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OPTIMIZATION OF URBAN SOLID WASTE COLLECTION ROUTES AND MULTI-VEHICLE COLLABORATIVE DISPATCH DECISION-MAKING

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Abstract: Addressing the core demands of enhancing transportation efficiency and controlling costs in urban solid waste management, this study constructs a multi-objective optimization model for waste collection routes and multi-vehicle coordination scheduling based on multi-dimensional constraints. During the fundamental route planning phase, a mathematical model minimizing total travel distance is established for single-type waste collection points, alongside an improved genetic algorithm incorporating a Markov chain adaptive mechanism. This algorithm employs a hybrid coding scheme for primary and auxiliary chromosomes, dynamically adjusts crossover and mutation operators, and incorporates local optimization strategies like embedded neighborhood search. It successfully achieves efficient task allocation, with experimental results yielding a total travel distance of 1,144.5 kilometers. During the complex multi-vehicle coordination phase, the model was extended to a joint transportation scenario involving four specialized waste collection vehicle types, comprehensively considering constraints such as vehicle payload, volume, unit transportation cost, and maximum daily driving time. An improved multi-objective genetic algorithm was employed for solution, achieving Pareto-optimal scheduling of multi-source waste streams through segmented sequence encoding and feasibility correction mechanisms. Results demonstrate the model's ability to clearly characterize operational efficiency and cost structures across vehicle categories, with food waste collection and transportation accounting for the highest cost proportion at 38.3%.
Keywords: Vehicle path planning; Adaptive genetic algorithm; Multi-vehicle collaborative optimization

1 INTRODUCTION

Accelerating urbanization in China has led to a continuous rise in municipal solid waste generation, posing severe challenges to the collection and transportation capacity of urban sanitation systems. How to coordinate transportation routes to minimize overall costs while satisfying multiple constraints—such as vehicle load limits, transfer station capacities, and time windows—has become a critical issue in smart city development. This study first focuses on fundamental route optimization, aiming to minimize total vehicle mileage through rational task allocation[1-2]. Subsequently, the research scope is extended to multi-vehicle coordination to address resource allocation challenges in sorted waste collection scenarios. Previous studies often overlooked the possibility of batch transporting waste volumes or cost differences between vehicle types, limiting model generalization in complex environments. This research innovates by establishing a hybrid coding mechanism for primary and auxiliary chromosomes, effectively resolving the bottleneck in coordinating path segmentation and vehicle switching. It further introduces a dynamic time window penalty factor based on timeline shifts, significantly enhancing the real-time responsiveness of scheduling solutions. The research approach follows a logical framework progressing from single-source to multi-source scenarios and from single-load to multi-dimensional constraints[3]. Through preprocessing static data such as collection point coordinates and waste generation rates, it sequentially implements genetic algorithm heuristic search, multi-objective fitness evaluation, and visual performance analysis, ultimately forming a closed-loop intelligent decision-making system for sanitation logistics[4-5].

2 Construction of a Single-Vehicle Path Optimization Model and Design of an Improved Genetic Algorithm

2.1 Data Preprocessing

Based on the data, which includes 30 garbage classification collection points, the characteristics of the collection points are as follows:
(1) Numbering $i \in V$, where $V=\{0,1,2,...,n\}$.
(2) Coordinates (x_i,y_i) in a two-dimensional coordinate system.
(3) Total garbage volume w_i in tons.
The garbage treatment plant (numbered 0) is defined as $(x_0,y_0)=(0,0)$ with a total garbage volume $w_0=0$.

2.2 Variable Definition

c_{ij}: Distance between node i and node j, calculated by the formula:

$$c_{ij}=\sqrt{(x_i-x_j)^2+(y_i-y_j)^2}, \forall i,j \in V \tag{1}$$

$$x_{ij}^k=\begin{cases}1, & \text{if vehicle k travels from node i to node j}\\ 0, & \text{otherwise}\end{cases}, \forall i,j \in V; k \in K \tag{2}$$

$$y_i^k=\begin{cases}1, & \text{if vehicle k serves node i}\\ 0, & \text{otherwise}\end{cases} \tag{3}$$

Where K is the set of available vehicles[6-7].
Objective function: Minimize the total travel distance of all vehicles.

$$\min Z=\sum_{k\in K}\sum_{i\in V}\sum_{j\in V} c_{ij}\cdot x_{ij}^k \tag{4}$$

2.3 Constraint Conditions

Each node is served by exactly one vehicle.

$$\sum_{k\in K} y_i^k=1, \forall i \in V \tag{5}$$

For each node, the incoming flow equals the outgoing flow.

$$\begin{cases}\sum_{i\in V} x_{ij}^k=\sum_{i\in V} x_{ji}^k=y_i^k, \forall i \in V, k \in K\\ \sum_{j\in V} x_{0j}^k=\sum_{j\in V} x_{j0}^k\leq 1, \forall k \in K\end{cases} \tag{6}$$

Load constraint: The load of each vehicle does not exceed the limit.

$$\sum_{i=1}^{n} w_i\cdot y_i^k\leq Q, \forall k \in K \tag{7}$$

2.4 Solution with Genetic Algorithm

Genetic algorithm draws on the laws of natural selection and genetic mechanisms in the biological evolution process, and adopts a swarm intelligence search strategy to solve complex optimization problems[8].

2.4.1 Chromosome encoding scheme

An improved hybrid encoding method is adopted:
Main chromosome: Permutation encoding based on the sequence of collection points.
Gene positions represent collection point numbers (1-30), and the gene order represents the visiting order[9-10].
Auxiliary chromosome: Binary encoding based on vehicle assignment, marking the segmentation points of gene segments to determine the transportation task scope of each vehicle.
Example:
Main chromosome: [5, 12, 8, 3, 19, 25, ...].
Auxiliary chromosome: [0, 1, 0, 0, 1, 0, ...] (1 indicates a vehicle switching point).

2.4.2 Fitness function design

A multi-objective fitness evaluation function is constructed:

$$F(C)=\frac{1}{\omega_1 Z_1(C)+\omega_2 Z_2(C)+\alpha P(C)} \tag{8}$$

Where:
$Z_1(C)$ = Total transportation distance (km);
$Z_2(C)$ = Number of vehicles used;
$P(C)$ = Constraint penalty term, calculated by the formula (9):

$$P(C)=\sum_{k=1} \max(0,W_k-Q)^2+\sum_{i=1} \max(0,S_i-1)^2 \tag{9}$$

Weight coefficients: ω_1=0.7, ω_2=0.3.
Penalty coefficient: $\alpha=10^6$.

2.4.3 Improved genetic operators

Elite retention selection strategy:
Combine tournament selection with elite retention: Randomly select 5 individuals from the population each time, and select the top 2 with the highest fitness to enter the mating pool.
Retain the optimal individual of the current generation to directly enter the next generation.

2.4.4 Adaptive crossover operator

Design two crossover methods for dynamic switching:

Order Crossover (OX): Applicable when the population diversity is high ($\sigma_F>0.15$) to maintain the integrity of excellent gene segments.
Path Segmentation-based Crossover (PSC): Enabled when the population converges ($\sigma_F\leq0.15$), exchanging according to vehicle task segments.
Adaptive adjustment of crossover probability:

$$p_c=0.85-0.2\times\frac{g}{G} \tag{10}$$

Where: g is the current generation number, G is the total number of generations.

2.4.5 Intelligent mutation strategy

Adopt a three-level mutation mechanism:
Regular mutation: Swap two random gene positions (probability 0.1);
Heuristic mutation: Adopt 2-opt local optimization (probability 0.05);
Catastrophic mutation: Randomly reset part of the chromosome (probability 0.01);

2.4.6 Hybrid optimization strategy

Embed local search after each generation of genetic operations:
Perform Variable Neighborhood Search (VNS) on the optimal individual;
Perform Tabu Search (TS) on 5 randomly selected individuals;
Adopt Simulated Annealing (SA) mechanism to accept inferior solutions:

$$P_{accept}=\exp\left(-\frac{\Delta F}{T}\right) \tag{11}$$

The temperature parameter T decays linearly with iterations.

2.4.7 Parameter optimization and setting

Determine the optimal parameter combination through orthogonal test method (Table 1):

Table 1 Parameter Settings of Genetic Operators

Parameter	Value range	Optimal value	Adjustment strategy
Population size	50-200	120	Fixed
Initial crossover probability	0.7-0.9	0.85	Adaptive decay
Initial mutation probability	0.05-0.2	0.12	Adaptive increase
Elite retention rate	5%-20%	10%	Fixed
Local search proportion	10%-30%	20%	Increase with the number of iterations

2.4.8 Algorithm performance analysis

Time complexity analysis results are shown in Table 2.

Table 2 Time Complexity Analysis Results

Content	Time complexity
Initialization phase	$O(N\cdot n)$
Fitness calculation	$O(N\cdot n^2)$
Genetic operations	$O(G\cdot N\cdot n)$
Local optimization	$O(G\cdot N\cdot n^2)$
Total complexity	$O(G\cdot N\cdot n^2)$

2.4.9 Convergence proof

Through Markov chain analysis, the algorithm satisfies: The probability measure of the optimal solution set is non-decreasing, and when $G\to\infty$, the probability of converging to the global optimal solution is 1.

2.4.10 Result presentation

Optimization parameter configuration and Complexity calculation result analysis are shown in Table 3 and Table 4, respectively.

Table 3 Optimization Parameter Configuration

Parameter	Value
Population size	200
Number of iterations	1000
Crossover rate	0.85
Mutation rate	0.10252718826976889
Number of elite retentions	20

Table 4 Complexity Calculation Result Analysis

Content	Time complexity
Distance matrix calculation	$O(n^2)$
Initial population generation	$O(P\times n)$
Fitness evaluation	$O(P\times n)$

Individual selection	$O(P^2)$
Crossover operation	$O(P\times n)$
Mutation operation	$O(P\times n)$
Single-generation calculation amount	$O(P\times n+P^2)$
Total calculation amount	$O(G\times(P\times n+P^2))$
Actual number of operations	46000000 times

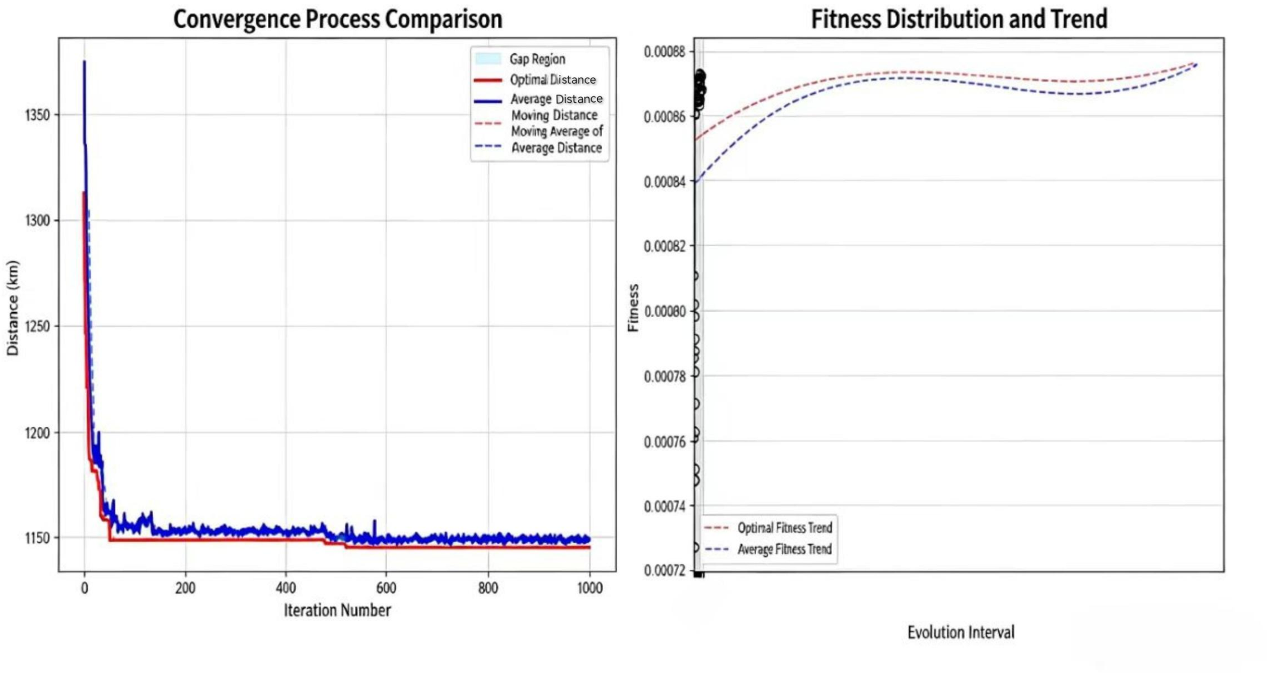

Figure 1 Convergence Process Comparison and Fitness Distribution and Trend

Convergence process comparison and fitness distribution and trend is shown in Figure 1.

2.4.11 Algorithm convergence performance analysis

Figure 1 shows the change curves of the optimal distance and average distance of the population with the number of iterations when the genetic algorithm solves the CVRP problem. The horizontal axis is the number of iterations, and the vertical axis is the total travel distance (km).

In the early stage of the algorithm (about the first 100 generations), the optimal distance and average distance decrease rapidly, indicating that the algorithm can quickly search for better solutions at this stage. At this time, the gap between the best distance and the average distance is large, reflecting high population diversity, which is conducive to global exploration. As the iteration proceeds (after about 100 generations), the curve decline rate slows down and tends to be stable, and the algorithm enters the convergence stage. The average distance gradually approaches the best distance, and the gap area shrinks, indicating that the population diversity decreases and turns to local optimization. At the end of the iteration (after about 800 generations), the best distance is basically stable, indicating that the algorithm has approached convergence and found the current optimal solution. The moving average further smoothly shows the overall convergence trend.

Figure 2 analyzes the evolutionary process of the algorithm from the perspective of fitness. Fitness is positively correlated with solution quality. Through box plots and trend lines, this figure shows the distribution and overall changes of population fitness in different evolutionary intervals. The horizontal axis is the evolutionary interval, and the vertical axis is the fitness.

3 Multi-Vehicle Collaborative Scheduling Model and Hierarchical Task Decomposition Strategy

3.1 Basic Multi-Vehicle Collaborative Transportation Problem

Objective: Minimize the total transportation cost, and the objective function is:

$$\min W=\sum_{k=1}^{4} C_k\times\sum_{v=1}\sum_{i\in V}\sum_{j\in V} c_{ij}\times x_{ij}^{k,v} \tag{12}$$

Where W is the total transportation cost, and C_k is the unit distance cost of the k-th type of vehicle.

Constraint conditions:

a. Each type of garbage at each collection point must be covered:

$$\sum_{v=1}^{M_k} y_i^{k,v}=1, \forall i \in V, k \in K \tag{13}$$

b. The load and volume of each task do not exceed the limits:

$$\begin{cases} \sum_i w_{i,k} \le Q_k, \sum_i w_{i,k} \times \rho_k \le V_k, \forall k, m>0 \\ Q_k \cdot y_i^{k,v} \le u_i^k \le Q_k \cdot z_k^v, \forall i \in V, k \in K, v \in \{1,2,...,M_k\} \end{cases} \tag{14}$$

Where u_i^k is the cumulative load of the v-th vehicle of type k when arriving at node i.

c. Vehicles depart from and return to the treatment plant:

$$\sum_{i \in V} x_{0,j}^{k,v} = \sum_{i \in V} x_{j,0}^{k,v} = 1, \forall k \in K \tag{15}$$

d. Use MTZ constraints to ensure no cycles in the path:

$$u_{i,k} - u_{j,k} + Q_k \times x_{i,j,k} \le Q_k - w_{j,k}, \forall i,j,k>0 \tag{16}$$

Variable domain constraints:

$$x_{ij}^{k,v} \in \{0,1\}, \forall i,j \in V, k \in K, v \in \{1,2,...,M_k\} \tag{17}$$

$$y_i^{k,v} \in \{0,1\}, \forall i \in V, k \in K, v \in \{1,2,...,M_k\} \tag{18}$$

$$z_k^v \in \{0,1\}, \forall k \in K, v \in \{1,2,...,M_k\} \tag{19}$$

3.2 Adjusted Multi-Vehicle Collaborative Transportation Problem

Model adjustment:

According to the problem requirements, it is necessary to extend the algorithm in Problem 1 and analyze the changes in constraint conditions. Therefore, the objective function is fixed, but multiple tasks need to be supported; a new variable is added: $z_{k,m,i} \in \{0,1\}$, indicating whether the m-th task of vehicle k serves collection point i. Constraint condition extension:

Completeness of task assignment: $\sum_m z_{k,m,i} = y_{i,k}, \forall i \in V, k \in K$

Single task capacity: $\sum_{i \in V} z_{k,m,i} \times w_{i,k} \le Q_k, \forall k \in K$

3.3 Integration of Time Constraints

The problem adds the constraint of "maximum daily travel time of vehicles", so the parameter T_{max} is introduced: the maximum daily travel time of vehicles (hours).

Assume the vehicle speed is v=40 km/h, then the relationship: maximum travel distance $D_{max}=T_{max} \times v$ holds; modify the model, that is, add a time constraint:

$$\sum \frac{d_{i,j}}{v} \le T_{max}, \forall k, m \tag{20}$$

If the path exceeds the time limit, the task shall be decomposed and the following equation shall be satisfied:

$$\sum_m z_{k,m,i} \times w_{i,k} \le w_{i,k}, \forall i, k \tag{21}$$

To control time calculation, a penalty factor λ (e.g., 100 yuan/hour) can be added to the fitness function to penalize overtime paths, resulting in equation (22):

$$\text{Minimize} W = \sum C_k \times d_{m,k} + \lambda \times \max(0, t_{m,k} - T_{max}) \tag{22}$$

Where $t_{m,k}$ is the travel time of the m-th task of vehicle k.

3.4 Problem Solving Strategy Based on Genetic Algorithm

Considering the NP-hard nature of MTW-CMVRP and its complex constraint coupling, this model adopts an Improved Multi-Objective Genetic Algorithm (IMMOGA) to find approximate optimal solutions. The algorithm simulates the evolutionary process of nature, and gradually converges to high-quality solutions by iteratively optimizing individuals (i.e., potential scheduling schemes) in the population. The specific algorithm implementation steps are detailed as follows:

Algorithm parameter setting: Determine the core parameters of the genetic algorithm, including population size S, maximum iteration cycle T_{MAX}, gene crossover probability P_c, gene mutation probability P_m, excellent individual retention ratio E_r, number of tournament competitors in the selection process N_t, and weight coefficients of each objective for constructing the comprehensive evaluation standard.

Representation of solution process and related operations (encoding and decoding):

Chromosome encoding: Introduce a segmented sequence encoding method. Each potential solution (individual) is composed of a set of chromosomes, and each chromosome corresponds to a specific type of garbage and the sequence of collection points it is responsible for. For example, the chromosome of type k is a sequence of integers containing the unique identifiers of all collection points producing type k garbage. Special markers (such as -1) in the sequence are used to define the service segments responsible for different vehicles. This encoding method intuitively represents the access order and the initial structure of vehicle allocation.
Path decoding: Convert the abstract gene sequence into a specific set of vehicle travel routes according to the chromosome sequence and vehicle separators.
Feasibility correction: Check the preliminary path decoded. If it is found that the total amount of a specific type of garbage collected by a vehicle on its service path exceeds the load limit (or volume limit) of the vehicle model, the over -limit path is decomposed into multiple sub-paths that meet the constraints according to preset rules (such as sequential splitting) to ensure that all generated vehicle tasks are physically feasible.
Population initialization: First, construct an initial population containing S individuals. To improve search efficiency and avoid premature convergence, a diversification strategy is adopted: some individuals are generated completely randomly; some individuals are constructed with the help of a simple greedy strategy (for example, the algorithm will give priority to visiting the nearest feasible collection point); other individuals are generated by geographically clustering collection points and performing random or heuristic sorting within the clusters, introducing the diversity of spatial distribution into the problem-solving process.
Evaluation of individuals (i.e., fitness calculation): We quantify the quality of each solution by defining a comprehensive fitness function to find the optimal solution. The function integrates multiple performance indicators: total transportation cost (the lower the better), transportation path efficiency (such as average single-vehicle travel distance, the lower the better), and vehicle load balance (such as the standard deviation of the actual load rate of each vehicle, the smaller the better). Each indicator is standardized and weighted and summed according to preset weights to obtain the final comprehensive fitness score.

$$\text{EvaluatedScore}=\omega_1\cdot\ \Phi_1(\text{Cost})+\omega_2\cdot\ \Phi_2(\text{Efficiency})+\omega_3\cdot\ \Phi_3(\text{Balance}) \tag{23}$$

Where ω_i is the weight coefficient, and Φ_i is the function that maps the original indicator to the scoring space.
Selection operation: Adopt the tournament selection mechanism, that is, randomly select N_t individuals from the current population for "competition" each time, and the individual with the highest comprehensive fitness is selected as the parent for reproduction in the next generation. This process is repeated until a sufficient number of parent individuals are accumulated.
Gene crossover: Perform crossover operation on the selected parent pairs with probability P_c. This algorithm adopts the Order Crossover (OX) operator for path problems, which acts on the collection point sequence obtained after removing vehicle separators. The OX operator retains the relative order and position of the selected segments in the parent, and fills the vacancies by sequentially selecting the remaining genes from the other parent, which helps maintain the effective combination of genes. After crossover, reinsert vehicle separators into the offspring chromosome sequence according to the vehicle capacity constraints.
Gene mutation: Perform mutation operation on the generated offspring individuals with probability P_m to introduce new genetic diversity and explore a broader solution space. A combination of multiple mutation methods is used, such as randomly swapping the positions of two points in the chromosome, randomly inserting a point into another position, randomly reversing the order of chromosome segments, or randomly shuffling the order of segments (Scramble mutation). After mutation, vehicle separators are also reinserted.
Population evolution: Merge the new offspring individuals generated by crossover and mutation with the original population to form a new population pool. To ensure the convergence of the algorithm and retain the discovered excellent solutions, an elite strategy is implemented: directly promote the top $E_r\times S$ individuals with the highest fitness in the current population to the next generation. The remaining new population members are supplemented by screening from the offspring generated by crossover and mutation until the population size S is reached.
Termination criterion: The algorithm iteratively performs selection, crossover, mutation, and population update processes until the preset maximum number of iterations T_{max} is reached.

3.5 Result Presentation

After the algorithm terminates, the individual with the highest comprehensive fitness in the current population is taken as the optimal optimization scheme for the problem. The output content includes but is not limited to: the overall objective function value (total cost), the total number of vehicles called, the specific service routes of various garbage vehicles, the load, travel distance, and corresponding cost details of each route. In addition, various visualization tools (such as vehicle path diagrams, cost composition pie charts, load rate distribution histograms, etc.) can be used to intuitively display the characteristics and performance of the optimization results.

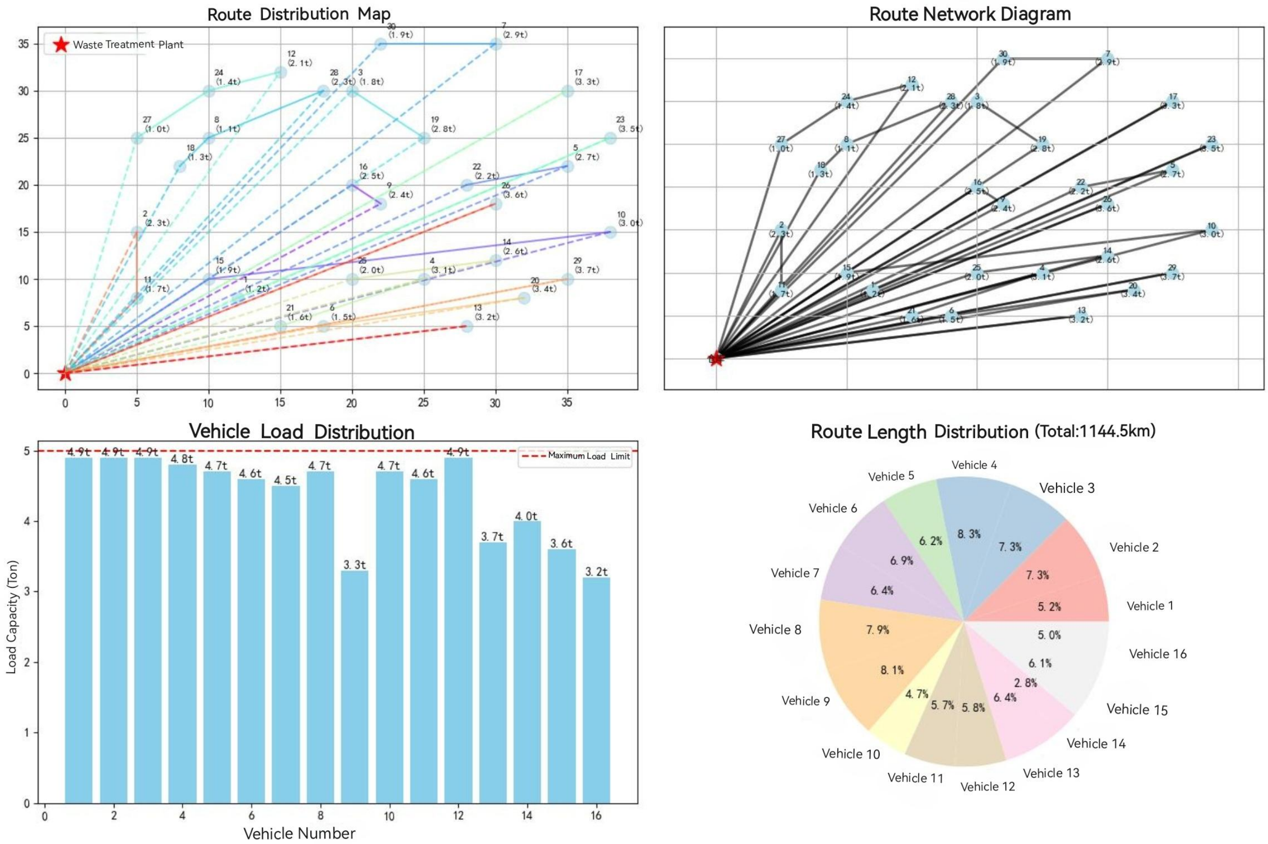

Figure 2 3D Path Planning Diagram

This Figure 2 depicts the planned path of the collection and transportation vehicles in a three-dimensional space coordinate system. The plane coordinate axes (X, Y) represent geographical locations, and the vertical axis (Z) reflects the garbage load of each service node. The red star marks in the figure identify the transfer center (starting/ending point), the curves of different colors correspond to the travel trajectories of various professional garbage collection and transportation vehicles, and the scattered points represent the garbage collection points to be served. The figure clearly shows how vehicles of various types depart from the transfer center, cover the discrete garbage points within their responsible scope in an orderly manner, and depict the spatial distribution characteristics of the garbage volume at different collection points through the height difference of the Z-axis. The obtained path set forms a series of interrelated sub-routes, which jointly serve the garbage collection and transportation needs in the region.

4 CONCLUSIONS

This study comprehensively constructs a multi-level decision model for urban waste transportation systems, achieving theoretical breakthroughs from basic route planning to complex collaborative scheduling. The improved genetic algorithm resolves single-type waste collection and transportation for 30 collection points, with convergence analysis validating the algorithm's stability in global search. Subsequently, addressing multi-vehicle transportation demands under waste sorting policies, a collaborative model targeting total cost minimization was established, quantifying the intrinsic relationship between load utilization rate, transportation distance, and cost composition.

Limitations and Future Research Prospects

Although the model demonstrated high computational accuracy in the pilot area, certain limitations remain. The current model oversimplifies real-world traffic conditions by neglecting random variables such as traffic congestion, dynamic road speed limits, and loading/unloading efficiency variations, potentially leading to prediction errors in practical applications. Furthermore, while multi-stage optimization enhances accuracy, it significantly increases the algorithm's time complexity, making it unsuitable for real-time, second-level scheduling demands in ultra-large-scale road networks. Future research should focus on developing lightweight algorithms by adopting hybrid strategies combining tabu search and greedy insertion to reduce computational time. Concurrently, robust optimization mechanisms should be introduced to handle random fluctuations in waste generation. Exploring the construction of a multi-agent collaboration platform between sanitation departments and transportation enterprises is also essential, leveraging dynamic pricing mechanisms to better balance system operational costs and service quality.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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