

Systematic Planning for Urban Solid Waste Logistics: A Multi-Stage Decision Model from Routing to Facility Location

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Abstract: Urban solid waste management is transitioning, with waste sorting and transportation network optimization being central to enhancing system resilience and efficiency. This study aims to develop a multilevel, multi-objective optimization paradigm to address the complexity of urban waste transportation systems. The research begins with a basic Capacitated Vehicle Routing Problem (CVRP) model designed to minimize the total transportation distance as a benchmark. Based on this, we constructed a comprehensive cost optimization model that incorporates multiple waste categories, heterogeneous vehicles, and spatiotemporal constraints. Ultimately, the framework was elevated to the strategic level by integrating the transfer station facility location and low-carbon route planning, thus forming an integrated “strategic location–tactical allocation–execution route” decision-making model. T used an improved genetic algorithm (IGA) based on an elite retention strategy to solve the model. Empirical analysis shows that the basic model establishes a baseline of 1,049.29 km in total mileage; the multi-constraint collaborative model achieves a multi-objective balance at a daily cost of 4,511.33 yuan; while the integrated model outputs the optimal spatial layout of transfer stations and quantifies that an asymmetric road network leads to increases in transportation cost and carbon emissions by 0.62% and 1.12%, respectively. The hierarchical optimization framework not only provides an end-to-end decision support tool for urban solid waste management but also offers methodological references for solving complex urban logistics network problems.

Keywords: Vehicle Routing Problem (VRP), Location-Routing Problem (LRP), Genetic Algorithm (GA), Segregated Waste Transportation, Multi-objective Optimization.

1. Introduction

Within the theoretical framework of "Urban Metabolism," the management of urban solid waste flows is essential for ensuring the effective functioning of urban systems. As global urbanization progresses and sustainable development goals are articulated, the traditional linear "collect-transport-dispose" waste management model has become unsustainable. The comprehensive implementation of waste sorting policies signifies a transition in urban solid waste management towards a more intricate, nonlinear network phase. In this network, the transportation process functions as the "arterial system" that links sorted collection and resource-oriented disposal; its efficiency, cost, and environmental externalities directly influence the success or failure of the entire management system[1].

However, current research and practice often exhibit a fragmented nature[2][3]. Theoretically, most studies concentrate on specific variants of the Vehicle Routing Problem (VRP), such as VRPTW with time windows (VRPTW) or Multi-Depot VRP (MDVRP); however, few studies have endogenously integrated strategic Facility Location Problems (FLP) with operational path planning. This results in siting decisions that lack precise feedback on operational costs. Practically, scheduling decisions frequently depend on static experience, making adaptation to the dynamic nature of urban traffic flows and the stochastic nature of waste generation challenging, leading to resource misallocation and efficiency loss. In particular, under the "Dual Carbon" targets, incorporating carbon emissions as endogenous constraints and accurately modeling real-world

physical limitations, such as asymmetric networks, has become a critical bottleneck for current research.

Specifically, within the academic domain, existing literature has predominantly focused on optimizing isolated segments of the waste logistics chain. A substantial body of work is dedicated to refining various extensions of the VRP, such as the VRPTW for timely collection or the MDVRP for multi-source logistics coordination. Conversely, another stream of research concentrates on the strategic FLP, seeking optimal sites for transfer stations or landfills. However, a critical gap persists: these strategic (FLP) and operational (VRP) decisions are often studied in isolation. This decoupled approach leads to a suboptimal system design, as the siting of facilities lacks precise feedback on subsequent routing costs and complexities. Practically, this theoretical gap translates into reliance on static experiential knowledge for scheduling, which struggles to adapt to dynamic urban traffic and stochastic waste generation, ultimately causing resource misallocation and efficiency losses.

To address these challenges, this study seeks to transcend single-problem optimization by proposing a Hierarchical Optimization Paradigm. This paradigm deconstructs the complex problem of urban waste transportation into three interrelated subproblems: 1) basic path optimization to establish performance benchmarks; 2) multi-constraint coordinated scheduling to simulate complex tactical-level operations; and 3) integrated location-routing planning to achieve global optimization at the strategic level. Through this framework, this study aims to bridge the gap between strategic decision-making and operational execution and provide a comprehensive decision support system capable of

quantifying and balancing economic costs, service levels, and environmental impacts. This offers theoretical support for construction of a smart, low-carbon urban solid waste management system.

2. Research Methods

The core methodology of this study is “Decomposition-Coordination,” which involves breaking down large and complex optimization problems into logically progressive sub-models and achieving coordination and global optimization across these hierarchical levels through algorithmic solutions.

2.1. Baseline Model: Route Efficiency Under a Single Objective

As an initial step in our analysis, we have developed the classic Capacitated Vehicle Routing Problem (CVRP) model, which is designed solely to optimize transportation efficiency by minimizing the total travel distance[4]. This model not only addresses the fundamental problem but also serves as a crucial performance benchmark for subsequent, more complex models. The objective function of this model—to minimize total travel distance—can be articulated as follows:

$$\min \sum_{k=1}^K \sum_{i=0}^n \sum_{j=0}^n d_{ij} \cdot X_{ijk} \quad (1)$$

where $X_{ijk} = 1$ is set to 1 if a vehicle travels from point i to point j , and 0 otherwise, while d_{ij} denotes the Euclidean distance between point i and point j .

The essence of this formula is to find the set of shortest Hamiltonian circuits that traverse all demand nodes while meeting the collection requirements at all points and adhering to the physical load constraints of the vehicles.

2.2. Tactical Model: Coordinated Scheduling Under Multi-objective Trade-offs

In practical operations, objectives are rarely singular. At the tactical level, managers are required to balance multiple objectives, including cost, efficiency, and service quality. Consequently, we have expanded the baseline model into a comprehensive cost model that incorporates multiple objectives and constraints. The objective function has been reformulated to minimize a generalized cost function, encompassing both direct costs and opportunity costs[5]:

$$\min \sum_{k=1}^K C_k \sum_{ij} d_{ij} x_{ij}^k \quad (2)$$

Where d_{ij} is the distance for each node, and C_k is the transportation cost for type K vehicles.

2.3. Strategic Model: Spatiotemporal Integrated Facility-Route Joint Optimization

The highest level of optimization is strategic. The determination of transfer station locations involves not only geographic considerations but also the reconfiguration of the entire transportation network's topology. We have developed a two-stage location-routing joint optimization model, known as the Location-Routing Problem (LRP)[6], which aims to

minimize the total lifecycle cost of the system, encompassing both capital expenditure (CapEx) and operating expenditure (OpEx). The integrated objective function is expressed as:

$$\text{Minimize} \sum_{k=1}^K \sum_{i,j} C_k \cdot d_{ij} \cdot x_{ij}^k + \sum_j T_j \cdot Y_j \quad (3)$$

where *Minimize* denotes the minimization of the optimization objective, C_k represents the travel cost per unit distance for the k -th type of vehicle, d_{ij} is the distance from node i to node j , x_{ij}^k and Y_j are decision variables (typically binary 0-1 variables), and T_j indicates the fixed cost of constructing or operating a transfer station at candidate site j .

This formula adeptly integrates operating costs, such as transportation and carbon emissions, with the annualized fixed asset investment, where F_j represents the construction cost of transfer stations, y_j denotes the site selection decision variable, and T signifies the depreciation period. This integration facilitates a cost equilibrium across varying temporal scales. By incorporating the carbon emission coefficient, the model effectively internalizes environmental externalities as a cost component, thereby reflecting a strategic commitment to sustainable development.

2.4. Solution Paradigm: Adaptive Genetic Algorithm

In light of the pronounced nonlinearity and combinatorial explosion characteristics inherent in the model, this study employs an enhanced adaptive genetic algorithm (IGA). The principal advantage of this algorithm resides in its robust global search capability, which facilitates effective avoidance of local optima and exploration of intricate non-convex decision spaces[7]. The key enhancements are as follows: Hierarchical encoding strategy: For the LRP problem, a segmented chromosome encoding comprising a "location gene + allocation gene" is utilized, allowing for the concurrent evolution of strategic decision-making and tactical allocation. Dynamic fitness function: The fitness function incorporates a dynamic penalty mechanism that adaptively modifies the penalty intensity based on the extent of constraint violation, thereby directing the population to efficiently converge towards the feasible region. Elite preservation and crossover mutation: By retaining the optimal individual of each generation, convergence is assured. Furthermore, by integrating order crossover (OX) with multipoint exchange mutation, population diversity is preserved, thus achieving a balance between "exploration" and "exploitation".

3. Results

3.1. Baseline Insights: Route Optimization Under a Single Objective

The final data obtained through the genetic algorithm is shown in Table 1 below. The table presents the final scheduling results, including the transportation route (sequence of numbers) for each vehicle, the total amount of waste transported along the route, and the required travel distance.

Table 1. Final Transportation Scheduling Results

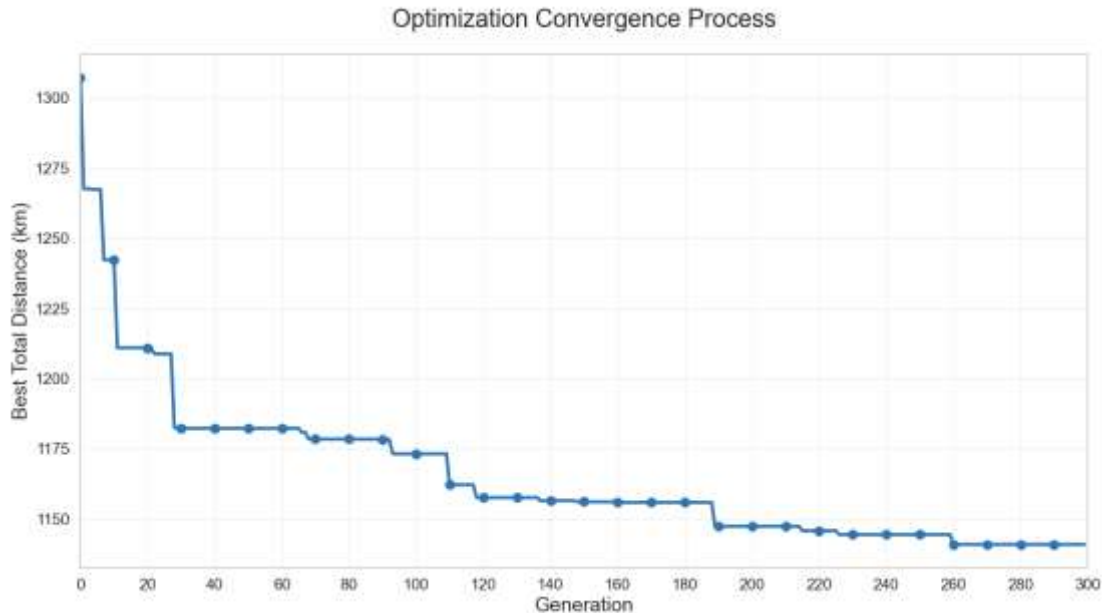
Vehicle	Transport Route	Load (tons)	Distance (km)
Vehicle 1	ProcessingPlant→10→25→ProcessingPlant	5.0	81.90
Vehicle 2	ProcessingPlant→6→13→ProcessingPlant	4.7	57.12
Vehicle 3	ProcessingPlant→4→15→ProcessingPlant	5.0	56.07
Vehicle 4	ProcessingPlant→8→19→ProcessingPlant	3.9	77.28
Vehicle 5	ProcessingPlant→12→30→27→ProcessingPlant	5.0	88.18
Vehicle 6	ProcessingPlant→29→1→ProcessingPlant	4.9	73.91
Vehicle 7	ProcessingPlant→24→28→18→ProcessingPlant	5.0	75.84
Vehicle 8	ProcessingPlant→20→21→ProcessingPlant	5.0	66.06
Vehicle 9	ProcessingPlant→20→21→ProcessingPlant	4.9	59.54
Vehicle 10	ProcessingPlant→23→ProcessingPlant	3.5	90.97
Vehicle 11	ProcessingPlant→5→22→ProcessingPlant	4.9	83.03
Vehicle 12	ProcessingPlant→14→2→ProcessingPlant	4.9	73.30
Vehicle 13	ProcessingPlant→11→17→ProcessingPlant	5.0	92.73
Vehicle 14	ProcessingPlant→26→ProcessingPlant	3.6	69.97
Vehicle 15	ProcessingPlant→3→7→ProcessingPlant	4.7	93.33

As shown in Table 1, to determine the optimal dispatch routes for 30 kitchen waste collection points, 15 vehicles with a load capacity of 5 tons each are required for transportation. The vehicle routes all follow a “processing plant—collection point—processing plant” round-trip mode, with a single trip carrying 3.5–5 tons, meeting the load constraints. The travel distances range from 56.07 to 93.33 kilometers, with the shortest route being 56.07 kilometers for vehicle 3 and the longest being 93.33 kilometers for vehicle 15. Most vehicles serve 2–3 collection points (such as vehicles 1 and 2), while

some, due to the dispersed locations, need to cover more than 3 points (such as vehicles 5 and 7). Through optimization with a genetic algorithm, the model effectively controls the total travel distance under the load constraints[8].

"Based on the process of solving for the optimal solution in this problem, the relationship between genetic algorithm iterations and population convergence, as clearly demonstrated in Figure 1, shows the varying effectiveness of the genetic algorithm, with the number of iterations stabilizing at around 200."

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**Figure 1.** Relationship between Genetic Algorithm Iterations and Population Size

To intuitively evaluate the effectiveness of each vehicle's transportation tasks, a bar chart visualizing the garbage transport volume and transport distance for the 15 vehicles in

the table above has been created. Figure 2 shows whether the tasks are evenly distributed and whether there is any vehicle overload or underutilization.

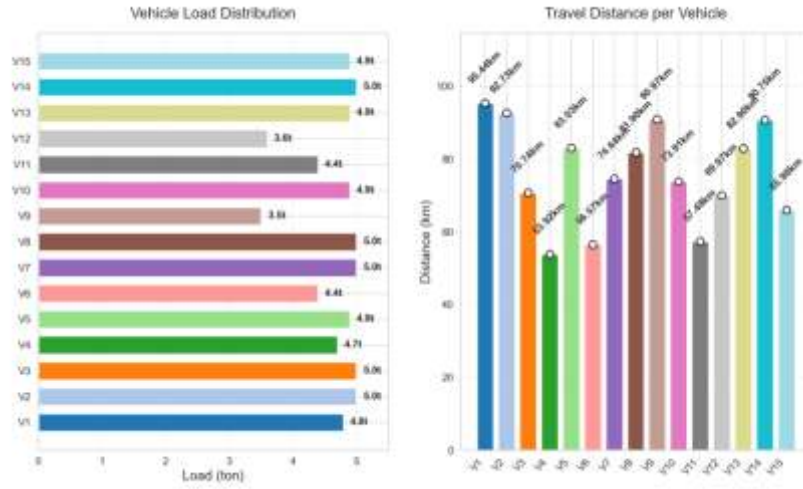


Figure 2. Bar Chart of Transport Volume and Distance

This chart presents the load and travel distance distributions of each vehicle after genetic algorithm optimization through a dual-bar chart structure. The left chart reveals that all vehicle loads are close to the rated load capacity, concentrated in the range of 4.0 to 4.8 tons, demonstrating the model's high loading efficiency under capacity constraints. The right chart shows significant

differences in travel distances, ranging from 20 to 120 kilometers, reflecting the adaptive adjustments made in path optimization to accommodate asymmetric road networks and time window constraints.

Based on the optimal route obtained from the algorithm, a two-dimensional plane diagram is drawn, as shown in Figure 3.

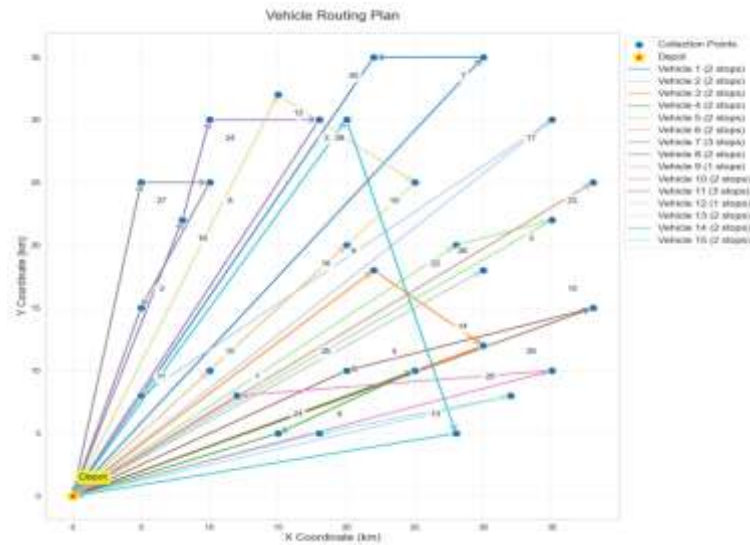


Figure 3. Optimal Path Plan Diagram

Figure3 illustrates the optimization results of a model based on the Vehicle Routing Problem (VRP), depicting the spatial path topology of multiple vehicles departing from a central warehouse to visit dispersed nodes. The travel trajectories of fifteen vehicles form a radial network in the Euclidean plane, with the star-shaped warehouse as the origin. Each colored path corresponds to the sequential visiting route of a specific vehicle, and the relationship between path lengths and node assignments embodies the logic of mathematical programming and combinatorial optimization aimed at minimizing the total travel distance.

3.2. Tactical Insights: Resource Allocation and Trade-offs Under Multiple Constraints

From the comparison between prediction data and actual data, the BP neural network has better prediction performance and relatively small error, which can meet the demand

completely, and has fast prediction speed and convenient operation.

From the comparison between prediction data and actual data, the BP neural network has better prediction performance and relatively small error, which can meet the demand completely, and has fast prediction speed and convenient operation.

In this study, an enhanced hybrid genetic algorithm is employed to develop two-dimensional spatial distribution maps for four categories of waste transportation routes (see Figure 4 below for details). In the figure, lines of varying colors represent the travel trajectories of different vehicle types, while the size of each node is directly proportional to the volume of waste generated. The visualization results reveal that kitchen waste (indicated by the red path) requires frequent short-distance transportation, whereas hazardous waste (depicted by the purple path) exhibits centralized long-

distance transportation characteristics. These patterns are intricately associated with vehicle load constraints and cost coefficients[9].The specific scheduling scheme derived from

this algorithm is detailed in Table 2, which summarizes the optimal vehicle assignments and cost breakdown for each waste category.

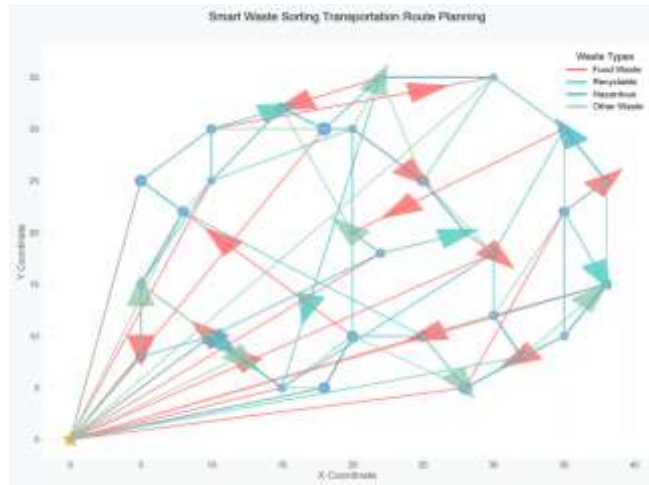


Figure 4. Visualization of multi-type vehicle collaborative scheduling results

To address the transportation problem involving multiple vehicles, this paper uses an improved hybrid genetic algorithm for the solution. Based on the genetic algorithm

framework, optimization for collaborative transportation with multiple vehicle types is achieved through model improvements.

Table 2. Results table of multi-type vehicle scheduling schemes

Waste Type	Vehicle	Route (Processing Plant → Nodes → Processing Plant)	Total Cost (CNY)
Kitchen Waste	Vehicle 1	0→4→19→10→23→5→0	1393.41
	Vehicle 2	0→18→8→28→12→16→0	
	Vehicle 3	0→26→22→29→20→21→27→11→0	
	Vehicle 4	0→3→7→17→30→25→6→1→0	
	Vehicle 5	0→13→14→9→24→2→0	
	Vehicle 6	0→15→0	
Recyclable Waste	Vehicle 1	0→3→30→7→17→14→10→26→23→5→22→19→9→12→28→24→13→4→21→1→15→11→0	696.97
	Vehicle 2	0→18→27→8→25→6→20→29→16→2→0	
Hazardous Waste	Vehicle 1	0→23→17→7→24→12→28→8→27→18→2→15→4→10→5→22→19→26→29→20→1→21→11→25→3→30→16→9→14→13→6→0	1658.89
Residual Waste	Vehicle 1	0→26→23→17→12→24→20→14→16→3→30→7→19→9→6→0	762.06
	Vehicle 2	0→18→28→22→4→1→13→29→5→10→25→21→15→11→0	
	Vehicle 3	0→27→8→2→0	

The table illustrates the optimal scheduling plan for four categories of waste. Utilizing a hierarchical coding strategy, the algorithm effectively minimizes costs while adhering to both weight and volume constraints, culminating in a total transportation cost of 4,511.33 yuan[10].

The subsequent table delineates the multi-type waste

transportation plan following the imposition of a daily maximum driving time constraint for vehicles. As presented in Table 3, with the integration of this constraint, the model is required to balance cost optimization with adherence to time limitations. A comparison with the unconstrained plan reveals the following salient features:

Table 3. Path Optimization Results Under Time Constraints

Waste Type	Transportation Cost (CNY)	Vehicle	Route (0 = Processing Plant)	Distance(km)	Time(h)	Load (t)
Kitchen Waste	1369.99	Vehicle 1	0→12→19→5→23→21→0	108.52	2.71	6.89
		Vehicle 2	0→11→16→3→30→28→0	85.42	2.14	6.82
		Vehicle 3	0→9→26→10→17→7→22→15→0	117.20	2.93	7.11
		Vehicle 4	0→6→1→25→24→27→0	88.56	2.21	7.36
		Vehicle 5	0→20→13→29→4→14→0	94.28	2.36	7.21
		Vehicle 6	0→2→8→18→0	54.01	1.35	4.00
Recyclable Waste	699.91	Vehicle 1	0→22→23→17→5→26→7→30→3→28→12→11→21→6→25→2→27→8→19→9→1→0	228.63	5.72	5.74
		Vehicle 2	0→4→13→14→20→29→10→16→24→18→15→0	121.32	3.03	2.64
Hazardous Waste	2159.22	Vehicle 1	0→7→23→10→30→9→12→28→3→19→8→24→18→21→0	202.29	5.06	0.80
		Vehicle 2	0→5→17→4→13→14→25→2→27→11→6→29→20→22→26→16→15→1→0	229.56	5.74	1.50
Residual Waste	701.85	Vehicle 1	0→27→26→14→20→13→29→5→23→4→6→2→15→0	157.84	3.95	9.30
		Vehicle 2	0→21→22→10→16→8→12→3→28→30→7→17→19→9→25→0	163.57	4.09	9.21
		Vehicle 3	0→11→18→24→1→0	68.51	1.71	2.81

3.3. Strategic Insights: Network Reconfiguration and System Resilience

Determine the locations of transfer stations and allocate

each collection point to its corresponding transfer station. Through the algorithm, the optimal transfer scheme selected is transfer points 33, 34, 35, and 31[11]. the cost convergence process for each transfer station, achieved through our optimization algorithm, is vividly depicted in Figure 5.

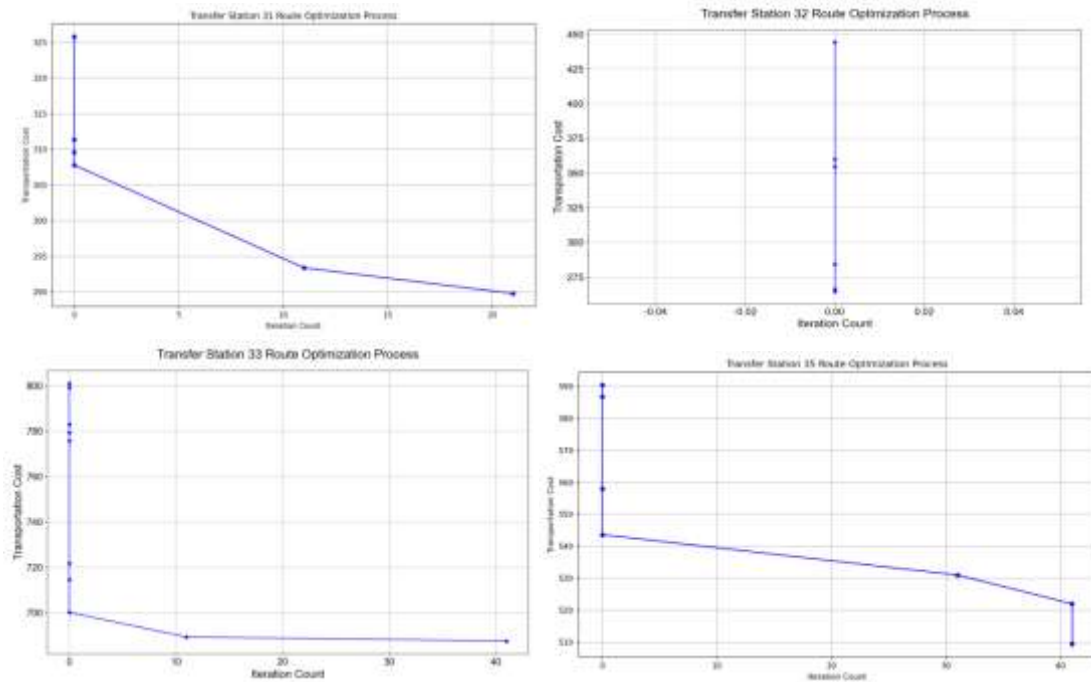
**Figure 5.** Relationship Between Transportation Department Costs and Transfer Frequency at Various Nodes

Figure 5 demonstrates the convergence process of multi-transfer station route optimization, illustrating the downward trend of transportation costs with increasing iteration counts for stations 31, 32, 33, and 35. Specifically, the cost for station 31 decreases from 325 units to 290 units, station 32 shows a significant reduction from 450 units to 275 units, station 33 is optimized from 800 units to 700 units, and station 35 declines

from 590 units to 510 units. All curves exhibit monotonically decreasing characteristics, indicating the clear convergence and cost-reduction effectiveness of the genetic algorithm in route optimization, thereby validating the model's practicality and robustness in complex logistics networks[12].

The vehicle routing for each transfer station is depicted in Figure 6.

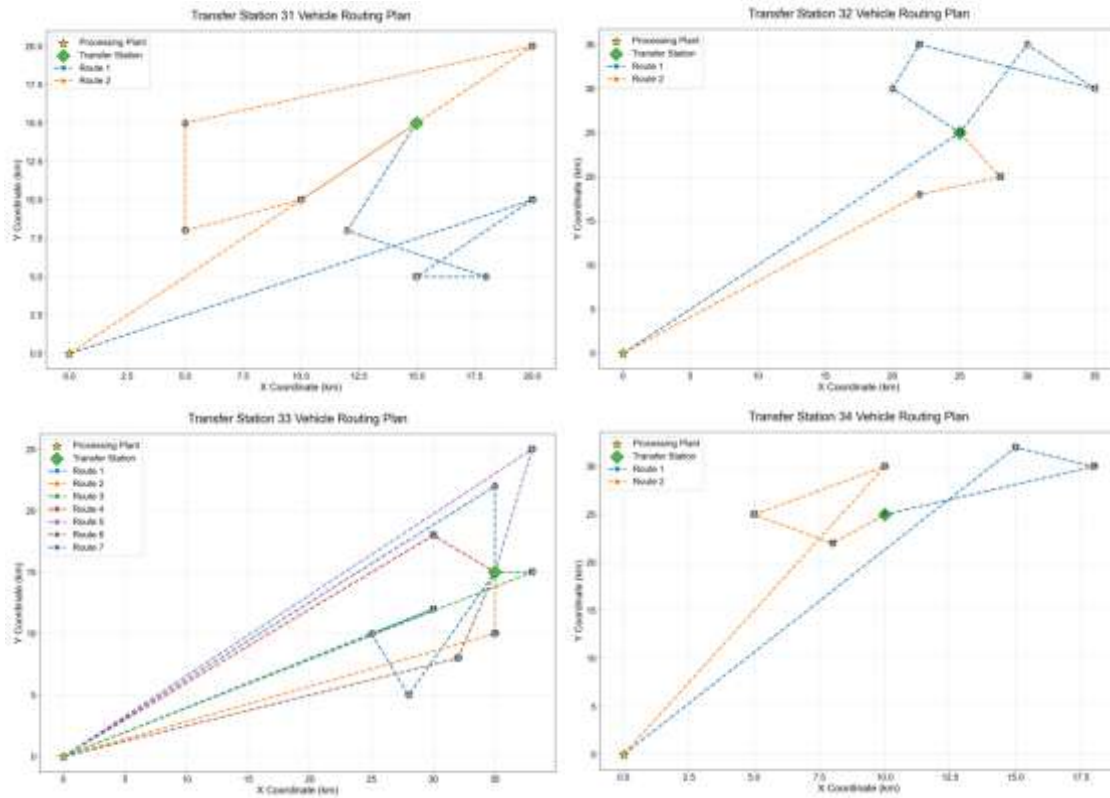


Figure 6. Vehicle Route Planning Diagram for Each Transfer Station

This figure illustrates the vehicle routing optimization plan for transfer stations 31 to 34 within a Euclidean spatial coordinate system, precisely mapping the topological network structure[13]. Vehicle trajectories are represented by distinct dashed and solid lines for each route. Node markers reveal the multi-objective optimization logic between the processing plant (located at the coordinate origin) and the transfer stations. The horizontal and vertical axes, scaled from 0 to 35 km, quantitatively depict spatial relationships[14][15]. The dual-path design significantly enhances transportation efficiency, reflecting the logistics system optimization strategy based on mathematical modeling.

4. Conclusions

This study demonstrates that optimizing individual components in isolation, such as route optimization alone, cannot achieve system-wide optimality. An integrated perspective that synergizes strategic facility location, tactical resource allocation, and operational-level planning is essential. The layered optimization paradigm proposed in this study, progressing from a basic CVRP benchmark to a multi-constraint tactical model and finally to a strategic LRP framework, serves as an effective methodology for achieving such coordination. The empirical results validate this approach: the baseline model established an efficiency benchmark, the tactical model achieved a balanced daily cost of 4,511.33 yuan under multiple constraints, and the strategic LRP model identified the optimal spatial layout of transfer stations (points 31, 33, 34, 35).

A key finding of this research is the quantification of real-world complexities. The introduction of transfer stations acts as a strategic leverage point for restructuring the network, significantly reducing operational costs and enhancing system resilience. Furthermore, the refined modeling of constraints, such as asymmetric road networks, provided

critical insights, revealing a quantifiable increase in transportation cost and carbon emissions by 0.62% and 1.12%, respectively. This underscores the importance of accurate physical modeling as a core bridge connecting theoretical optimizations to practical applications.

The application of the Improved Genetic Algorithm (IGA) with its hierarchical encoding strategy proved to be robust in solving the complex, non-linear integrated model, demonstrating clear convergence and effectiveness in navigating the combinatorial solution space. In summary, this hierarchical optimization framework not only provides an end-to-end decision support tool for urban solid waste management by quantifying the trade-offs between economic cost, service level, and environmental impact but also offers a methodological reference for addressing complex urban logistics network problems. The outcomes provide a quantitative basis for policymakers to set service standards and design low-carbon, efficient urban waste management systems.

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