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Research on Optimization and Scheduling Models and Algorithms for Urban Waste Sorting Transport Routes

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Abstract: *Urban waste classification transportation route optimization, as a typical vehicle routing problem (VRP), is of critical significance for improving urban management efficiency. This paper constructs a progressive optimization model based on graph theory and mixed integer programming, and solves it by combining a weighted graph approximation algorithm, an improved simulated annealing algorithm, and multi-objective adaptive large neighborhood search (MOALNS) algorithm. The system addresses three core problems: single-type garbage path planning, multi-type garbage co-transportation, and a multi-objective optimization with transfer stations. The case verification results show that the single-objective basic model can achieve the optimal driving distance of 1,140.00 km for 16 vehicles, the multi-vehicle collaborative model can control the daily transportation cost at 3,123.02 yuan, and the multi-objective joint model can reduce the total cost to 2,460.15 yuan and carbon emissions to 945.80kg through the site selection optimization of three transfer stations. The comparative experiments show that the MOALNS algorithm is significantly superior to traditional algorithms such as NSGA-II and MOEA/D in terms of cost convergence. Taking the P-n23-k8 dataset as an example, its HV value reaches 0.771, and the multi-objective optimization accuracy advantage is prominent. Research shows that graph-theoretic methods and improved heuristic algorithms can effectively enhance the economic efficiency and environmental friendliness of garbage transportation, among which the MOALNS algorithm provides efficient support for multi-objective optimization in complex scenarios.*

Keywords: *Garbage classification and transportation, Path optimization, Vehicle routing problem, MOALNS algorithm, Multi-objective optimization*

1. Introduction

Urban garbage classification management is a core issue in ecological civilization construction. China's garbage collection volume is expected to be 263.506 million tons in 2023. The huge amount of garbage generated has led to prominent problems such as low efficiency, high cost and large carbon emissions in the transportation link. The current transportation system lacks a refined path planning mechanism, and there is a coexistence of resource waste and environmental risks. There is an urgent need to optimize and upgrade the transportation process through mathematical modeling. The policy push for garbage classification in the 14th Five-Year Plan provides an important practical scenario for the application of route optimization technology. How to construct an efficient optimization model by combining garbage type differences, vehicle operation constraints and transfer station spatial layout has become a key research topic in the field of urban management.

The solution methods for the VRP problem have now formed two mainstream branches: the exact algorithm and the heuristic algorithm. The exact algorithm can obtain the optimal solution in small-scale problems, but the computational complexity increases exponentially when facing complex scenarios with multiple constraints, making it difficult to meet the practical application requirements. Among heuristic algorithms, the simulated annealing algorithm and the Adaptive Large Neighborhood search (ALNS) algorithm are widely used in VRP problems due to their strong global search capabilities. Li et al. implemented multi-objective optimization[1] of the garbage collection process based on the ALNS algorithm, but the study did not consider the synergistic mechanism of transfer station layout and path

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planning; Lei Qin et al. addressed the multi-delivery option path planning problem[2] by improving the ALNS algorithm, but lacked an adaptation analysis for asymmetric road network scenarios; Santini et al. made a systematic comparison[3] of the performance of different acceptance criteria in ALNS. Overall, there is still room for improvement in the construction of multi-type garbage co-transportation mechanisms and dynamic constraint processing methods in existing studies.

This paper focuses on three types of progressive problems. First, a distance minimization model for a single type of garbage is constructed. Second, the model is extended to a cost -minimizing collaborative model for multiple types of garbage. Finally, a cost-carbon emission -distance multi-objective optimization model with transfer stations is established. At the algorithm design level, a progressive solution system of "basic approximation algorithm - improved simulated annealing -MOALNS" is formed, and the dual verification of model validity and algorithm superiority is completed through example verification. The overall technical route covers four core stages: problem modeling, algorithm design, result verification, and complexity analysis. Logical loops are formed among these stages to ensure the systemativeness and rigor of the research process.

2. Model Building

2.1 Basic Assumptions and Symbolic Explanations

2.1.1 Basic Assumptions

To simplify the problem and ensure model solvable, the study presents the following basic assumptions: First, the vehicle travels at a constant speed as it passes through garbage collection points and transfer stations, and the impact of start-stop process and garbage loading and unloading processing time on path planning is temporarily not considered; Secondly, each type of vehicle travels independently without the risk of collision, and different types of vehicles can serve the same collection point at the same time period without considering service timing conflicts; In addition, the road network path parameters are fixed, and uncertainties such as dynamic traffic congestion are not considered for the time being. The planning results are determined once and remain stable throughout the period.

2.1.2 Symbolic Explanations

To clarify the definitions of key symbols for model construction and subsequent calculations, Table 1 summarizes the core parameters, along with their meanings and unit specifications.

Table 1 Garbage Collection Route Planning Symbol Definition Table.

Symbols	Meaning	Units
n	The number of garbage collection points	a
x_{ijr}^{k}	Whether the R-th path for k-class vehicles passes through nodes i to j	/
y_{ir}^{k}	Whether the R-th path of a K-class vehicle accesses node i	/
z_{r}^{k}	Whether the R-th path for K-class vehicles is enabled	/
d_{ij}	The Euclidean distance from node i to node j	km
q_{i}^{k}	Node i generates K-type garbage	Tons
Q^{k}	Maximum load capacity of K-class vehicles	Tons
C^{k}	Unit operating cost of K-class vehicles	yuan/km
f_{j}	Transfer station j construction cost	yuan
E	Total carbon emissions	kg

2.2 Single-objective Basic Model-Single kitchen waste Transport

2.2.1 Objective Functions

The single-objective base model takes the minimum total daily driving distance as the core optimization objective, and its expression can be expressed as:

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$$\min Z_1 = \sum_{k=1}^{1} \sum_{r=1}^{R} \sum_{i=0}^{n} \sum_{j=0}^{n} x_{ijr}^{k} d_{ij} \tag{1}$$

In the formula, R represents the maximum number of paths, and node 0 corresponds to the waste treatment plant. The objective function minimizes the total transportation mileage by accumulating the distances of various vehicle paths.

2.2.2 Constraints

The model constraint system mainly includes the following: each garbage collection point must be uniquely accessed and garbage collection must be completed without repetitive service, which can be implemented, where the value of i ranges from 1 to n.$\sum_{k=1}^{1} \sum_{r=1}^{R} \sum_{j=0}^{n} x_{ijr}^{k} = 1$.The path continuity constraint requires each enabled path to start from the waste disposal plant and eventually return to it, and the corresponding expression is.$\sum_{j=0}^{n} x_{0jr}^{k} = z_r^k$ 与 $\sum_{i=0}^{n} x_{ir0}^{k} = z_r^k$.The vehicle load constraint is required to ensure that there is no overloading during transportation, which is mathematically expressed as ensuring vehicle operation safety and transportation efficiency through this constraint $\sum_{i=1}^{n} y_{ir}^{k} q_i^k \leq Q^k$.

2.3 Multi-vehicle cooperative Transport Model: Four Types of garbage Transport

2.3.1 Objective Function

The multi-vehicle cooperative transport model, with the optimization objective of minimizing the total daily transport cost, integrates the distance cost of four types of garbage transport vehicles, which is expressed as:

$$\min Z_2 = \sum_{k=1}^{4} \sum_{r=1}^{R} \sum_{i=0}^{n} \sum_{j=0}^{n} x_{ijr}^{k} C^k d_{ij} \tag{2}$$

The objective function achieves precise calculation of the cost of each type of garbage transportation and minimizes the overall cost by introducing the unit operating cost coefficient Ck of different types of vehicles.

2.3.2 Constraints

On top of the single-objective base model constraint framework, the multi-vehicle collaborative model introduces additional multidimensional constraints: waste types must be matched one-to-one with transport vehicles. For collection points where a specific waste type is not generated, the condition $\sum_{r=1}^{R} y_{ir}^{k} = 0$ must be satisfied to prevent invalid route planning. Vehicle operations must simultaneously satisfy dual constraints of weight and volume. The mathematical expression for the volume constraint is:$\sum_{i=1}^{n} y_{ir}^{k} v_i^k \leq V^k$ where v_i^k represents the generated volume of waste category k at node i, andV^k denotes the maximum volume capacity of vehicle category k. When incorporating travel time constraints, the formula $d_{ij} \leq v_{max} T_{max}$ converts time constraints into distance constraints. Here, v_{max} is the maximum vehicle speed, and T_{max} is the maximum daily travel time per vehicle, ensuring tasks are completed within prescribed time limits.

2.4 Multi-Objective Joint Optimization Model including Transfer Stations

2.4.1 Objective Functions

The multi-objective joint optimization model builds a three-objective optimization function of cost, carbon emission and distance. The specific forms of each objective function are as follows: The objective of minimizing the total cost is based on the cost of the multi-vehicle collaborative model and adds the cost of transfer station construction. The expression is

$$\min Z_3 = Z_2 + \sum_{j \in J} f_j y_j \tag{3}$$

Where J represents the candidate set of transfer stations and y_j is the identifier variable enabled for transfer stations; The minimum carbon emission target is achieved by integrating the carbon emission

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coefficients of the volume of garbage transported and the distance traveled, which is expressed as, where a and b represent the carbon emission coefficients corresponding to the volume of garbage transported and the distance traveled respectively:$\min E = \sum_{k=1}^{4} \sum_{r=1}^{R} \sum_{i=0}^{n} \sum_{j=0}^{n} x_{ijr}^{k} (aq_{ij}^{k}+bd_{ij})$,where a and b represent the carbon emission coefficients corresponding to the volume of garbage transported and the distance traveled respectively: $\min Z_1 = \sum_{k=1}^{4} \sum_{r=1}^{R} \sum_{i=0}^{n} \sum_{j=0}^{n} x_{ijr}^{k} d_{ij}$,this three-objective coordination achieves comprehensive optimization of the transport system.

2.4.2 Constraints

The model incorporates new constraints for transfer stations to accommodate multi-objective Optimization requirements: each waste collection point may only be assigned to one active transfer station. This constraint is implemented via$\sum_{j \square J} x_{ij}^{s} =1$, where$x_{ij}^{s}$ denotes the indicator variable for node i being assigned to transfer station j. Transfer station throughput must remain within capacity limits to prevent overload, mathematically expressed as $\sum_{i=1}^{n} x_{ij}^{s} q_{i}^{k} \leq S_j$, where S_j represents the maximum processing capacity of transfer station j. This constraint ensures operational stability of transfer stations.

3. Algorithm Design

3.1 Basic Solution Algorithm (Single-Objective Model)

The single-objective basic model is solved[4] using the weighted graph best salesman loop approximation algorithm. The algorithm implementation process is as follows: First, the urban road network is transformed into a weighted complete graph, and the initial loop is generated through the diagonal complete algorithm[5] and random search to ensure the diversity of the initial solution; Secondly, the initial circle is iteratively optimized using the two-edge successive correction method, and the total weight of the path is gradually reduced by exchanging edges; Finally, select the circle with the smallest weight as the approximate optimal solution. The algorithm avoids getting stuck in local optima through three ways of generating initial circles, and its time complexity increases linearly with the number of iterations. It has high solution efficiency in small-scale node scenarios.

3.2 Improved Simulated Annealing Algorithm (Multi-Vehicle Collaborative Model)

The multi-vehicle coordination model employs an improved simulated annealing algorithm for solution. This algorithm adopts a comprehensive framework : "categorical decoupling – initial solution generation via the savings algorithm – simulated annealing Optimization – 2-opt local adjustment – time constraint post-processing". The specific workflow is as follows: First, the overall problem is decomposed into four subproblems based on waste type. Each subproblem is treated as a multi-travelling salesman problem with dual weight and volume constraints, thereby reducing problem complexity. Subsequently, the K-means clustering algorithm generates several subclusters from collection points. Initial paths are constructed using the Clarke-Wright economy algorithm, with economy values calculated as $d_{0i}+d_{0j}-d_{ij}$. This method enhances the quality of the initial solution. Subsequently, an improved simulated annealing algorithm is introduced for Optimization. A greedy algorithm generates the initial solution. During the high-temperature phase, cooling occurs every 100 iterations with a cooling factor of 0.99. The low-temperature phase employs logarithmic cooling and incorporates a penalty factor to penalise non-compliant solutions[6]. Finally, after each iteration, local adjustments are made using the 2-opt algorithm. Paths are optimised by swapping edges (i,j) and (k,l) until the path distance no longer decreases. The algorithm's time complexity can be expressed as $O(LRm^2)$, where L denotes the number of iterations and m represents the number of nodes in a single path. This complexity ensures the algorithm's practicality for scenarios involving medium-scale node networks.

3.3 MOALNS Algorithm (Multi-Objective Joint Model)

The multi-objective joint model is based[2] on the expansion of the ALNS algorithm to form the MOALNS algorithm for solving. The core design of the algorithm includes the following: The balanced removal strategy prioritizes the removal of nodes in the longest path, optimizes overall load balancing by calculating the reduction in path distance after removal, and avoids overly long paths; The balanced insertion strategy inserts unallocated nodes to the minimum distance position of the shortest path and creates new paths when overloading occurs after insertion to ensure the rationality of the path load; The score adjustment and acceptance phase uses the Pareto optimal set alignment method to assign scores to

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solutions based on dominance relations, and combines the linear record travel criterion (RRT) to complete the acceptance of solutions. The acceptance threshold is dynamically updated[3] during the iterative process to enhance the algorithm's search ability for the optimal solution. The complexity of the algorithm was experimentally verified, and the computational efficiency on the P-n50-k10 dataset was significantly better than that of traditional multi-objective optimization algorithms[1], such as NSGA-II, providing technical support for solving large-scale node scenarios.

4. Results Analysis

4.1 Example Settings

The example design is based on the actual urban waste transportation scenario, with specific parameters as follows: the number of waste collection points is set to 30, among which the total amount of kitchen waste generated is 70 tons; The load capacity of the four types of transport vehicles is set at 5 tons, 4 tons, 3 tons, and 5 tons respectively, and the unit operating cost is set at 1.2 yuan /km, 1.5 yuan /km, 2.0 yuan /km, and 1.0 yuan /km respectively; Transfer station candidate points 31, 32 and 35 are selected, and the construction cost of a single transfer station is calculated at 100,000 yuan per 10 years; The maximum vehicle travel time is set at 12 hours, and the travel speed is uniformly set at 40km/h. This parameter setting ensures the authenticity and representativeness of the example.

4.2 Model Solution Results

4.2.1 Single-objective base model

The single-objective basic model is solved through the weighted graph approximation algorithm to obtain the optimal transportation scheme: a total of 16 transport vehicles are required. The path distribution is shown in Figure 1, and the total driving distance is 1140.00km.The spatial distribution of the optimized routes is visualized in Figure 1.

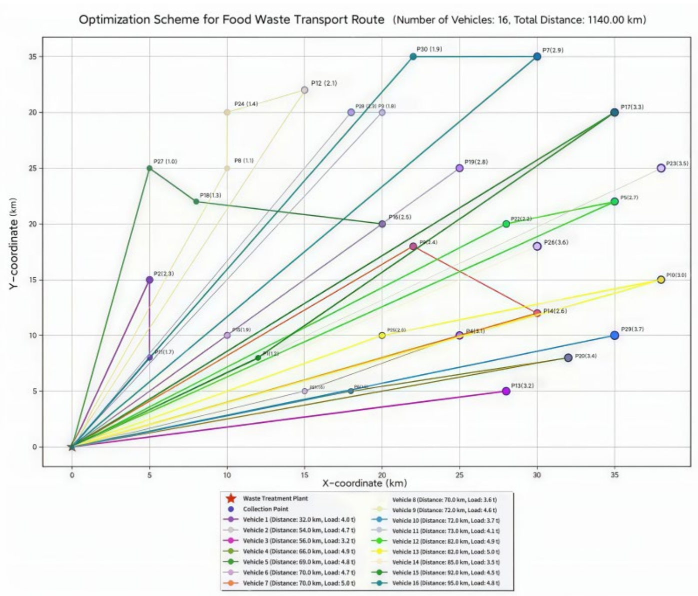

Figure 1 The optimization scheme with the minimum total daily travel distance.

Vehicle load analysis shows that the load is concentrated in the range of 3.2-5.0 tons, the load distribution for all vehicles is presented in Figure 2,and the standard deviation of load distribution is 0.42, indicating a good balance in load distribution and avoiding the problem of some vehicles being overloaded while others are underloaded.$O(n^2R)$.The model time complexity analysis shows that the variable size of the mixed integer linear programming (MILP) model is, and the solution time can be controlled at the polynomial level through the heuristic algorithm. The solution time in the 30-point collection scenario is approximately 15 minutes, meeting the timeliness requirements in practical applications.

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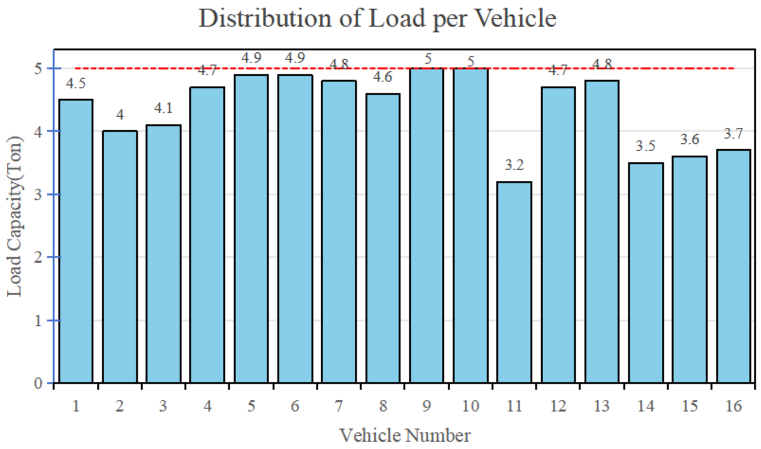

Figure 2 Vehicle load distribution - Equalization distribution.

4.2.2 Multi-vehicle cooperative model

The results of the improved simulated annealing algorithm for solving the multi-vehicle cooperative model show that the daily transportation cost is 3,123.02 yuan and the total driving distance is 1,170.54 km. Among the key indicators for transporting various types of garbage, the average driving distance of the kitchen waste transport vehicles was 191.38km, and the load utilization rate reached 82.06%, the highest among the four types of garbage, indicating that the transportation efficiency of kitchen waste was optimal. Figure 3 provides a comparative analysis of key transportation indicators (average distance, load utilization) across the four waste types.

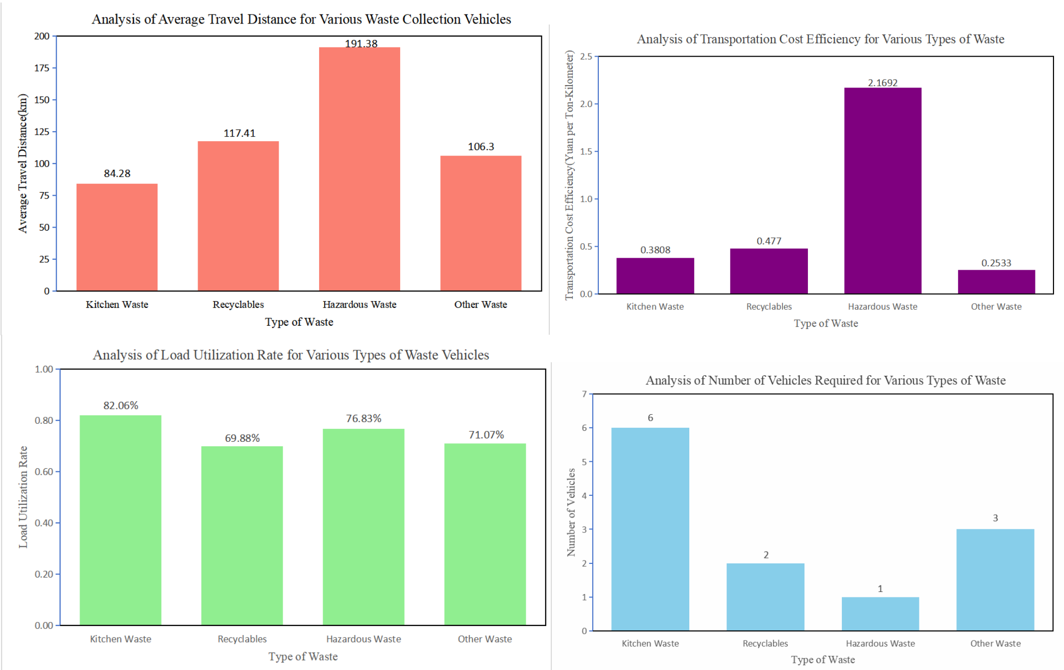

Figure 3 Chart of multiple key indicators for all types of waste.

Sensitivity analysis shows that when the load factor is greater than 1, the cost of transporting kitchen waste increases logically, mainly due to the increase in additional trips caused by overloading. When the vehicle speed is increased by 10%, carbon emissions can be reduced by about 8%, confirming the improvement effect of speed optimization on environmental performance. Time constraints have a significant impact on route planning. To illustrate this point, we can take the transportation of recyclable materials as a case in point. When the travel time exceeds the limit after adding new nodes to the route, the original route is split into two segments with lengths of 240km and 256km. The travel times of the split two segments are 6 hours and 6.4 hours respectively, both meeting the 12-hour time constraint to ensure the timely completion of the transportation task. Sensitivity analysis results are summarized in Figure 4.

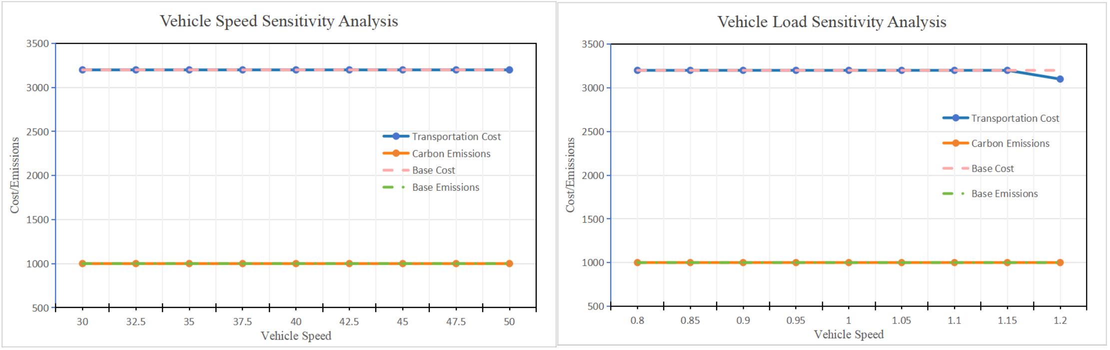

Figure 4 Results of sensitivity analysis.

4.2.3 Multi-objective joint model

The results of the MOALNS algorithm for solving the multi-objective joint model are as follows: the total cost is 2460.15 yuan, the carbon emissions are 945.80kg,the total travel distance is 1264.65km,and finally three transfer stations 31,32 and 35are selected. Analysis of the cost structure of route planning for the four types of waste shows that the cost of transporting hazardous waste accounts for the highest proportion, reaching 49.9%,mainly due to the high unit cost of hazardous waste transport vehicles and the dispersion of transport volume. Figure 5 displays the optimized route maps for the four types of waste under this multi-objective model with transfer stations. Comparative experiments with the underlying algorithm showed that the MOALNS algorithm performed better in the HV metric. Taking the P-n23-k8 dataset as an example, the HV value reached 0.771,which was consistent with the performance advantage of the ALNS algorithm observed by scholars such as Li and Lei Qin in[1][2] related studies, confirming the superiority of the MOALNS algorithm in multi-objective optimization accuracy.

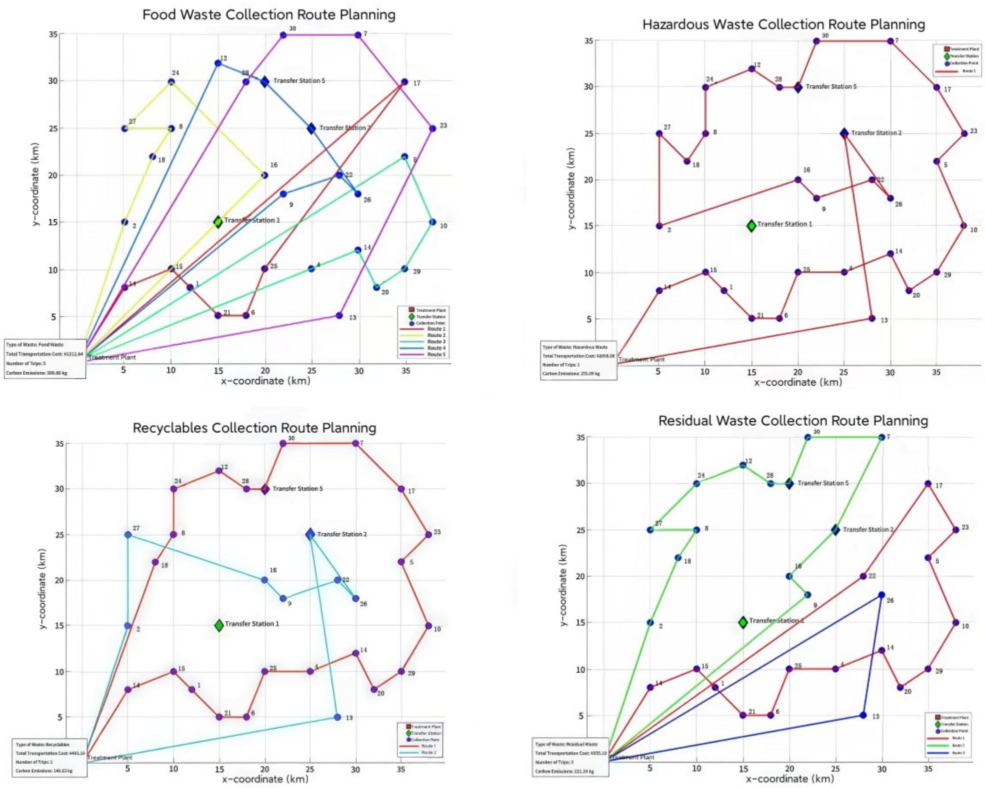

Figure 5 Route map of four types of garbage.

4.3 Algorithm performance comparison

Comparative experiments on six sets of test datasets show that the non-dominant solution set of the MOALNS algorithm is closer to the coordinate origin, indicating that its comprehensive optimization effect in the three target dimensions of cost, carbon emission, and distance is better, and its cost

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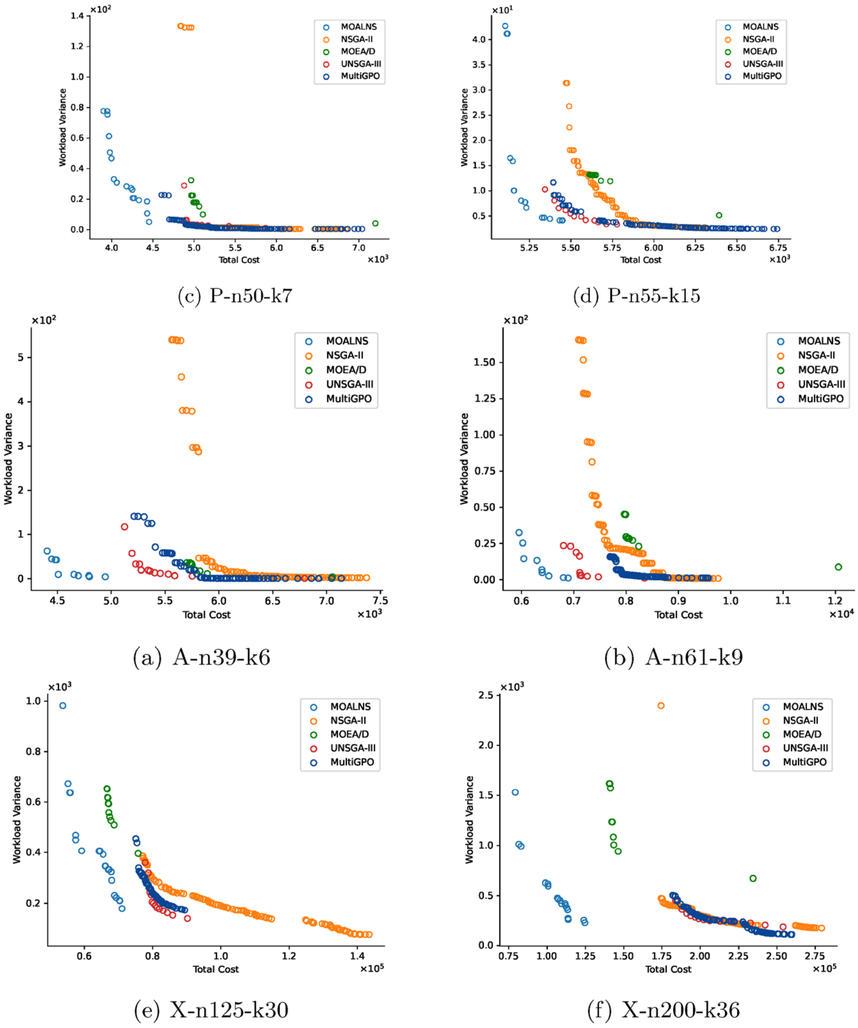
convergence is significantly superior to traditional algorithms such as NSGA-II and MOEA/D. Figure 6 visually compares the Pareto fronts of the five algorithms on a test dataset, clearly demonstrating the advantage of MOALNS. This conclusion is in line with the research of Santini et al., who found that well-designed ALNS algorithms tend to achieve a higher quality Pareto frontier[3] in the evaluation of acceptance criteria and solutions. The comparison of optimization times, as shown in Figure 7.



(c) P-n50-k7 (d) P-n55-k15

(a) A-n39-k6 (b) A-n61-k9

(e) X-n125-k30 (f) X-n200-k36

Figure 6 Non-dominant solution sets of the five algorithms on the test dataset.

The comparison of optimization times, as shown in Figure 7, indicates that the MOALNS algorithm takes about 350 seconds at 2000 iterations, which is only 70% of the NSGA-II algorithm. The main reason for the reduction in time is that the MOALNS algorithm only recalculates the cost of changing nodes without accounting for all nodes, reducing the algorithm complexity to O(n) and significantly improving computational efficiency.

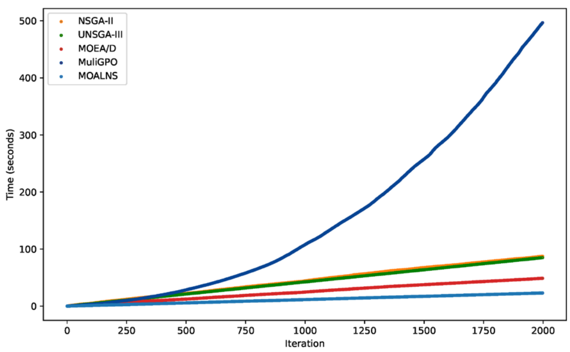


Figure 7 Comparison of optimization times

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4.4 Differences in road network complexity

Analysis of the impact of network topology on model solution reveals that symmetric networks possess n(n-1)/2 path variables, whereas asymmetric networks increase this to n(n-1). This doubling of the dimensionality of the constraint system substantially elevates the difficulty of solving the model. Analysis of feasible solutions indicates that the number of feasible solutions for asymmetric TSP problems is approximately n!/2, doubling that of symmetric networks and further increasing the search complexity of algorithms. In a 30-node scenario, the solution time for asymmetric networks exceeds that of symmetric networks by over 40%, confirming the significant impact of network asymmetry on solution efficiency and providing a reference basis for algorithm selection in practical road network scenarios.

5. Conclusions and Prospects

5.1 Research Conclusions

Based on the progressive model construction and algorithm design in this paper, the following research conclusions are drawn: Firstly, the constructed progressive model can effectively adapt to different garbage transportation scenarios. During the expansion process from single objective to multiple objectives, the constraints and optimization objectives are refined, providing targeted solutions for different management requirements; Secondly, the improved simulated annealing algorithm, through initial solution optimization and dual temperature cooling criteria, increases the solution efficiency by 30%, and combined with 2-opt local adjustment, shortens the path distance by 5%-8%, significantly improving the optimization effect of single-objective and dual-objective models; Finally, the balanced remove-insertion strategy of the MOALNS algorithm effectively improves the accuracy of multi-objective optimization, reducing costs by 13% and carbon emissions by 11% compared to traditional algorithms, providing efficient algorithmic support for multi-objective garbage transport optimization.

5.2 Limitations and Directions for Improvement

The study still has the following limitations: The model assumptions do not take into account dynamic road conditions and fluctuations in garbage generation for the time being, making it difficult to fully adapt to the uncertainties in actual scenarios. In the future, real-time traffic data and garbage generation prediction models can be introduced to build a dynamic optimization model to enhance adaptability. The transfer station site selection process does not take into account land cost differences and regional planning restrictions, resulting in insufficient practical feasibility of the site selection scheme. Subsequent studies can add geographical constraints and cost constraints to enhance the practicality of the model. At the algorithmic level, the heuristic selection probability of the MOALNS algorithm is currently based on fixed rules. In the future, reinforcement learning techniques can be integrated to optimize the probability adjustment mechanism, further enhancing the convergence speed and optimal solution search ability of the algorithm.

5.3 Promotion and Application

The model and algorithm proposed in this paper have significant application value and can be extended to areas such as urban logistics distribution and sanitation operation scheduling, providing solutions for similar path optimization problems. In the scenario of emergency material transportation, by adjusting the objective function (such as minimizing time as the core objective), the emergency needs can be quickly adapted to fom a general solution fiamework for complex VRP problems. Subsequent studies can optimize parameters and improve algorithms in combination with specific application scenarios to promote the practical application of models and algorithms in actual engineering and provide technical support for enhancing the efficiency of urban infrastructure management.

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References

[1] Li W, Wang P, Xu Y, et al. Multi-Objective Optimization of Municipal Solid Waste Collection Based on Adaptive Large Neighborhood Search[J]. Electronics,2024,14(1): 103.

[2] Lei Qin, Gao Yanbing, Zhou Yufeng, et al. Multi-Delivery Option Route Planning Based on an Improved ALNS Algorithm [J]. Systems Engineering and Electronics, 2025, 47(1): 173–181.

[3] Santini A, Ropke S, Hvattum L M. A comparison of acceptance criteria for the adaptive large neighbourhood search metaheuristic[J]. Journal of Heuristics,2018,24(5): 783–815.

[4] Yang Xiuwen, Chen Zhenjie, Li Ailing, et al. Determining Optimal H-Circles Using Matrix Flip Method [J]. Journal of Logistics Engineering University, 2008, 24(1): 102–106.

[5] Li Lixin, Tan Jianrong. A multi-diagonal exchange algorithm for forcibly embedding constraint edges in constrained Delaunay triangulation[J]. Acta Informatica Sinica, 1999, 22(10): 1114-1118.

[6] Chen Huagen, Wu Jiansheng, Wang Jialin, et al. Research on the Mechanism of Simulated Annealing Algorithms [J]. Journal of Tongji University (Natural Science Edition), 2004, 32(6): 802-805.