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Location – Routing Optimization for Metro – Truck Joint Distribution Considering Carbon Emissions

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Abstract. A metro – truck integrated location-routing optimization model is proposed to address the high cost and carbon emissions of traditional truck-based delivery systems by leveraging metro off-peak residual capacity under time window and carbon emission constraints. A two-stage solution framework is developed, combining improved K-means clustering for simultaneous facility location and customer assignment with a cluster-guided genetic algorithm for routing optimization.A case study based on the Beijing Metro Yizhuang Line is conducted for validation. Results show that, compared with a truck-only delivery system, the proposed approach reduces total cost by 22% and carbon emissions by 38.5%, while improving the time window satisfaction rate by 12%. The results demonstrate that utilizing metro off-peak capacity can significantly enhance both economic efficiency and environmental sustainability in urban distribution systems.

Keywords: urban logistics; metro freight transportation; joint distribution; clustering algorithms; carbon emissions; genetic algorithm

1. Introduction

With the rapid growth of e-commerce and on-demand delivery services, urban logistics systems face increasing challenges from congestion, rising costs, and carbon emission reduction requirements. Traditional truck-based distribution has become inefficient in dense urban areas, while metro systems offer high capacity, reliability, and significant off-peak residual capacity that can be utilized for freight transport. Therefore, integrating metro off-peak capacity into urban freight systems has attracted growing attention.

Existing studies mainly focus on metro-based freight systems, location-routing problems, and green logistics. Metro freight feasibility and operational coordination have been widely investigated [1 – 7]. Location-routing models have been developed using heuristic approaches [8 – 13]. Carbon emissions have also been incorporated into optimization frameworks to improve sustainability [14 – 17]. However, most studies separate location and routing decisions, simplify metro capacity utilization, and rarely consider both time window constraints and carbon emissions simultaneously.

To address these issues, a metro – truck integrated location-routing model is proposed considering carbon emissions and time window constraints. A two-stage solution framework is developed, combining improved K-means clustering for station location and demand assignment with a cluster-guided genetic algorithm for routing optimization. A case study on the Beijing Metro Yizhuang Line is conducted, and sensitivity analyses are performed to evaluate the effects of metro capacity and customer scale.

2. Problem Description

This study investigates a metro – truck joint distribution system, in which a two-echelon logistics network consisting of metro trunk transportation and truck-based last-mile delivery is established. Goods are first transported from the distribution center to the metro origin station, then carried to multiple transfer stations via metro off-peak residual capacity, and finally delivered to customers by trucks, as illustrated in Fig. 1.

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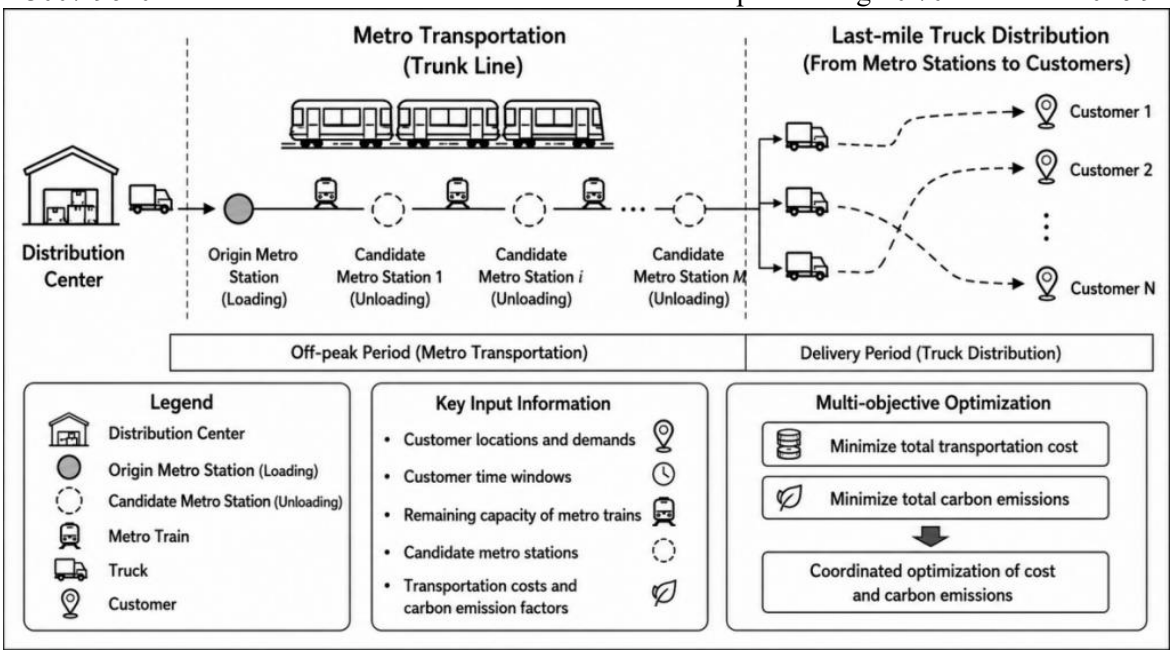


Fig. 1 Metro-truck joint distribution optimization framework

The problem involves three interrelated decisions: transfer station location, customer assignment, and vehicle routing. These decisions are jointly optimized while considering customer demand, time window constraints, metro residual capacity, transportation cost, and carbon emission cost. The objective is to minimize total system cost subject to capacity, vehicle loading, and service constraints.

Metro freight capacity is derived from off-peak residual passenger capacity. The available capacity of each train is pre-estimated based on operational data and aggregated over the planning horizon, which is used as a capacity constraint in the model.

The following assumptions are made for modeling purposes: (i) customer demand, location, and time windows are known and deterministic; (ii) metro operation during off-peak periods is stable with known residual capacity; (iii) transfer stations are equipped with basic loading/unloading facilities with constant handling time; and (iv) transportation cost and carbon emission factors are proportional to distance and remain constant.

3. Mathematical Model

To clearly formulate the problem and construct the optimization model for the joint distribution system, this section uniformly defines the sets, parameters, and decision variables involved in the model. The specific meaning of each notation is presented as follows.

Symbols	Definition
J	Set of customers, indexed by i, j
S	Set of metro delivery stations, indexed by s
R	Set of metro trips, indexed by r
V	Set of trucks, indexed by v
D	Set of metro origin stations
q_j	Demand of customer j
$[e_j, l_j]$	Service time window of customer j ,where e_j is the earliest service time and l_j is the latest service time
t_j	Arrival time of the truck at node j
s_j	Service time for customer j

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Q_v	Load capacity of truck v
Q_r	Residual transport capacity of the r-th metro trip
d_{ij}^{v}	Actual travel distance of the truck between node i and node j
d_{ds}^{r}	Travel distance of the r-th metro trip from origin station d to delivery station s
c_{ds}^{r}	Unit distance transportation cost of the metro
c_v	Unit distance transportation cost of the truck
f_v	Fixed usage cost of the truck
t_f	Transfer and loading/unloading time between metro and truck
M	Sufficiently large positive number
μ	Proportion of thermal power generation
Z	Carbon emission generated by train traction
E_r α_v	Carbon emission factors of the metro and trucks respectively
E	Traction power of train operation
γ	Penalty cost per unit of carbon emission
η	Metro operation time
x_{ij}^{v}	Equals 1 if truck v travels from node i to node j; 0 otherwise
$y_{ds}^{r} \in \{0,1\}$	Equals 1 if the goods of customer j are transported from origin station d to delivery station s via the r-th metro trip; 0 otherwise
$z_s = \{0,1\}$	Equals 1 if station $s \in S$ is selected as a delivery station; 0 otherwise
n_s	Number of connecting delivery trucks at delivery station s

3.1 Improved K-means Clustering for Delivery Station Siting

An improved K-means clustering algorithm is employed to determine delivery station locations by partitioning customer demands in the metro–truck distribution system. Compared with the conventional Euclidean-distance-based method, both time window characteristics and carbon emission costs are incorporated into the distance metric to better capture operational delivery requirements and enhance clustering realism. This provides a structured basis for subsequent customer assignment and routing optimization under operational constraints.

(1).Intermodal carbon cost between customer j and station s.

$$E_{js} = \alpha_v \cdot d_{js}^{v} \cdot q_j + E_r \cdot d_{ds}^{r} \cdot \frac{q_j}{Q_r} \tag{1}$$

(2).Time window dissimilarity between cluster center and customer.

$$Sim_{js} = 1 - \frac{\left| t_j - \overline{t_s} \right|}{\Delta t_{\max}} \tag{2}$$

(3).Normalized comprehensive clustering distance.

$$\omega_{js} = \lambda_1 \tilde{D}_{geo} + \lambda_2 \tilde{t}_{js} + \lambda_3 \tilde{E}_{js} \tag{3}$$

where D_{geo} is geometric distance; $\lambda_1, \lambda_2, \lambda_3$ are weight coefficients balancing space, time and environmental cost.

Clustering centers and customer assignments are updated iteratively until convergence to obtain depot locations and customer partitions for downstream routing optimization..

3.2 Model Construction

To minimize the total system cost, the metro–truck joint distribution cost is decomposed into transportation cost and carbon emission cost. A unified objective function is then formulated to capture both economic and environmental impacts.

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3.2.1 Carbon Emission Cost

The carbon emission cost is introduced to quantify environmental impacts of the system. Emissions from metro trunk transport are calculated by Eq. (4), while emissions from last-mile truck distribution are given in Eq. (9).Metro emission estimation incorporates traction power, operating speed, electricity mix, and load factor to ensure consistency with operational conditions. The traction power is further derived in Eqs. (5)–(8).

$$Z_1 = E \times t \times \mu \times \delta Z_2 \tag{4}$$

$$E = \frac{1}{3600}(F_\mu + \omega_0 \times P_\mu \times g) \times \sum_{j\in J}\sum_{r\in R}\sum_{s\in S} x_j^{rs} d_{ds}^r \tag{5}$$

$$\omega_0 = a + bv_m + cv_m{}^2 \tag{6}$$

$$F_\mu = P_\mu \times g \times u_j \tag{7}$$

$$u_j = 0.24 + \frac{12}{100 + 8v_m} \tag{8}$$

$$Z_2 = E_r \sum_{v\in V}\sum_{s\in S}\sum_{i\neq j\in J} y_v^{js} d_{ij}^v \tag{9}$$

Where $\delta = 0.345 \times 29.3 \times 94600 \times 10^{-6}$, F_μ denotes the adhesive traction force of the train in KN; ω_0 represents the unit basic resistance in N/KN; a, b, c are the basic resistance coefficients (set to 2.4, 0.014 and 0.001293 respectively in this paper); P_μ refers to the adhesive weight of the train in t; g is the gravitational acceleration; u_j stands for the adhesion coefficient; and v_m is the operating speed of the metro, which is set to 60 km/h.

3.2.2 Transportation Cost

Total transportation cost covers metro trunk fees, truck travel expenses and fixed truck usage cost, formulated in Eq. (10)

$$Z_3 = c_{ds}^r \sum_{r\in R}\sum_{s\in S}\sum_{j\in J} q_j x_j^{rs} d_{ds}^r + c_v \sum\sum\sum y_v^{js} d_{ij}^v + f_v \sum_{s\in S} n_s \tag{10}$$

3.2.3 Objective Function

The model minimizes overall system cost combining economic and carbon expenditure via weighted unified objective Eq. (11).

$$\min Z = \gamma(Z_1 + Z_2) + Z_3 \tag{11}$$

3.3 Constraint Conditions

$$\sum_{v\in V}\sum_{i\in N} x_{ij}^v = 1, \forall j \in J \tag{12}$$

$$\sum_{v\in V}\sum_{i\in N} x_{ij}^v \le z_s, \forall s \in S, j \in J \tag{13}$$

$$\sum_{i\in N}\sum_{j\in J} x_{ij}^v q_j \le Q_v, \forall v \in V \tag{14}$$

$$\sum_{j\in J} y_{ds}^r q_j \le Q_r, \forall r \in R, d \neq s \tag{15}$$

$$u_i^v - u_j^v + Q_v \cdot x_{ij}^v \le Q_v - q_j, \forall v \in V, i \neq j \tag{16}$$

$$e_j \le t_j \le l_j, \forall j \in J \tag{17}$$

$$t_i + (t_{ij} + s_i) \le t_j + M(1 - x_{ij}^v), \forall i, j \in J, v \in V \tag{18}$$

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Constraints (12)–(18) ensure feasibility of the proposed model. Each customer is assigned exactly once, and station activation is triggered if any customer is allocated to it. Vehicle allocation is restricted to active stations, and truck capacity is not exceeded. Metro transport capacity is limited by residual train capacity, while route feasibility is guaranteed through connectivity and sub-tour elimination constraints. Finally, time window constraints ensure that all customer service times fall within allowable intervals.

4. Algorithm Design

As the metro – truck location-routing problem is NP-hard, exact algorithms become computationally intractable for large-scale instances. To improve solution efficiency, a two-stage framework combining improved K-means clustering and a genetic algorithm is proposed.

In the first stage, an enhanced K-means algorithm is employed to cluster customers based on spatial distance, time window similarity, and carbon emission cost, while simultaneously determining facility locations and customer assignments. The original problem is thus decomposed into multiple smaller subproblems. In the second stage, vehicle routing subproblems with capacity and time window constraints are constructed, and a genetic algorithm is applied to optimize last-mile routes, enabling coordinated location – routing decisions.

4.1 Improved K-means for Facility Location

Conventional K-means relies solely on spatial distance and cannot capture temporal and environmental factors in joint distribution systems. To address this issue, time window similarity and carbon emission cost are incorporated into the distance metric. Feasibility constraints on metro capacity and vehicle loading are enforced during clustering.

Cluster centers and assignments are iteratively updated until convergence, producing facility locations and customer partitions that provide high-quality initial solutions for routing optimization.

4.2 Cluster-Guided Genetic Algorithm

Routing optimization is performed independently for each customer cluster. Unlike standard genetic algorithms that rely on global search, clustering information is embedded into population initialization and evolution, restricting the search to within clusters and reducing solution space.

A natural-number encoding scheme is used, and the initial population is generated according to clustering structure. The fitness function considers transportation cost, carbon emissions, and time window penalties, with the objective of minimizing total system cost.

The algorithm employs tournament selection, OX crossover, and adaptive mutation. A 2-opt local search is applied to improve solutions, and an elitism strategy preserves high-quality individuals. The mutation rate is dynamically adjusted to balance exploration and exploitation.

The algorithm terminates when the maximum iteration limit is reached, and the best solution is output. The proposed clustering-guided mechanism decomposes the problem into structured subproblems, transforming global search into a guided hierarchical search and improving computational efficiency.

5. Experimental Design

To validate the effectiveness of the proposed model and algorithm, a case study based on the Beijing Metro Yizhuang Line is conducted. The Yizhuang Line consists of 14 stations, with an average off-peak load factor of approximately 40%, providing available residual capacity for freight transportation.

Fifty customer nodes are randomly generated, with demand following a normal distribution. The total demand is constrained within metro available capacity, and a unified time window of 10:30 – 12:30 is adopted. All metro stations are considered as candidate transfer stations, and the transshipment time is set to 4 minutes. Key parameters are summarized in Table 1.

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Table 1 Parameter Values

Symbol	Definition	Value
c_{ds}^{r}	Metro transportation cost	0.6 yuan/(ton·km)
c_{v}	Truck transportation cost	0.2 yuan/ton·km
Q_v	Truck load capacity	800kg
v	Average speed of truck	30 km/h
f_v	Fixed usage cost of truck	100 yuan
E_r	Metro carbon emission factor	0.085 kg CO_2/ton·km
α_v	Truck carbon emission factor	0.22 kg CO_2/km
γ	Carbon emission penalty cost	0.2 yuan/kg

5.1 Results Analysis

Under the proposed framework, the improved K-means algorithm selects Xiaohongmen Station and Rongchangdongjie Station as transfer hubs, forming two independent distribution sub-systems. Based on clustering results, the improved genetic algorithm is applied for last-mile routing optimization, as shown in Fig. 2. To evaluate the advantages of the proposed system, a truck-only delivery scenario is used as a benchmark, as illustrated in Fig. 3. A comparison of key performance indicators is presented in Table 2.

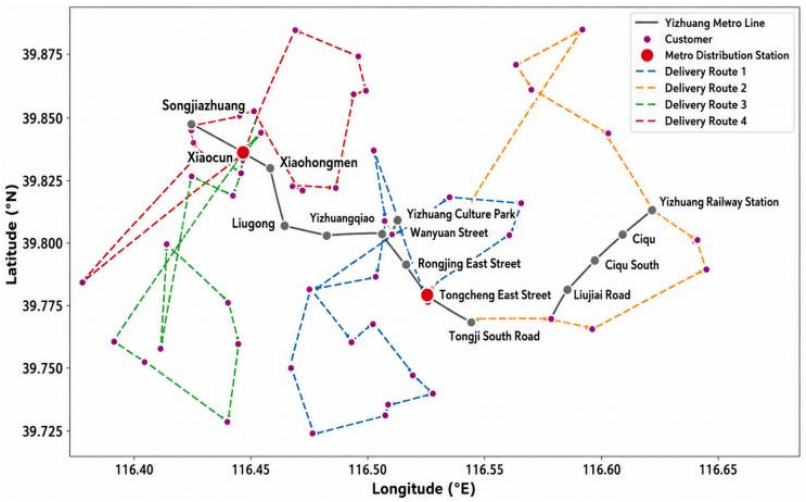


Fig. 2 Joint Distribution Routes

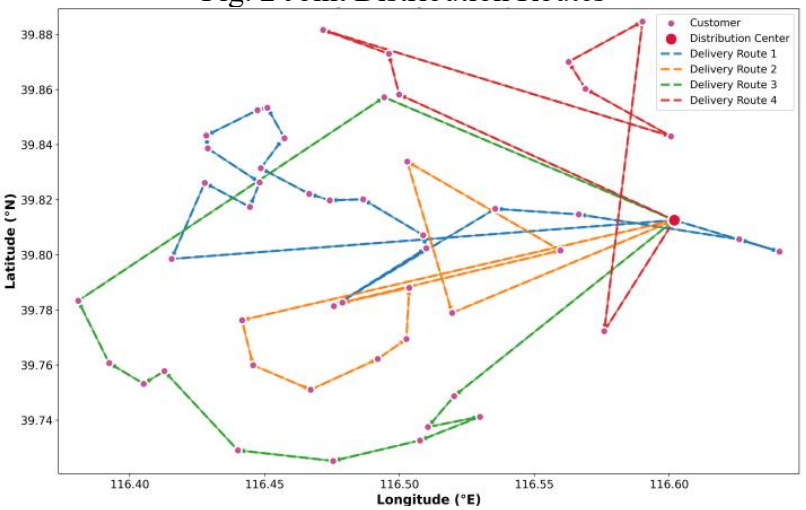


Fig. 3 Single Truck Distribution Routes

Table 2. Comparison of Core Indicators Between Intermodal Distribution and Truck-Only Distribution

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Indicator	Intermodal Distribution Scheme	Truck-Only Distribution Scheme	Optimization Degree
Total System Cost (yuan)	1395.28	1789.28	Reduced by 22%
Total System Carbon Emissions (kg)	42.67	69.41	Reduced by39%
Truck Distribution Distance (km)	246.57	315.49	Reduced by 22%
Number of Trucks Used (vehicles)	4	4	—
Customer Time Window Satisfaction Rate	98%	86%	Improved by 12%

As shown in Table 2, the proposed joint distribution system outperforms the truck-only mode in terms of cost efficiency, environmental impact, and service level. Compared with the truck-only scheme, total cost is reduced from 1789.28 CNY to 1395.28 CNY, carbon emissions decrease from 69.41 kg to 42.67 kg, travel distance is reduced by 22%, and time window satisfaction increases from 86% to 98%.

Results indicate that utilizing metro off-peak residual capacity for trunk transportation significantly reduces truck travel distance and carbon emissions. Meanwhile, improved K-means clustering enables spatial aggregation of customers and coordinated facility location, reducing last-mile delivery cost, while the cluster-guided genetic algorithm enhances routing efficiency and service performance. These results validate the effectiveness of the proposed model and algorithm in reducing system cost, lowering carbon emissions, and improving distribution efficiency.

5.2 Sensitivity Analysis

A sensitivity analysis was conducted to investigate the impact of key parameters on system performance from two perspectives: customer scale and metro residual capacity.

5.2.1 Analysis of Customer Scale Variation

The total metro residual capacity was fixed at 1200 kg, while the number of customers was set to 40, 50, 60, and 80, respectively, as reported in Table 3.

Table 3. Sensitivity Analysis Results for the Number of Customer

Number of Customers	Intermodal			Truck-Only			Cost Optimization Rate	Carbon Emission Optimization Rate
	Total System Cost (yuan)	Distribution Distance (km)	Carbon Emissions (kg)	Total System Cost (yuan)	Distribution Distance (km)	Carbon Emissions (kg)		
40	1132.52	200.77	32.29	1346.09	234.65	51.62	16%	37%
50	1395.28	246.57	42.67	1789.28	315.49	69.41	22%	39%
60	1602.76	293.93	53.16	1936.36	328.73	72.32	17%	26%
80	2201.89	366.5	66.36	2896.53	495.86	99.17	24%	33%

It can be observed that the total system cost, delivery distance, and carbon emissions of both delivery schemes increase with customer size. This is primarily attributed to the expanded delivery demand, resulting in higher routing complexity and fleet scheduling pressure. In terms of optimization performance, the proposed integrated delivery system consistently outperforms the conventional truck-only scheme across all scales, with cost reduction rates ranging from 16% to 24% and carbon emission reductions between 26% and 39%. The results indicate that using metro systems for trunk transportation effectively reduces truck travel distance and emissions, while maintaining robustness and scalability under increasing demand.

5.2.2 Analysis of Variation in Metro Train Remaining Capacity

With the number of customers fixed at 50, the total metro residual capacity was varied across 800, 1000, 1100, 1200, and 1500 kg, as illustrated in Fig. 4.

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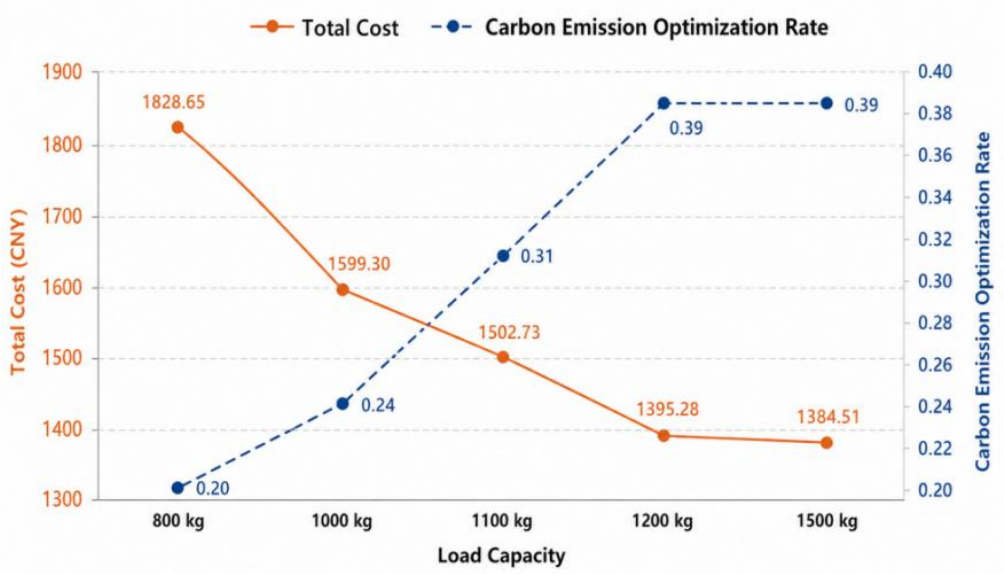


Fig.4. Sensitivity Analysis Results of Residual Capacity of Metro Trains

It is observed that the total system cost gradually decreases as metro capacity increases, while the carbon emission reduction rate continuously improves. A significant performance improvement is achieved when capacity increases from 800 kg to 1200 kg; however, further increases lead to diminishing reductions in cost and emissions. This indicates that metro capacity has a significant impact on system performance, while exhibiting diminishing marginal effects. Once the capacity is sufficient to satisfy most delivery demand, additional capacity expansion provides limited additional improvement. Therefore, metro capacity should be properly allocated in accordance with demand scale to achieve a balanced optimization of cost efficiency and environmental benefits.

6. Conclusion

A location-routing optimization model considering time window constraints and carbon emission costs is developed for a metro–truck integrated distribution system utilizing off-peak metro residual capacity. A two-stage solution framework, combining an improved K-means clustering-based location method and a clustering-guided genetic algorithm, is proposed.

The effectiveness of the model is validated through a case study of the Beijing Yizhuang metro line. Results demonstrate that the integrated delivery system significantly reduces total cost and carbon emissions while improving customer time-window satisfaction compared with the traditional truck-only scheme. The improved K-means algorithm enables coordinated depot location and customer assignment, while the clustering-guided genetic algorithm enhances routing efficiency and solution quality. The feasibility and advantages of utilizing metro residual capacity for urban distribution are confirmed. Future research will incorporate stochastic factors such as passenger flow fluctuation and traffic congestion, and extend the model to multi-line collaborative distribution systems to improve practical applicability.

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