness is selected and retained in each generation, which improves the convergence rate of the algorithm and the quality of the solution.

F. Mutation

This paper uses the 2-swap mutation operator to perform mutation operations on a single chromosome. Two non-zero genes are randomly picked from the chromosome, and the values at these positions are swapped to form a new chromosome. The process is illustrated in Fig. 3. To increase the diversity and quality of the solution, the mutation is repeated and implemented several times to produce a series of new chromosomes. Using a combination of crossover and mutation operations ensures a high level of fitness for individuals in each population generation.

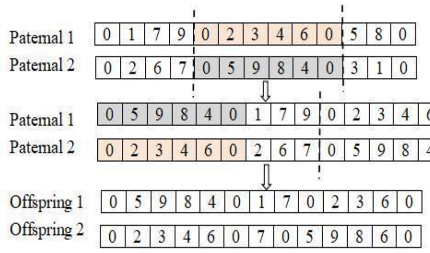

Fig. 2. Schematic diagram of the step-crossing operator

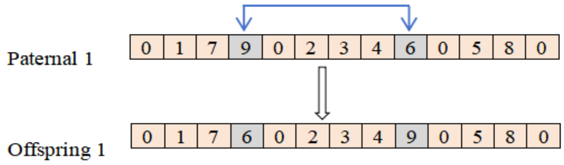

Fig. 3. 2-swap mutation operator

G. Local Search

The essence of the ALNS algorithm lies in employing a variety of neighborhood search operators, which enhance the algorithm's ability to perform comprehensive searches and fully explore the solution space.This paper introduces three kinds of destruction and four kinds of repair operators. We adopt a dynamic strategy to search for neighborhood solutions by continuously perfor-
ming destruction and repair operations on individuals [25].

(1) Destruction operators

①Random removal: A random perturbation strategy is utilized to broaden the search for the global optimum by expanding the exploration of the solution space. The route with the highest cost in the current solution set is selected, and then a garbage drop is randomly removed from that route to be deposited in remove_list, and the path is updated accordingly. The process continues until the set number of removal points is achieved.

② Worst-cost removal: Optimize cost efficiency by removing the node with the most significant impact on the route cost. Calculate the amount of change in the objective function before and after each garbage drop point is removed, and select the garbage drop point that maximizes the difference in the objective function for removal. Repeat the removal operation until the preset number of removal points is reached.

③ Longest Time Removal: The core of this operator is to identify and remove the nodes in the current route that significantly impact the total travel time. Tentatively evaluate the nodes on the route one by one and quantify the reduction in travel time after each node removal. Continuously update the route until a predetermined node removal goal is reached.

(2) Repair operator

① Random Repair: As with random removal, a random insertion strategy is used to randomly reinsert the garbage drop points in remove_list into the solution to form a new solution in the corrupted solution.

② Greedy repair: A point from the remove_list is randomly selected, and its cost is analyzed for all potential insertion locations in the current route. By selecting the location with the smallest increase in the total cost of the route for insertion, the repair operation is performed continuously until all points in the remove_list are reinserted.

③Regret repair: This operator's core lies in its integrated consideration of the dual objectives of short-term cost optimization and long-term cost impact. The specific strategy is to evaluate each garbage drop point in remove_list and calculate the amount of change in the objective function when inserted at the route's suboptimal position. The point that maximizes the change in the objective function and its insertion location is selected for the restoration operation.

(3) Adaptive operator weight update strategy

Assign the same weight and score for each operator, and all are 1, and score according to the operator's performance; the higher the score of the operator, the better the performance. At the same time, the decay coefficient p is set reasonably to balance the relationship between the solution time and weight update [26]. The adaptive operator weights are updated as shown in equation (20).

$$\theta(a) = \begin{cases} \theta(a), & h(a) = 0 \\ (1-p) * \theta(a) + p * \left(\dfrac{s(a)}{h(a)}\right), & h(a) > 0 \end{cases} \tag{20}$$

Where: $\theta(a)$ is the weight, $s(a)$ is the cumulative score, $h(a)$ is the cumulative number of times used.

IV. Algorithm Performance Verification

A. Experimental and parameter settings

This algorithm was coded using Matlab R2018b. The computer is configured with 11th Generation Intel(R) Core(TM) i5-1155G7 @ 2.50GHz. In order to verify the superiority of the proposed algorithm, this paper experimentally compares GA and ALNS with the hybrid algorithm GA-ALNS. To ensure the fairness of the results and the rigor of the parameter comparison, the parameter settings of the GA-ALNS algorithm are consistent with those of the GA and ALNS algorithms. The initial parameters of GA are set as follows: population size gene Num = 100; iteration number generation Num = 500; variance probability P_c = 0.05; crossover probability P_m = 0.9. ALNS search range N_r =5, weight inertia Factor Υ=0.6.

B. Test instances

In order to verify the performance of the designed hybrid genetic algorithm Adaptive Large neighborhood search (GA-ALNS) algorithm, this paper uses the Solomon standard algorithm set for testing (Solomon standard algorithm set: http://web.cba. neu.edu/~msolomon/problems .htm). These datasets are randomly generated based on specific distributional characteristics and contain information such as each point's X and Y coordinate axes, the number of customers and their demands, vehicle numbers, and license plate numbers. According to the distribution types, Solomon datasets can be categorized into three types: R-type with random distribution of customer points, C-type with aggregated customer points, and RC-type with both.

To avoid the influence of the distribution type of customer points on the algorithm's performance, nine cases of the top 20, 50, and 100 scales in the three categories of C101, R101, and RC101 are selected from the Solomon standard set of cases, respectively. The objective function is set to include vehicle fixed costs and transportation costs.

C. Results on FMCVRPTW

The three algorithms GA, ALNS, and GA-ALNS are used to run the above nine algorithms 10 times, respectively, and the results are shown in Table I. Where the first column is the number of the algorithm, the second column is the algorithm, e.g., the algorithm C101-20 represents the first 20 customer points in Solomon's standard set of algorithms, Min represents the optimal solution obtained in the 10 runs of the algorithm, Avg represents the average value of the results of the 10 runs, and rate represents the rate of performance improvement in terms of the average value of the GA-ALNS algorithm relative to the other algorithms.

As can be seen from Table I, the designed GA-ALNS algorithm demonstrates excellent performance in the nine standard arithmetic cases. Regarding Min and Avg, when the problem size is small, the GA-ALNS algorithm and ALNS algorithm have similar performance, significantly better than GA. On the other hand, on larger problem sizes, the GA-ALNS algorithm is better in optimal value search, and its average performance is also excellent. The GA-ALNS algorithm proposed in this paper combines the advantages of the two algorithms, GA and ALNS, to maintain efficient searchability and accuracy in problems of different scales and effectively improve the solution quality. Therefore, the GA-ALNS algorithm outperforms the GA and ALNS algorithms in solving the FMCVRPTW problem.

D. Stability analysis of the proposed algorithm

In this section, we systematically analyzed the stability of the proposed GA-ALNS algorithm. We evaluated its performance in different types of instances (i.e., class C (clustering), class R (random), and class RC (random and clustering combination)). We compared it with the existing genetic algorithm (GA) and adaptive large neighborhood search algorithm (ALNS). The comparison results are shown in Fig. 4. Experimental results show that the GA-ALNS algorithm has a significantly lower mean standard deviation in all instance types, showing superior stability and reliability.

Specifically, in class C instances, the average standard deviation of the GA-ALNS algorithm is 9.13, significantly lower than that of the traditional GA algorithm (13.40) and ALNs algorithm (12.10). This significant decline shows that the GA-ALNS algorithm shows excellent stability and accuracy when dealing with cluster scenarios, especially when it is necessary to maintain the consistency of solution quality. In class R instances, the performance of the GA-ALNS algorithm is further improved, and its average standard deviation is 8.49, which is 3.68 and 3.27 lower than GA (12.17) and ALNS (11.76), respectively, which fully shows the dual advantages of efficiency and reliability of GA-ALNS in dealing with random scenes. In these random scenarios, the robustness and stability of the algorithm are particularly critical due to the increased uncertainty and var-

TABLE I
COMPARISON OF GA-ALNS WITH GA AND ALNS ALGORITHMS ON DIFFERENT SIZES OF LITTERING SITES

num	formula	GA-ALNS		GA			ALNS		
		Min/km	Avg/km	Min/km	Avg/km	rate/%	Min/km	Avg/km	Rate/%
1	C101-20	155.4	155.4	163.1	168.4	8.3	159.3	164.7	5.9
2	R101-20	473.3	473.3	486.4	497.3	5.1	481.7	483.6	2.2
3	RC101-20	383.2	393.7	400.6	411.7	4.6	391.1	398.3	1.2
4	C101-50	361.8	370.2	410.3	425.1	14.8	398.7	409.1	10.5
5	R101-50	1025.8	1064.3	1092.4	1205.7	13.3	1175.3	1189.7	11.8
6	RC101-50	969.8	983.4	1027.3	1066.1	8.4	1064.1	1074.1	9.2
7	C101-100	828.9	842.1	901.2	938.3	11.4	937.2	948.3	12.6
8	R101-100	1676.5	1703.9	1834.7	1892.8	11.1	1994.3	2045.2	20
9	RC101100	1740.9	1753.2	1987.4	2026.4	15.6	2113.7	2150.4	22.7

iability of the solution. The excellent performance of GA-ALNS on such problems further verifies its comprehensive performance.

In the most challenging RC instance, the GA-ALNS algorithm is adaptable in complex scenes. The RC class examples integrate the complexity of cluster scenes and the high uncertainty of random scenes, while the average standard deviation of the GA-ALNS algorithm in such problems is 14.54, which is significantly lower than that of GA (22.40) and ALNs (24.31), which is reduced by 7.86 and 9.77 respectively. These results prove that the GA-ALNS algorithm can effectively deal with multiple challenges in complex optimization problems, and its robustness, adaptability, and efficiency performance are much better than traditional algorithms.

To sum up, the average standard deviation of the GA-ALNS algorithm in C-type, R-type, and RC-type problems is always kept at a low level, proving its superior performance in terms of computational efficiency and stability. Especially in RC-type complex scenes, the GA-ALNS algorithm shows significant advantages, highlighting its robustness and adaptability in solving complex optimization problems. Compared with the traditional GA algorithm and ALNs algorithm, GA-ALNS not only performs better in computational efficiency but also significantly improves the quality and stability of the solution .

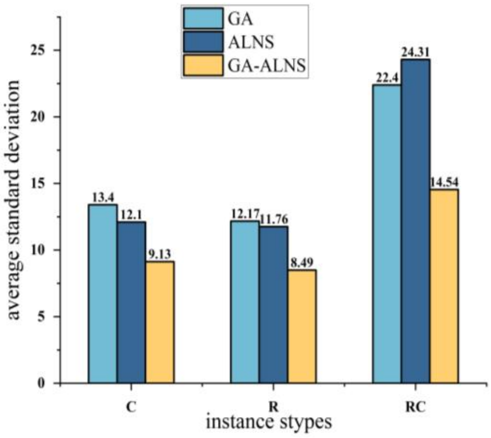

Fig.4. average standard deviation of the algorithm and its comparison on different types of instances

V. CASE STUDY OF HONGSHAN DISTRICT, WUHAN CITY

A. Background information

Taking the whole-cycle eco-operation center in Hongshan District, Wuhan City, Hubei Province as the research object, and selecting 24 garbage drop-off points served by this sanitation company as the research target, combining with ArcGIS to visualize the 24 garbage drop-off points it serves, and the geographic location is shown in Fig.5. The sanitation company needs to dispatch several vehicles with flexible compartments to the 24 garbage drop-off points for garbage sorting and collection. The information on the sanitation company and the garbage drop-off points is shown in Table II. The coordinates of the sanitation company are (114.33166 and 30.482391). Parameter Settings: Vehicle fixed cost f_k =160, vehicle average driving speed v =40km/h, the current fuel price of p =7.92 CNY / L, carbon tax e_{co2}=0.05, a total of 10 garbage transfer station collection trucks, the relevant models refer to the Shenzhen Dongfeng Automobile, in order to Foton BJ1045V9JB3-55, for example, the vehicle's maximum load capacity of 2000kg, the vehicle's gross mass 4495kg, traveling unit distance carbon emissions μ=0.0075kg/km, carbon emission coefficient χ =2.76 kg/L, per kilometer fuel emission standard γ=0.13L/km.

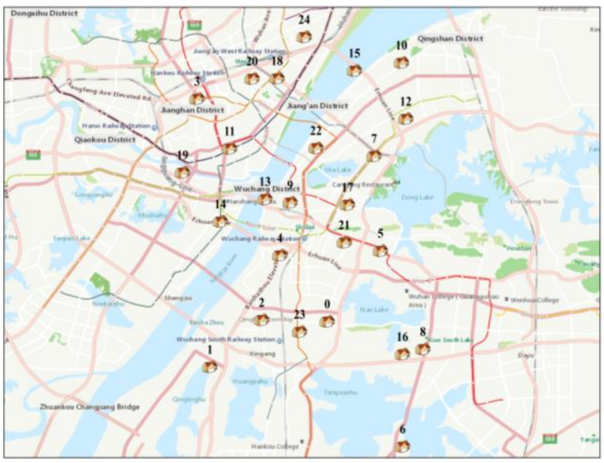

Fig. 5. Refuse collection points in Hongshan District, Wuhan City, Hubei Province

TABLE II
SPAM NODE RELATED INFORMATION

Nodal	Coordinate (geometry)		Volume /kg	Left time window	Right time window	Service time/min
0	114.3317	30.482391	0	6:10	9:00	0
1	114.2598	30.457026	216	7:20	9:20	12
2	114.2915	30.483238	372	7:40	9:20	16
3	114.252	30.606688	240	7:00	10:00	14
4	114.3026	30.519323	240	8:00	10:20	15
5	114.3643	30.52187	360	7:00	10:30	18
6	114.3778	30.412592	264	8:00	10:40	15
7	114.3603	30.574747	282	8:00	9:50	16
8	114.3902	30.466942	210	7:50	9:50	11
9	114.3089	30.548801	246	7:00	9:50	14
10	114.3771	30.6268	300	8:50	10:50	12
11	114.2719	30.57886	228	7:00	9:50	15
12	114.3797	30.595478	288	7:50	10:00	13
13	114.2936	30.550716	232	6:30	9:35	13
14	114.2663	30.538183	241	6:00	9:20	12
15	114.3483	30.622379	276	6:15	9:35	18
16	114.3777	30.464103	306	6:30	10:05	20
17	114.3441	30.547532	246	6:30	9:50	16
18	114.301	30.618076	234	7:00	10:05	22
19	114.2431	30.56554	240	6:05	9:20	13
20	114.2856	30.617871	300	6:45	9:50	13
21	114.3421	30.526526	186	6:30	10:05	11
22	114.3248	30.57917	264	6:15	9:35	14
23	114.3147	30.476637	252	6:25	10:05	17
24	114.3176	30.641193	240	7:00	10:05	10

B. *Optimization scheme of vehicle dispatching*

Through the above-mentioned solution steps based on the GA-ALNS algorithm, the urban waste collection and transportation problem is systematically solved. After 290 iterations, the optimal collection and transportation scheme is obtained, and the collection and transportation scheme is visually displayed in combination with ArcGIS. The iteration curve and the optimal collection and transportation path are shown in Fig. 6 and Fig. 7. Among them, the total driving distance of vehicles is 108.81 km, the comprehensive cost is 1008.487 CNY, and the number of vehicles is 4.

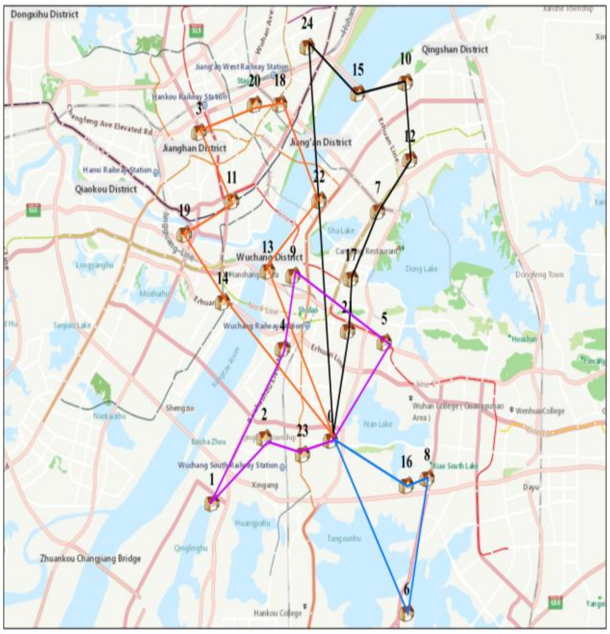

Fig. 6. Optimal waste collection and transportation solutions obtained by the GA-ALNS

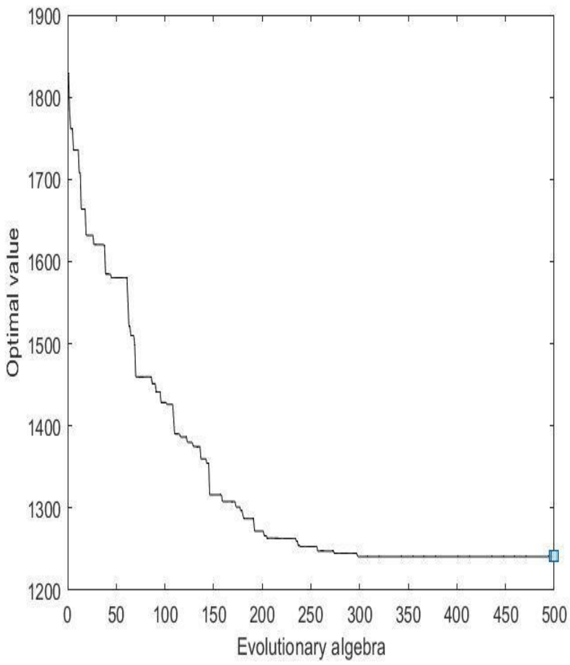

Fig. 7. GA-ALNS Iteration Curve

The specific collection and transportation sequence is shown in Table III. It can be seen from Table III that by comprehensively considering multidimensional factors such as collection and transportation cost, driving distance, and carbon emission cost, the collection and transportation tasks of 24 waste delivery points in Hongshan District are reasonably allocated to 4 vehicles numbered 1-4 in the optimization scheme. The optimization results show that the task allocation of each vehicle can achieve the equilibrium of the driving path and the minimization of cost to meet the constraints of capacity and time window.

Table III
ORDER OF GARBAGE COLLECTION AND TRANSPORT

Vehicle	Garbage collection and transportation sequence	Driving distance/km	Cost/CNY
1	0→16→8→6→0	20.178	184.807
2	0→21→17→7→12→10→15→24→0	38.253	284.673
3	0→14→19→11→3→20→18→22→13→0	40.462	285.484
4	0→23→2→1→4→9→5→0	30.163	253.523

According to the analysis results of the actual vehicle trajectory data in Hongshan District, Wuhan, the total driving distance of the GA collection and transportation scheme is 139.253 km, and the total driving distance of the ALNS algorithm collection and transportation scheme is 136.34 km. In comparison, the total driving distance of the GA-ALNS algorithm collection and transportation scheme is further optimized to 129.056 km. The comparison of the specific vehicle configuration and driving distance of each scheme is shown in Fig. 8. The collection and transportation route optimization scheme based on the GA-ALNS algorithm is superior to other vehicle configuration and driving distance algorithms.

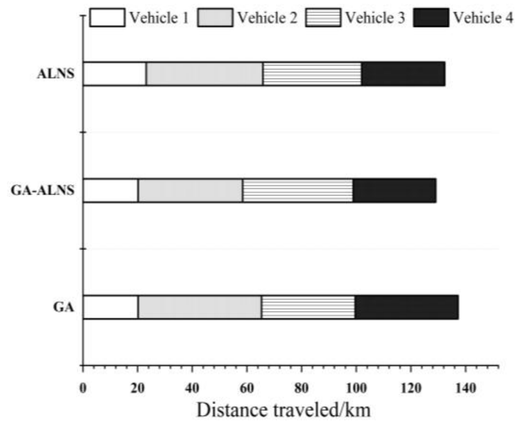

Fig. 8. Comparison of travel distances of collection and transport vehicles

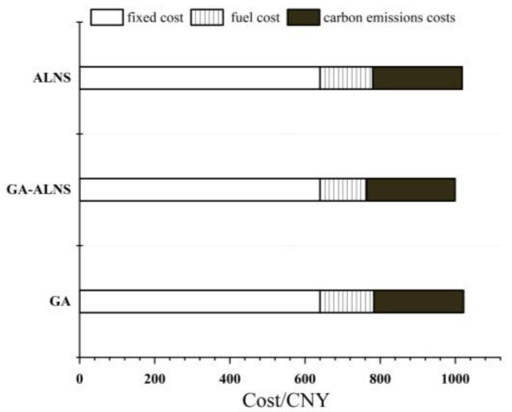

Fig. 9. Comparison of costs of waste collection andtransport schemes

As shown in Fig. 9, we have compared the performance of various cost indicators of waste collection and transportation schemes generated by different algorithms. Specifically, the fixed cost of the GA algorithm, ALNS algorithm, and GA-ALNS algorithm is 640 CNY, indicating that the three algorithms are consistent regarding fixed cost. However, the GA-ALNS algorithm shows a significant optimization effect in terms of fuel consumption and carbon emission costs.

Regarding fuel consumption cost, the GA-ALNS algorithm has the lowest cost, only 123.609 CNY. Compared with the GA algorithm (143.381 CNY) and the ALNS algorithm (140.376 CNY), it has a year-on-year decrease of 15.96% and 13.56%, reflecting its apparent advantages in path optimization and energy consumption reduction. In terms of carbon emission cost, the cost of the GA-ALNS algorithm is 235.616 CNY, which is 3.051 CNY and 2.048 CNY lower than that of the GA algorithm (238.667 CNY) and ALNS algorithm (237.664 CNY), respectively, with a year-on-year decrease of 1.3% and 0.87%, further verifying its optimization potential in reducing environmental costs.

To sum up, the garbage collection and transportation scheme generated based on the GA-ALNS algorithm shows superior performance in terms of fuel consumption, carbon emissions, and total cost. The total cost is 1008.847 CNY, which is significantly lower than the total cost of the GA algorithm and ALNs algorithm.

C. Sensitivity analysis of storage capacity proportion

In the actual collection and transportation process of garbage, the ratio of kitchen waste and other garbage storage capacity significantly impacts the efficiency of the two. As the proportion of kitchen waste is more significant than that of other wastes, this paper gradually increases the storage capacity of kitchen waste from 45% to 80%, sets up five groups of proportion control experiments, and takes the average value after solving each proportion 10 times. The results are shown in Fig. 10.

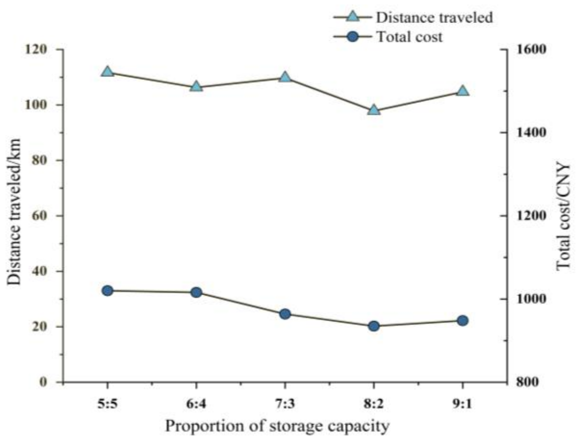

Fig. 10. Total distance and total cost of collection and transportation vehicles under different proportions of warehouse capacity

As can be seen from Fig. 10, when the capacity ratio of kitchen waste bins to other waste bins is 7:3, the total cost of collection and transportation decreases significantly. When the proportion is further adjusted to 8:2, the total distance of the combined transport vehicles is the shortest, and the total cost is the lowest. The analysis results show that when the proportion of the storage capacity of kitchen waste bin and other waste bins is close to the actual proportion of the two types of waste, the overall loading rate of the vehicle has been significantly improved, which effectively reduces the total mileage of the vehicle, and thus reduces the total collection and transportation cost.Carbon price sensitivity analysis

D. Sensitivity analysis of carbon price

Changes in the price of the carbon tax will lead to changes in the cost of carbon emissions, leading to changes in the scheduling program for waste collection vehicles. Higher or lower carbon tax prices directly impact carbon dioxide emissions [27]. The carbon tax price is set at 0.05 CNY/kg when solving the model in this paper, and in order to measure the impact of different carbon tax prices on carbon dioxide emissions and carbon emission costs, the carbon tax price is set at 0.02 CNY/kg, 0.04CNY/kg, 0.1CNY/kg, 0.15CNY/kg, respectively, and the carbon emission costs, total collection and transportation costs, and carbon dioxide emissions under different levels of the carbon tax price are as shown in Table IV and Fig. 11.

Table IV
IMPACTS OF CARBON TAX PRICE CHANGES ON CARBON EMISSIONS AND TOTAL COSTS

Carbon tax price/ (CNY/kg)	Carbon emissions/kg	Total collection and transportation costs/CNY
0.02	4801.23	868.8956
0.04	4779.16	964.0374
0.05	4712.32	1018.487
0.1	4683.74	1241.245
0.15	4671.42	1473.584

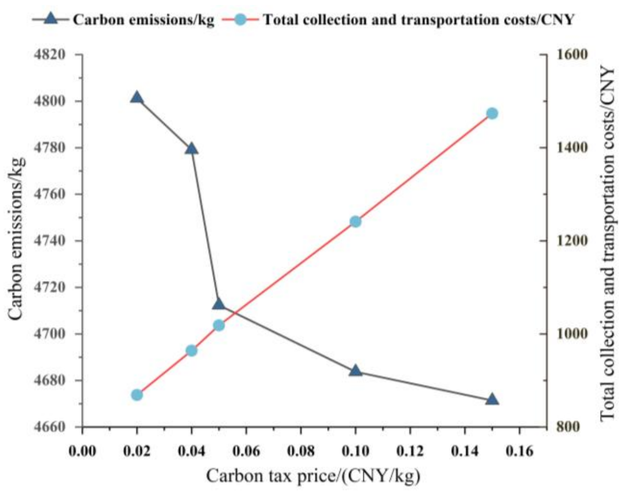

Fig.11.Trends in total costs and carbon emissions with carbon tax prices

VI. CONCLUSION

This paper introduces multi-vehicle compartment vehicles into the transportation of garbage classification and proposes a flexible multi-vehicle compartment collection vehicle path problem with a time window(FMCVRPTW).

(1) This study constructs a waste collection and transportation optimization model that integrates vehicle operating, fixed, and carbon emission costs and introduces a carbon tax mechanism to incentivize low-carbon operations. To solve the proposed problem, a hybrid genetic adaptive large neighborhood search algorithm (GA-ALNS) is designed, which combines the global search capability of the genetic algorithm and the local optimization property of extensive neighborhood search, significantly improving the problem-solving efficiency and the quality of the solution. The standard case tests of Solomon's problem library show that the GA-LNS algorithm outperforms the traditional genetic algorithm (GA) and the adaptive large neighbor search algorithm (ALNS) in solving garbage collection and transportation problems.

(2) The empirical analysis verifies the effectiveness and feasibility of the model and algorithm using Wuhan City in Hubei Province as an example. The optimized waste collection system significantly reduces operation costs, driving distance, and carbon emissions, demonstrating economic and environmental benefits.

(3) Sensitivity analysis reveals that optimizing the compartment capacity ratio in multi-compartment vehicles enhances collection efficiency and reduces operational costs by improving loading rates and minimizing transportation distance. Thus, sanitation agencies should allocate storage capacity strategically when implementing classified waste collection.

(4) This study further explores the impact of the carbon tax on waste collection and transportation optimization. Sensitivity analysis reveals the trend of cost and carbon emission changes under different carbon tax levels, which provides an important theoretical basis and decision support for policy formulation.

In future research, more factors such as residents' satisfaction, heterogeneous models, cross-regional waste collection, and transportation synergy can enhance the model's practicality. In addition, considering the dynamic nature of the operation, a real-time data processing mechanism can be introduced to dynamically optimize the collection and transportation routes to cope with the challenges of unexpected events and traffic changes.

REFERENCES

[1] Dantzig G B and Ramser J H,"The truck dispatching problem,"Management Science", vol. 6, no. 1, pp. 80-91, 1959.
[2] Ahkamiraad A and Wang Y,"Capaciitated and multiple cross-docked vehicle routing problem with pickup,delivery and time windows,"Computers & Industrial Engineering, vol. 119, no. 5, pp. 76-84,2018.
[3] Rahma L,Anne-Lise G and Leandro C C,"A hybrid adaptive large neighbourhood search for m-ulti-depot open vehicle routing problems," International Journal of Production Research, vol. 57, no. 22, pp. 6963-6976,2019.
[4] Zhongjun Hu and Hong Zhou,"Research on demand splitting vehicle path optimization for improvi-ng genetic algorithms," Computer Simulation, vol. 35, no. 3, pp. 80-83,2018.
[5] Matijevi L,Ilin V,Davidovi T, Jaki-Krü ger T and Pardalos PM,"General VNS for asymmetric vehicle routing problem with time and capacity constraints," Computers & Operations Research,2024, https://doi.org /10.1016 /j.cor.2024.106630.

[6] Rizkiani F, Geraudy I,and Imran A,“ Solving the Vehicle Routing Problem with MultipleTrips and Simultaneous Delivery-Pickup for Drinking Water Distribution Company,” E3S Web of Conferences,2024,https://doi.org/10.1051/e3sconf/202448401003.

[7] Jianhua Xiao,Chaowen Wang and Ping Chen,“ Path optimization of multi energy and multi vehicle models based on urban road restrictions,” Systems Engineering Theory and Practice, vol. 37, no. 5, pp. 1339-1348,2017.

[8] Xiancheng Zhou,Weiying Yu and Sonming Li,“Research on the Dual Objective Green Vehicle Routing Problem Considering Time Dependence and Simultaneous Picking and Delivery [J/OL],” Systems Science and Mathematics,1-18, 2023.

[9] Huanhuan Cui and Lihe Guan,“ Hybrid Heuristic Algorithm for Priority Delivery of Green VRP [J/OL],” Journal of System Simulation, 1-12,2023.

[10] Chunxia Zhai,“ A Snowmelt Optimization Algorithm Applied to Green Low Carbon Logistics Pathways Optimization Problems,” EAI Endorsed Transactions on EnergyWeb,2024,https://doi.org/10.4108/ew.4889.

[11] Jabir E,Panicker V, Sridharan R, “Design and development of a hybrid ant colonyvariable neighbourhood search algorithm for a multi-depot green vehicle routing problem,” Transportation Research Part D,2017, https://doi.org/10.1016/j.trd.2017.09.003.

[12] Yong Peng, Zhiyao Mo, Song Liu,“Passenger’s routes planning in stochastic common-lines’ multi-modal transportation network through integrating Genetic Algorithm and Monte Carlo simulation,” Archives of Transport, Vol. 59, No. 3,pp.73-92, 2021.

[13] Muyang Wen, Wei Sun, Yang Yu and Jiafu Tang,“An adaptive large neighborhood search for the larger-scale multi depot green vehicle routing problem with time windows,” Journal of Cleaner Production,2022, https://doi.org/10.1016/j.jclepro.2022.133916.

[14] I Jacyna-Gołda, M Izdebski and A Podviezko,“Assessment of efficiency of assignment of vehicles to tasks in supply chains:a case study of a municipal company,” Transport,2017, https://doi.org/10.3846/16484142.2016.1275040.

[15] M Reed, A Yiannakou, R Evering,“ An ant colony algorithm for the multi-compartment vehicle routing problem,” Applied Soft Computing,2014, https://doi.org/10.1016/j.asoc.2013.10.017.

[16] Mahmuda Akhtar, M.A. Hannan, R.A. Begum and Hassan Basri,“ Backtracking search algorithm in CVRP models for efficient solid waste collection and route optimization,” Waste Management, Vol. 61, pp. 117-128,2017.

[17] Zhishuo Liu, Yuqing Li, Junzhe Xu and Donglu Bai,“Multi-Compartment Electric Vehicle Routing Problem for Perishable Products,” International Journal of Crowd Science,Vol.8,No.1,pp.38-48,2024.

[18] Tingting Li,Shejun Deng,Caoye Lu,“A low-carbon collection and transportation path optimization method for garbage vehicles based on improved ant colony algorithm,” Highway Transp-ortation Technology,Vol.40,No.5,pp.221-228,2023.

[19] Jianhua Xiao,Wenxue Zhang and Yuya Pan,“Research on Multi cycle and Multi cabin Path Optimiza-tion Based on the Timeliness of Classified Waste Collection and Transportation,” Chinese Management Science,2023,https://doi.org/10.16381/j.cnki.issn1003-207x.2023.0050.

[20] Narat Rattanawai,Sirawadee Arunyanart and Supachai Pathumnakul, “Optimizing municipal solid waste collection vehicle routing with a priority on infectious waste in a mountainous city landscape context,” Transportation Research Interdisciplinary Perspectives,20-24, https://doi.org/10.1016/j.trip.2024.101066.

[21] Shuangniu Zhou,Zhi Li and Jie Wang,“Optimization of garbage collection and transportation path by improving DMBSO algorithm from a low-carbon perspective,” Science and Technolo-gy and Engineering,Vol.21,No.23,pp. 9932-9939,2021.3492.

[22] Liang Shen,Xiang Xu,Feng Shao,Hu Shao and Yanxin Ge,“A multi-objective optimization model for medical waste recy-cling network design under uncertainties,” Transportation Research Part E: Logistics and Transportation Review,2024, https://doi.org/10.1016/j.tre.2024.103492

[23] David Peña,Bernabé Dorronsoro and Patricia Ruiz,“Sustainable waste collection optimization using electric vehicles,” Sustainable Cities and Society,2024, https://doi.org/10.1016/j.scs.2024.105343.

[24] Hongxing Deng,Jie Zhou and Yi Hu,“.Optimization model for cold chain logistics distribution path of fresh agricultural products considering carbon emissions,” Journal of Chongqing University of Technology (Natural Science),Vol. 37,No.2,pp.289-297,2023.

[25] Nooshin Heidari and Ahmad Hemmati,“An ALNS-based matheuristic algorithm for a multi-pro-duct many-to-many maritime inventory routing problem,” Computational Management Science,2023, https://doi.org/10.1007/s10287-023-00478-8.

[26] Ruinan Sun,Xiang Chu and Yu Cheng,“Optimization study of courier end site selection path based on hybrid heuristic algorithm,” Computer Engineering and Science,Vol.46,No.1,pp.159-169,2024.

[27] Yunqian Jiang,Huiming Yang and Cheng Peng, “Research on Optimization of Cold Chain Logistics Distribution Paths Considering Carbon Emissions and Time Windows,” Packaging Engineering, Vol.45,No.3,pp.262-268,2024.

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