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The Optimization of Split Demand Route Planning Under Metro-Truck Collaborative Distribution

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Abstract   With the evolution of people's consumption habits and the rapid growth of urban logistics, the number of trucks and delivery frequency has increased significantly, exacerbating urban traffic congestion and environmental pollution. Consequently, there is an urgent need to improve the current inefficient and highly polluted distribution mode. Currently, in most cities in China, the metro passenger flow is insufficient, and the capacity is excessive during off-peak hours, resulting in underutilized carriage capacity. The integration of surface and underground transport resources can effectively address these issues and facilitate complementary advantages and win–win cooperation between express companies and metro enterprises. This study proposes an innovative problem of split demand route planning in the cooperative distribution system involving express companies and subways. A cooperative distribution model is developed to minimize the total cost, and solved by the Cuckoo Search algorithm to obtain the optimized solution. The model is applied to the urban rail transit network in Changchun, and the results demonstrate that it is effective in reducing truck mileage and distribution costs. Compared to the single delivery pattern by trucks, the cooperative distribution approach proves to be more cost-effective and environmentally friendly.

1 Introduction

The existing freight distribution model is inefficient and heavily polluting, and requires urgent reform to meet the growing demand for efficient and punctual logistics services. Currently, the increasing urban logistics predominantly rely on ground transportation, which occupies a significant portion of road resources, exacerbates traffic congestion and hinders the rational utilization of urban space. Furthermore, the limited availability of ground-level traffic facilities restricts logistics development. The development of urban underground space has been regarded as a feasible solution since Rijsenbrij [1] initially put forward the concept of an underground logistics system (ULS). Although the theory and technology of ULS have advanced, its implementation in the short term remains challenging due to difficulty in development, long construction cycles, and substantial investments involved. In this paper, collaborative distribution refers to the utilization of an existing urban rail transit network for cargo transportation, i.e., a kind of ULS. Leveraging the advantages of low cost, high efficiency, and sustainability of rail transit, it can serve as a temporary mode of urban underground freight transportation, facilitating the partial transfer of surface freight to the underground realm. Simultaneously, it can use surplus subway capacity during

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Communicated by Xuesong Zhou.

 Springer

off-peak hours, generating additional revenue for metro enterprises alongside ticket sales.

In the domain of freight transportation, the exploration of underground systems has been a focal point of numerous studies. These investigations delve into the feasibility and potential advantages of utilizing underground delivery systems for the efficient movement of goods. Qian [2] provided a comprehensive review and analysis of typical underground logistics systems in countries such as the Netherlands, Japan, and Germany, with a particular emphasis on the promising potential of freight transportation via subways. Building upon this groundwork, He et al. [3] envisioned a paradigm shift in urban logistics. Their proposal introduced a comprehensive system, featuring a management information center, a dedicated freight hub, rail transit, and specialized delivery personnel. Wang and Deng [4] extended this vision, suggesting the rapid utilization of subways for urban distribution, recognizing the efficiency and speed that this mode could bring to the transportation landscape. Further enriching the discourse, Fatnassi et al. [5] explored strategies aimed at optimizing urban highway capacity through the strategic interconnection of underground and surface resources. Their approach presented an innovative solution to enhance the effective utilization of available transportation infrastructure. In a similar vein, Chen et al. [6] employed advanced techniques, including k-means clustering and the Dijkstra algorithm, to delve into the nuances of cooperative transportation modes, shedding light on the intricate dynamics of these systems.

From an alternative perspective, various studies have proposed simulation models and feasibility analysis of specific subway systems. Kikuta et al. [7] developed an urban logistics system that integrated surplus subway capacity with traditional logistics vehicles, with a particular focus on achieving short delivery times for certain small and medium-sized goods. To analyze the existing subway system in Newcastle upon Tyne, Motraghi and Marinov [8] developed a simulation model to show that it was possible for railways to distribute goods in urban areas without consideration of how to get the goods to the subway stations, and there was no door-to-door transportation. Dampier and Marin [9] conducted an in-depth study of the Tyne Metro system and concluded that there was sufficient opportunity to add at least one dedicated freight train to the schedule. However, this study did not delineate the optimal location for deploying freight trains to minimize disruption to passenger services. Chen [10] used a logit model to calculate the sharing rate of subway logistics in Wuhan, China, and proposed the transportation organization plan, although with limited consideration to the pricing structures affecting shippers and the profits accruing to operators.

In recent times, some scholars have focused on examining subway hub locations but have overlooked the potential changes to platforms that might be required to accommodate freight transportation. Zhao et al. [11] segmented the subway network to propose a model for selecting urban subway distribution centers, aiming to minimize total distribution distance. Dong et al. [12] contributed by developing a network planning method and a mixed-integer programming model for addressing location planning issues in underground logistics systems. Ji et al. [13] introduced a hub-and-spoke structure, integrating metro, taxi, and truck services, along with a mixed-integer linear programming model to optimize multi-modal delivery networks. Kizil and Yildiz [14] established a two-stage stochastic program and a branch-price algorithm for a low-cost, environmentally friendly express delivery service. Notably, these studies assumed goods could enter and leave from the metro system to the ground at any selected stations without considering potential platform modifications resulting from freight transportation.

In addition, many researchers have conducted research on path planning under collaborative delivery. Zheng et al. [15] combined the subway system with trucks to develop an urban logistics distribution route optimization model by employing the Clarke–Wright (C-W) algorithm and improved tabu search algorithm. Xu et al. [16] utilized the system dynamics method to analyze the quantitative relationship between subway-based ULS and urban logistics, introducing a set of incentive policies. Di et al. [17] conducted research on the joint optimization of subway carriage assignment and passenger flow control. They formulated an integer linear programming model and devised an enhanced Benders algorithm. Liu et al. [18] proposed a three-level urban distribution model comprising a logistics park, subway distribution center, and customer nodes, established a multi-objective optimization model with the objective of minimizing transportation, vehicle, and time costs, and employed the genetic algorithm. Ghilas et al. [19] addressed the problem of receiving and delivering subway transportation based on frequencies and routes, designed an adaptive neighborhood search algorithm. Zhou et al. [20] developed an integrated model that encompassed distribution center location selection, subway line selection, and ground route optimization. Their model aimed to minimize the average delivery time and was solved by an improved recursive granular algorithm. Building upon previous research, Zhou et al. [21] considered additional constraints such as subway frequency, customer time window, and vehicle capacity. They constructed a subway-ground cooperative distribution network with time windows and utilized the random variable neighborhood search algorithm. Li [22] proposed a collaborative distribution approach between express companies and subway stations during off-peak periods, developed a collaborative route optimization model aiming at minimizing the total distribution cost, and employed the ant colony algorithm. Zhou et al. [23] proposed a truck-subway combined

transport model and established a path optimization model focusing on minimizing the distance, and designed an adaptive genetic algorithm. Yang et al. [24] considered transit time coordination between underground and surface logistics, introduced a penalty function for cargo stacking costs, and formulated a route optimization model aiming to minimize the total cost. The genetic algorithm was employed to solve the optimization problem.

Despite the extensive research, practical applications remain notably scarce, and many demonstration projects have faced premature termination for multifaceted reasons. The ensuing discussion explores the intricate challenges that impede the implementation of these innovative concepts. Firstly, the complex interplay of regulations governing passenger and goods transportation presents a significant hurdle [25]. Coordinated delivery would necessitate a fundamental revision of existing rules and policies. Additionally, economic feasibility becomes a pivotal determinant in these scenarios, encompassing aspects such as securing initial investments, ensuring profitability, and equitably distributing interests among stakeholders. Furthermore, passengers' reservations about sharing transportation with goods, rooted in safety and comfort concerns, pose a potential obstacle that may impact overall passenger satisfaction. Finally, addressing technical challenges, including identifying underutilized capacity and designing optimal routes and schedules, becomes imperative for successful implementation [26].

The path planning mentioned above usually uses the surplus capacity of the public transit system to solve first-mile and last-mile problems without considering the possible benefits of demand splitting. So, the split demand vehicle routing problem is introduced in this study, which differs from the classical vehicle routing problem by allowing multiple vehicles to serve a courier station. Dror and Trudeau [27] compared the solutions obtained from split demand and non-split scenarios, confirming that both total path length and number of vehicles could be reduced through split demand. In most cases, the delivery volume of a single courier station is lower than the vehicle capacity, and there is minimal variation in distribution demand among stations. Research by Archetti et al. [28] and Archetti et al. [29] and Nowak et al. [30] has shown that demand splitting yields significant benefits in such cases. This paper focuses on studying the metro and truck cooperative (MTC) delivery mode based on split demand routing and aims to design the optimal routes to achieve the lowest distribution cost. In this distribution process, vehicles are allowed to visit courier stations multiple times and are not required to return to the original departure point. Instead, they can choose nearby physical distribution centers (PDCs) or metro transfer points. While previous studies have focused on the feasibility and efficiency of metro-based logistics distribution and the benefits it offers, there is limited research on optimizing

collaborative distribution involving both metro and truck. Further investigation is needed to explore the coordination of transport times between underground logistics and surface logistics, as well as the benefits from collaborative distribution to metro enterprises. The specific contributions of this study can be summarized as follows:

(1) Selecting an appropriate number of metro transfer stations based on specific rules, introducing time window constraints for metro exits, considering the coordination of transportation times between underground and surface logistics to save time and reduce cargo accumulation, and determining the minimum-cost distribution paths.
(2) By determining the number of transfer points, the study provides decision support for urban logistics distribution network planning and the location of metro stations.
(3) The improved cuckoo search algorithm (ICS) offers advantages over the basic cuckoo search algorithm (CS) in terms of shorter running time, faster convergence speed, and better results.

The remainder of this paper is organized as follows: Section 2 describes in detail how costs are incurred in the whole distribution process and constructs the MTC distribution model. Section 3 designs the ICS to solve it. Section 4 presents an empirical study, obtains the optimal distribution rout, and discusses the optimized results. Section 5 summarizes the full text and proposes the future research direction.

2 Modeling Methodology

2.1 Problem Description

Currently, all expresses are transported by trucks from the PDC to each courier station. The MTC approach utilizes the existing urban rail transit network for express transportation, thereby integrating the rail transit network with the urban logistics distribution network. By selecting proper transfer points within the subway network, a portion of the express originating from the PDC is transferred to the courier station via the subway, while the remainder are directly delivered by trucks. The metro entrance near PDC is designated as the metro entrance, while all metro stations, excluding entrances, are considered as potential candidate exits. Decisions regarding the selection of metro exit locations are primarily influenced by the distribution of freight demand in their proximity. The MTC can be described as follows. There are r operating metro lines, m PDCs, and n courier stations. Firstly, cargos from the PDC are imported into the underground network through the nearby metro entrance. Then,

the subway train ships them to the exit, where they are finally delivered to each courier station. To minimize the transportation cost, labor cost, and time window penalty cost of the overall distribution process, it is essential to determine the optimal number and location of transfer points and plan the optimal delivery routes. This process is illustrated in Fig. 1.

2.2 Model Assumptions

(1) The location and delivery volume of each courier station are known in advance.
(2) The locations of the metro entrances and exits are selected according to certain rules, and all can be used for temporary goods storage and transfer.
(3) Freight transportation by subway will not affect passenger service quality.
(4) The subway schedule is known, and the frequency is constant,
(5) One shipment of goods on a given metro line is sorted according to its respective destination. The next shipment is not organized until the preceding delivery is finished.

2.3 Parameters and Decision Variables

The parameters and decision variables involved in the model are shown in Table 1.

2.4 Objective Function

The MTC is established according to the above assumptions, aiming at the minimum cost of the whole distribution process. The expression is as follows.
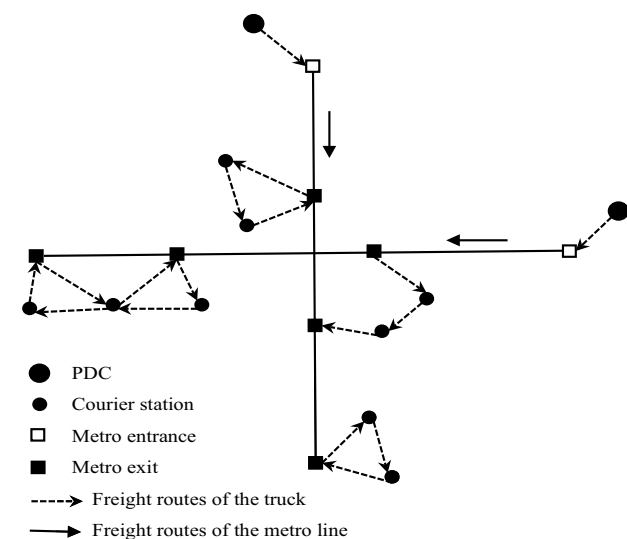

Fig. 1 Schematic diagram of cooperative distribution

$$min f(c) = c_1 + c_2 + c_3 + c_4 \tag{1}$$

(1) Trucking cost c_1

Trucking cost is composed of variable cost and fixed cost. The former is generated by ground transportation, that is, the dotted line in Fig. 1, which is decided by mileage. The fixed cost is mainly related to the number of trucks. The expression is as follows:

$$c_1 = c_{11} \sum_{v \in V} \sum_{i \in N} \sum_{j \in N} x_{ij}^v d_{ij}^v + c_{12} \sum_{v \in V} x_v. \tag{2}$$

(2) Time window penalty cost c_2

The study proposes the implementation of a soft time window, wherein no additional fees are levied if the subway arrives within the designated time frame. However, penalty fees are imposed if the subway fails to arrive within the stipulated time. Consequently, the penalty cost function is established. In the event of the early arrival of the subway and subsequent piling up of goods, a goods piling cost is incurred, which is upon the volume of goods and the piling time. Conversely, if the subway arrives late, the cost is incurred solely to the waiting time of the trucks. It assumes that all metro stations are applicable for temporary storage and transfer of goods, and there is no truck waiting time cost at the metro entrances. The penalty cost function is as follows:

$$c_2 = \varepsilon\rho \sum_{r \in R} \sum_{i \in N_c} \sum_{j \in N_k} \max\left(E_i - T_i^r\right) y_{rj} s_j y_{ij} + \theta \max\left(T_i^r - L_i, 0\right). \tag{3}$$

(3) Metro freight operation cost c_3

Upon analysis of historical passenger flow data, the remaining capacity of each train during off-peak hours is obtained, and metro freight transport is subsequently organized accordingly. Distribution services are executed through designated passenger carriages, while the original subway schedule remains unchanged. The metro freight turnover volume serves as the measurement index for calculating the freight operation cost of the metro enterprise. The metro freight operation cost is expressed as below.

$$c_3 = \sum_{r \in R} \sum_{i \in N_c} \sum_{j \in N_k} m_{ij} g s_j d_{ec}^r. \tag{4}$$

(4) Labor cost c_4

In the process of subway transfer, a supercargo is responsible for transporting goods from the surface to the subway platform and handling goods, ensuring the safety of goods transportation during the duty period. The supercargo's wage is based on workload and working hours. The expression is as follows:

Table 1 Summary of notations

Notations	Descriptions
Parameters	
d_{ij}^v	The distance between node i and j delivered by truck v
d_{ij}^r	The distance between node i and j delivered by subway r
c_{11}	Unit transport cost of truck
c_{12}	Unit truck fixed cost
ρ	Unit accumulated time cost coefficient (time-based)
ε	Unit accumulated cost coefficient (volume-based)
θ	truck waiting time cost coefficient
E_i	The earliest time the metro exit i can accept service
L_i	The latest time the metro exit i can accept service
T_i^r	The time the train arrives at the metro exit i
s_j	The delivery volume of courier station j
g	Unit metro transit cost
c_{41}	Unit hour labor cost
c_{42}	Unit cargo handling cost
s_j^v	The amount of goods delivered by truck v to courier station j
N	The set of all nods (PDCs, subway stations, courier stations)
N_D	The set of PDCs
N_e	The set of metro entrances
N_c	The set of metro exits
N_k	The set of courier stations
N_{vk}	The set of courier stations of the truck v in one path
R	The set of metro lines
V	The set of trucks
Q_v	The capacity of the truck
Q_r	The capacity of the carriage
m	Number of trucks
n	Number of courier stations
v	The average speed of the subway
t	Train dwell time
d_{ec}^r	The distance from the metro entrance to the exit
M	A large positive integer
Variables	
x_{ij}^v	1, if goods from node i to j are delivered by truck v; 0, otherwise
y_{ij}	1, if goods of node j depart from metro exit i; 0, otherwise
y_{rj}	1, if goods of node j are delivered by line r; 0, otherwise
x_v	1, if truck v is employed; 0, otherwise

$$c_4 = c_{41} \sum_{r \in R} \frac{d_{ec}^r}{v} + c_{42} \sum_{r \in R} \sum_{j \in N_k} y_{rj} s_j. \tag{5}$$

The time of train arrival at metro exits:

$$T_j^r = T_i^r + \frac{d_{ij}^r}{v} + \sum t, \quad \forall r \in R, \ i \le j. \tag{6}$$

Subject to the following:

$$\sum_{i \in N} \sum_{j \in N_k} x_{ij}^v s_j^v \le Q_v, \quad \forall v \in V, \ \forall N_{vk} \subseteq N_k, \ k \in [0,n] \tag{7}$$

$$\sum_{j \in N_k} \sum_{r \in R} y_{rj} s_j \le Q_r \tag{8}$$

$$\sum_{v \in V} \sum_{i \in N_D \cup N_c} x_{ij}^v = \sum_{v \in V} \sum_{i \in N_D \cup N_c} x_{ji}^v, \quad \forall j \in N_k \tag{9}$$

$$\sum_{i \in N_D \cup N_c} \sum_{j \in N_k} x_{ij}^v = \sum_{i \in N_D \cup N_c} \sum_{j \in N_k} x_{ji}^v, \quad \forall v \in V \tag{10}$$

$$d_{ec}^r = M, e \in l_r, c \notin l_r \tag{11}$$

$$1 \leq \sum_{v \in V} \sum_{i \in N_D \cup N_c} x_{ij}^v \leq 2, \quad \forall j \in N_k \tag{12}$$

$$\sum_{v \in V} x_v \leq m \tag{13}$$

$$\sum_{v \in V} s_j^v = s_j, \quad \forall j \in N_k \tag{14}$$

$$s_j^v > 0, \quad \forall j \in N_k, v \in V \tag{15}$$

$$\sum_{r \in R} \sum_{j \in N_k} y_{rj} \geq 1 \tag{16}$$

$$x_{ij}^v \in \{0, 1\}, \quad \forall i, j \in N, v \in V \tag{17}$$

$$y_{rj} \in \{0, 1\}, \quad \forall r \in R, j \in N_k \tag{18}$$

$$y_{ij} \in \{0, 1\}, \quad \forall i \in N_e, j \in N_k \tag{19}$$

$$x_v \in \{0, 1\}, \quad \forall v \in V. \tag{20}$$

Equation (7) is the capacity of the truck. When trucks serve multiple times, the total delivery volume of courier stations in a single service path is not greater than the capacity; Eq. (8) is the capacity of carriage; Eq. (9) indicates that the number of trucks entering the point is equal to the number of trucks leaving the point; Eq. (10) indicates that the truck departing from the PDC or metro exits may return to the PDC or the nearest metro exits; Eq. (11) ensures that the goods are transported without transfer, handling only once without secondary loading and unloading; Eq. (12) indicates that each courier station is visited one or two times; Eq. (13) is the limit of the number of available trucks; Eq. (14) indicates that the demand of the courier station must be met; Eq. (15) indicates that the distribution amount of the truck to the courier station is greater than 0; Eq. (16) indicates that the demand for courier stations can be split and served by multiple metro lines; Equations (17)–(20) are the 0–1 constraints of the decision variables.

2.5 Model Validation

In order to verify the robustness of MTC, we construct a small-scale example. The PDC is assigned the number 0, while courier stations are numbered 1–12. Additionally, M_1 denotes the metro entrance, and M_2, M_3, M_4 are defined as metro exits, and the truck has a capacity of $6t$. The example was established in IBM ILOG CPLEX Optimization Studio

20.1.0 and solved by CPLEX. The node locations and freight routes are shown in Tables 2 and 3.

Table 3 indicates that the MTC approach leads to a reduction in truck mileage and total costs. This observation supports the effectiveness of the MTC strategy, as it demonstrates tangible benefits in terms of both transportation efficiency and cost savings.

3 Solution Methods

3.1 Algorithm Description

Cuckoo search (CS) was first proposed by Yang and Deb in 2009. This algorithm is based on the obligate brood parasitic behavior of some cuckoo species in combination with the Levy flight behavior of some birds and fruit flies [31]. It combines the global search of Levy flight and the local search of the random walk so that the search space can be explored more effectively to find the global optimal solution with highest probability. It has the advantages of simple operation and easy implementation, fewer control parameters, and maintaining a balance between local search and global search. Thus, CS has been proven an effective method to solve nonlinear optimization problems and has been successfully applied in many fields of science and engineering. In CS, the assumptions are as follows: first, each cuckoo lays one egg at a time, and a host nest is randomly selected; second, when finding the nest, the cuckoo keeps the egg

Table 2 Node locations and delivery volumes

Number	Longitude	Latitude	Delivery volume (t)
0	125.495903	43.926495	–
1	125.390370	43.892261	2
2	125.389056	43.878782	3
3	125.369703	43.860466	2
4	125.348893	43.903748	4
5	125.341682	43.889365	4
6	125.341187	43.877105	2
7	125.299328	43.883656	2
8	125.290687	43.872846	4
9	125.282868	43.864007	2
10	125.415583	43.778954	3
11	125.192608	43.832789	4
12	125.221077	43.821413	3
M_1	125.427162	43.881485	–
M_2	125.345451	43.880804	–
M_3	125.240394	43.884145	–
M_4	125.172073	43.833954	–

Table 3 The results for the example

Number	MTC distribution route	Truck mileage (km)	Total cost (yuan)
1	$0 \rightarrow M_1 \rightarrow M_2 \rightarrow 5 \rightarrow 6 \rightarrow M_2 \rightarrow 4 \rightarrow M_2$	139.32	807.38
2	$0 \rightarrow M_1 \rightarrow M_3 \rightarrow 8 \rightarrow 9 \rightarrow M_3 \rightarrow 7 \rightarrow M_3$		
3	$0 \rightarrow M_1 \rightarrow M_4 \rightarrow 11 \rightarrow 10 \rightarrow M_4 \rightarrow 12 \rightarrow 10 \rightarrow M_4$		
4	$0 \rightarrow M_1 \rightarrow 0 \rightarrow M_1 \rightarrow 0 \rightarrow 1 \rightarrow 2 \rightarrow 0 \rightarrow 3 \rightarrow 0$		
	Truck distribution route		
5	$0 \rightarrow 1 \rightarrow 4 \rightarrow 0 \rightarrow 7 \rightarrow 8 \rightarrow 0$	211.23	1056.15
6	$0 \rightarrow 2 \rightarrow 3 \rightarrow 0 \rightarrow 5 \rightarrow 6 \rightarrow 0$		
7	$0 \rightarrow 9 \rightarrow 11 \rightarrow 12 \rightarrow 0$		
8	$0 \rightarrow 10 \rightarrow 11 \rightarrow 0$		

with the highest fitness until the next generation; third, the number of selected nests is fixed. At the same time, the host bird will find the cuckoo egg with a certain probability and abandon the original nest to build a new one. The algorithm is based on two strategies: one is that the cuckoo searches for parasitic nests through Levy flight to expand its search scope; the other is that the host bird finds the cuckoo eggs and abandons the nest, and then updates the nest location through a random walk.

There are many studies on how Levy flight and discovery probability affect the optimization process in CS. Tang and Xue [32] studied the influence of different distribution strategies on CS. Kumbhkar et al. [33] studied CS, Levy flight and their important variants, and found that dynamically adjusting discovery probability and optimal global search can lead to better results. Wang et al. [34] made adaptive adjustments to the discovery probability and step size, and obtained higher calculation accuracy. Barbosa and Vasconcelos [35] studied how Levy distribution, parameters N and pa affect the performance of the algorithm. and the results showed that the efficiency of cuckoo search was closely related to Levy distribution. Cheng et al. et al. [36] proposed an improved CS, which is superior when compared to seven other mature CS variants.

3.2 Encoding Method

Discrete integer encoding is the key to solve the vehicle routing problem (VRP). It transforms the solution of the problem into the position of the nest, that is, the encoding method. This paper designs an encoding method suitable for CS, and modifies the nest location update strategy. The route arrangement is coded as follows.

(1) Integer i is used to represent the courier station, where $(1, 2, ..., n)$ denote the n courier stations to be served.
(2) Every nest location is represented by an n-dimensional integer vector $\mathbf{V} = [a_1, a_2, ..., a_n]$, where a_i is an integer in $(1, 2, ..., n)$, corresponding to the service order

of each courier station, assuming that when $i \neq j$, then $a_i \neq a_j$.

(3) Every nest position corresponds to a solution vector, and the nest position is allocated to the vehicles in turn according to the principle that the distribution volume of the courier stations does not exceed the load limit of the vehicle. Finally, the courier stations corresponding to each vehicle constitute the solution vector.

3.3 Algorithm Flow

Compared with the basic CS, the ICS designed in this paper adopts the nonlinear inertia weight diminishing strategy to reduce the inertia weight logarithmically from the larger value to the smaller one when updating the nest position. In addition, the discovery probability is randomly adjusted, so that ICS has a stronger search ability. The procedures are as follows.

Step 0: Set the objective function $f(X)$, $X = (x_1...x_n)$. Based on clustering theory, this paper preliminarily selects the courier stations with a high probability of being delivered by subway as the initial group. Set algorithm parameters, including the number of nests N, discovery probability p_a, maximum iteration times T_{max}, etc.

Step 1: Calculate the value of the objective function for each nest and record the current optimal solution.

Step 2: Retain the optimal nest position of the previous generation, and update other nest positions according to Eqs. (21) and (22):

$$X_i^{(t+1)} = X_i^{(t)} + \alpha_{(t)} \oplus \text{levy}(\lambda) \tag{21}$$

$$\alpha_{(t)} = \alpha_{max} - \eta \times (\alpha_{max} - \alpha_{min}) \times \log_{T_{max}}^t, \tag{22}$$

where t is the number of current iterations; T_{max} is the maximum number of iterations; α_{max} represents the initial values of α; α_{min} represents the final values of α; and η is the logarithmic adjustment coefficient.

Step 3: Compare the position of the existing nest with that of the previous generation. If it is better, take it as the current optimal position.

Step 4: Use a random number R as the possibility of discovering external cuckoo eggs in the nest host, and compare with $pa_{(r)}$ (Eq. 23). If $R > pa_{(r)}$, the nest position is changed randomly to obtain a new set of nest positions (Eq. 24).

$$pa_{(r)} = pa_{\min} + \left(pa_{\max} - pa_{\min}\right) \times rand(0,1) - \lambda \times \tau(a,b)$$
(23)

where $pa_{(r)} \in [0.15, 0.55]$; $pa_{(r)\min}$ represents the minimum values of $pa_{(r)}$; $pa_{(r)\max}$ represents the maximum values of $pa_{(r)}$; $rand ()$ is a random number generated uniformly distributed between (0,1); $\tau (a, b)$ is a gamma-distributed random number obeying shape parameter a and scale parameter b; and λ is used to control the deviation between the inertia weight and the expected value [37].

$$X_i^{(t+1)} = X_i^t + \gamma \times \left(X_g^t - X_g^t\right)$$
(24)

where γ is the scaling factor and obeys uniform distribution within [0,1], and X_g^t, X_k^t are two random solutions of generation t.

Step 5: If the end condition is not met, return to step 1; if yes, output the global optimal position. The algorithm flow is shown in Fig. 2.

3.4 Performance Measures

3.4.1 Test 1: Applicability test

The VRP example (http://branchandcut.org/) P-n20-k2 is selected for analysis, and the results of 10 operations are observed with different populations and iteration times. The calculated results are shown in Table 4.

Table 4 shows that, for a small-scale VRP problem such as P-n20-k2, both the population size and the number of iterations have a great impact on the solution. In the case of the same population size, an increase in the number of iterations correlates with a better solution. It also shows
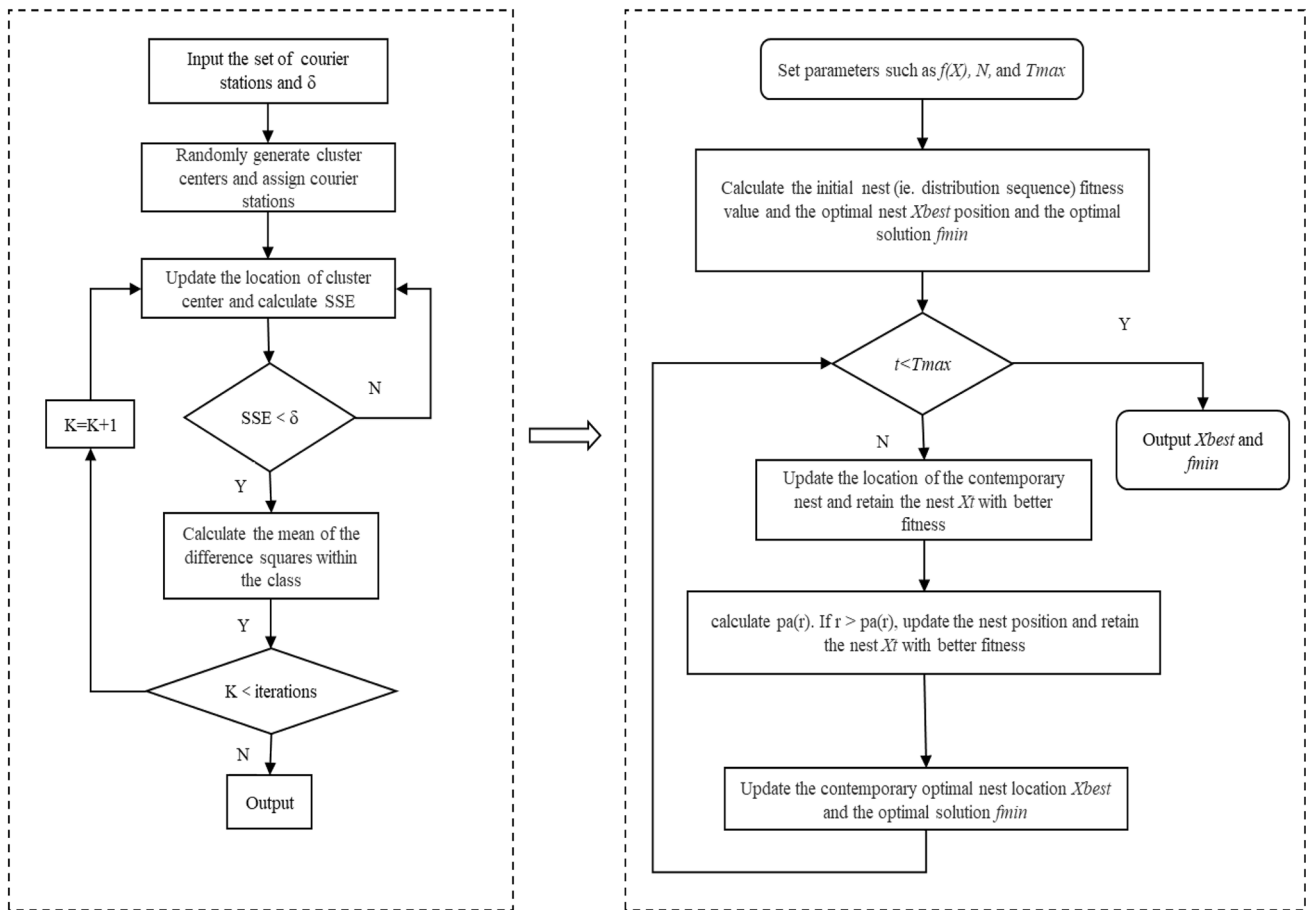

Fig. 2 Algorithm flow chart

Table 4 The calculation result for the P-n20-k2

Size of population	Number of iterations	The optimal solution obtained each time									
		$i = 1$	$i = 2$	$i = 3$	$i = 4$	$i = 5$	$i = 6$	$i = 7$	$i = 8$	$i = 9$	$i = 10$
20	20	249.05	246.42	260.74	223.20	246.00	259.25	226.91	244.76	246.26	247.94
20	50	240.06	246.88	241.95	230.93	236.11	229.72	225.62	243.22	227.68	231.00
50	100	218.25	221.68	223.61	224.00	218.30	219.93	224.40	225.77	219.13	230.12
50	200	215.80	215.80	215.80	215.80	215.80	215.80	220.15	215.80	215.80	215.80

Table 5 Calculation results of the ICS

Examples	Parameter setting	The known optimal solution	The best solution	The average solution	The worst solution
P-n16-k8	$N = 40$ $T_{max} = 500$	450	451.94	452.34	456.69
P-n23-k8	$N = 60$ $T_{max} = 600$	529	526.81	531.53	539.37
E-n51-k5	$N = 100$ $T_{max} = 2000$	521	602.07	627.64	638.91
E-n76-k10	$N = 200$ $T_{max} = 3000$	830	982.12	1074.86	1121.62

that the ability of finding an optimal solution is poor when the population size and the number of iterations are both 20, and the solution improves as the number of iterations and the population size increase. When the population size is 50 and the number of iterations is 200, a better solution (215.80) than the optimal value (216) is found in 9 out of 10 operations. The corresponding delivery path is as follows.

$0 \rightarrow 1 \rightarrow 10 \rightarrow 13 \rightarrow 8 \rightarrow 17 \rightarrow 18 \rightarrow 3 \rightarrow 12 \rightarrow 15 \rightarrow 11 \rightarrow 4 \rightarrow 0; 0 \rightarrow 6 \rightarrow 2 \rightarrow 7 \rightarrow 9 \rightarrow 16 \rightarrow 14 \rightarrow 5 \rightarrow 19 \rightarrow 0$.

3.4.2 Test 2: Robustness test

In order to further verify the robustness of the ICS when dealing with a large number of demand points, in test 2, four VRP examples of different sizes are selected to operate 10 times each, and the optimal solution, the average solution and the worst solution are recorded. The calculated results are shown in Table 5.

As seen from Table 5, with an increase in the number of demand points and vehicles, the difficulty in searching for the optimal solution increases. For small-scale P-n16-k8 and P-n23-k8, the ICS can find solutions close to the known optimal solutions. However, as the problem size increases, the search ability for E-n51-k5 and E-n76-k10 is poor. This shows that ICS is capable of solving VRP problems of moderate size.

3.4.3 Test 3: Accuracy test

In Test 3, the scenario can be described as follows: a distribution center delivers goods to eight demand points, and

Table 6 Calculation results of different algorithms

Index	ABC	PSO	CS	ICS
The best solution	67.50	67.50	67.50	67.50
The average solution	67.75	68.38	67.88	67.50
The worst solution	69.00	69.00	69.00	67.50

the demand of each demand point is q_i ($i=1, 2, …,8$), the distribution center has two trucks with a maximum capacity of 8 [38]. The population size is 60, the number of iterations is 50. The four algorithms run independently 20 times; the worst solution, the optimal solution, and the average solution obtained are shown in Table 6.

Table 6 shows that the solution results of the ICS are significantly better than those of CS, PSO and ABC when the population size and the number of iterations is certain. The optimal route as follows.

$0 \rightarrow 2 \rightarrow 8 \rightarrow 5 \rightarrow 3 \rightarrow 1 \rightarrow 0$;
$0 \rightarrow 6 \rightarrow 7 \rightarrow 4 \rightarrow 0$.

In summary, ICS is suitable for solving medium-scale VRP problems, and can search for better solutions faster.

4 Case Study

4.1 Background

Metro Line 1 and Line 2 of Changchun City are selected as the distribution lines, and stations A and B are terminal stations, and near PDC. The train stops at the platform for a long time, which is suitable for the organization of cargo collection and distribution operations. Therefore, stations
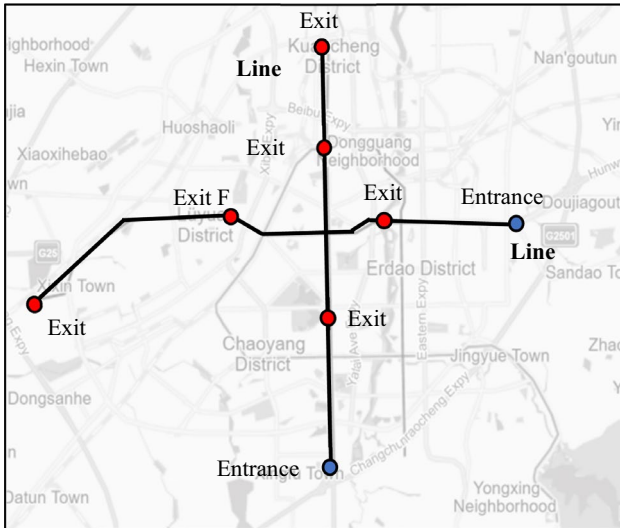
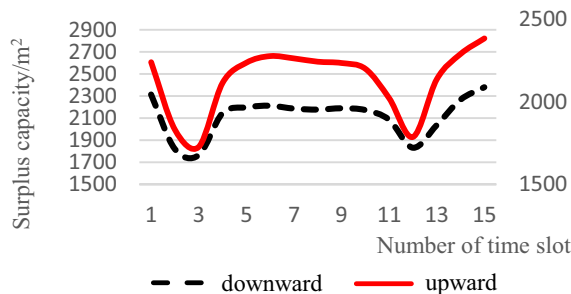**Fig. 3** Diagram of metro location information

Fig. 4 Surplus capacity for each period

A and B are set as the entrance stations, and the people living near subway stations C, D, E, F, G and H are densely located and the freight demand is large. With the results of clustering, if they are selected as the candidate exit stations, the radiation range of the subway transfer can be maximized. The locations of metro lines and transfer points are shown in Fig. 3.

The remaining capacity for each period of the entire day is estimated by reviewing the historical passenger flow statistics of Line 2. As indicated by Fig. 4, we can observe that, aside from peak hours, the subway surplus capacity is adequate and suitable for carrying out bulk cargo transit. On a given day, we choose some free carriages to convey express from 9:00 am to 12:00 am. The cargo carriage is not open to passengers, that is, passenger and cargo do not share the same carriage, and neither the cost of the carriage modification nor the ban from driving policy is taken into account.

Table 7 Parameter values

Parameters	Value
The capacity of the carriage Q_r	30
The capacity of truck Q_v	6
The average subway speed v	60
Truck unit distance transportation cost c_{11}	5
Fixed cost per vehicle c_{12}	100
Labor cost per unit hour c_{41}	15
Unit cargo handling cost c_{42}	3
Cost coefficient per unit of stacked goods ε	1.1
Cargo stacking cost time coefficient ρ	0.1
Truck waiting time coefficient θ	0.2
Metro unit transfer cost g	3
Train dwell time t	[1.5, 2.5]

Express companies have a known number of trucks and can guarantee at least one truck for each metro exit. Assuming that the PDC begins to work at eight o'clock every morning, the supercargo arrives at the designated place with the first truck bound for the subway station. After all the goods transferred by the subway have been assembled, the supercargo will follow the train and take charge of the transfer of goods in the middle.

4.2 Model Parameters and Case Data

Combined with the investigation, the model parameters are set as shown in Table 7. Tables 8 and 9 show the location and delivery volume of each courier station as well as the distance and time among subway stations. PDSs are located in nodes 0 and 1. The distribution of courier stations is shown in Fig. 5.

4.3 Results Analysis

(1) *Analysis of surface and underground cooperative distribution effects*. With the assistance of MATLAB2020a programming, we implemented the ICS to solve the above cases. The number of nests is 50, and the number of max iterations is 1000. Table 10 shows the optimal route for MTC and Table 11 shows the optimal route for independent delivery of trucks. The route map is shown in Figs. 6 and 7. The comparison between the two solutions shows that the MTC mode reduces the total cost from 2572.0 to 1994.3 yuan, a decrease of about 22.5%. The total travel distance of trucks decreased from 514.40 to 354.49 km, a reduction of 159.91 km, or nearly 31.1%, mainly due to a reduction of the deadhead kilometers of the truck when it

Table 8 Node location information

Number	Longitude	Latitude	Delivery volume (t)	Number	Longitude	Latitude	Delivery volume (t)
0	125.495903	43.926495	–	18	125.348267	43.892535	4
1	125.415583	43.778954	–	19	125.339301	43.950480	3
2	125.265075	43.812812	4	20	125.377530	43.926019	3
3	125.390370	43.892261	2	21	125.398468	43.792543	3
4	125.299328	43.883656	2	22	125.351962	43.938792	4
5	125.355245	43.927343	2	23	125.245140	43.907422	4
6	125.404909	43.918353	3	24	125.263994	43.988177	3
7	125.348697	43.901245	2	25	125.369703	43.860466	2
8	125.315081	43.799003	3	26	125.402134	43.903837	2
9	125.300986	43.795643	3	27	125.345679	43.879851	3
10	125.316168	43.940879	3	28	125.341187	43.877105	2
11	125.389056	43.878782	2	29	125.290687	43.872846	4
12	125.353379	43.881579	4	30	125.422325	43.908778	4
13	125.282868	43.864007	2	31	125.221077	43.821413	3
14	125.348893	43.903748	4	32	125.375910	43.827283	4
15	125.427910	43.968284	3	33	125.341682	43.889365	4
16	125.415583	43.778954	3	34	125.192608	43.832789	4
17	125.224515	43.823209	2				

Table 9 Metro lines information

Number of metro line	Metro entrance–exit	Time windows of metro exits	Distance (km)	Time (min)
1	A–C	9:15~9:20	15.4	18.2
	A–D	9:25~9:30	23.6	28.6
2	B–E	9:10~9:15	8.2	12.7
	B–F	9:20~9:25	13.1	22.5
	B–G	9:40~9:45	24.6	42.2
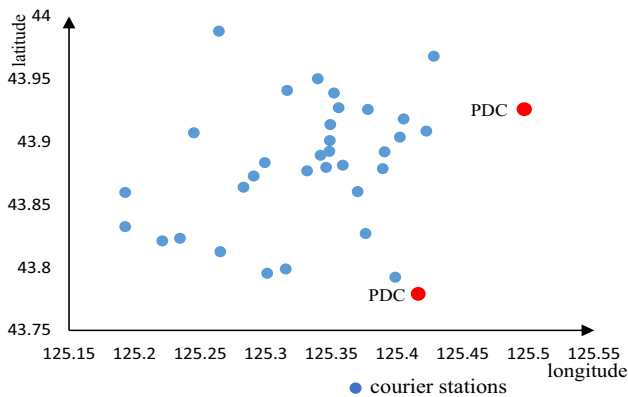
Fig. 5 Distribution of courier stations

returns to the PDC. Meanwhile, MTC not only reduces the total operating cost of express companies but increases the profits of metro companies by 179.97 yuan. The reduction of both total travel distance and delivery time allows a lower total cost in cooperative distribution mode. While reducing surface traffic congestion and pollution, MTC also benefits all stakeholders.

(2) *Algorithm analysis*. The artificial bee colony algorithm (ABC), particle swarm optimization algorithm (PSO), CS, and ICS were respectively used to solve the case. The average result of 50 iterations is shown in Table 12. As illustrated by Fig. 8, no matter convergence speed, minimum total cost, or running time, the ICS is excellent, because according to the relative positions of courier stations and subway stations, the courier stations with a higher probability of being transferred by subway are selected as the initial population. Two improvement strategies are proposed as well. One is to adapt the step size such that it diminishes logarithmically from a larger value to the smaller one, so as to coordinate the relationship between global search and local search. The other is to adjust the discovery probability randomly to eliminate the weaknesses by taking a fixed value. The PSO converges to a stable value quickly, but its final result is not as good as that of the ICS. The reason is that the parameters in PSO are difficult to calibrate, which results in poor search ability. The convergence rate of ABC is low in the early

Table 10 MTC distribution route

Truck 1		Truck 2		Truck 3		Truck 4		Truck 5		Truck 6		Truck 7	
Order	Time	Order	Time	Order	Time	Order	Time	Order	Time	Order	Time	Order	Time
1	8:00	1	8.00	D	9:00	C	9:00	0	8:00	0	8:00	F	9:00
A	8:12	A	8:12	19	9:27	14	9:20	B	8:11	B	8:11	4	9:26
1	8:25	1	8:25	22	9:30	7	9:28	0	8:23	0	8:23	23	9:36
A	8:37	A	8:37	D	9:42	C	9:31	B	8:35	B	8:35	F	9:42
1	8:50	1	8:50	22	9:48	18	9:35	0	8:46	0	8:46	29	9:46
A	9:02	8	9:03	5	9:53	33	9:38	30	8:55	B	8:58	13	9:50
1	9:15	9	9:07	20	9:56	C	9:42	25	9:07	0	9:10	F	9:55
21	9:18	1	9:23	D	10:06			E	9:12	B	9:23		
2	9:34	21	9:26	24	10:17			28	9:15	0	9:35		
G	9:45	32	9:35	10	10:29			27	9:18	15	9:48		
34	9:48	1	9:48	D	10:35			E	9:21	6	9:59		
31	9:54							18	9:25	0	10:10		
17	9:57							12	9:29	26	10:22		
G	10:07							E	9:32	3	10:27		
34	10:10									11	10:32		
16	10:17									E	10:37		
G	10:24												

Truck mileage, 354.49 km; total cost, 1994.3 yuan

Table 11 Non-MTC (truck only) distribution route

Truck 1		Truck 2		Truck 3		Truck 4		Truck 5	
Order	Time	Order	Time	Order	Time	Order	Time	Order	Time
0	8:00	0	8:00	1	8:00	1	8:00	1	8:00
15	8:13	19	8:20	23	8:30	16	8:32	13	8:23
24	8:35	10	8:25	25	8:47	34	8:37	29	8:27
0	9:05	0	8:47	1	9:02	1	9:07	1	8:50
4	9:56	7	9:05	8	9:15	21	9:23	32	9:00
33	10:11	14	9:09	9	9:19	27	9:40	4	9:08
0	10:21	0	9:27	1	9:34	1	10:00	1	9:32
20	10:35	18	9:47	25	9:50	2	10:19	31	9:58
6	10:41	7	9:50	11	9:56	1	10:40	17	10:01
0	10:53	0	10:08	3	10:00			34	10:07
22	11:05	12	10:28	0	10:35			1	10:36
5	11:08	28	10:31	30	10:45				
0	11:25	0	10:53	26	10:50				
				0	11:02				

Truck mileage, 514.40 km, total cost, 2257.0 yuan

stage, and the convergence process is not stable. The convergence speed of CS is lower because its discovery probability is assigned a fixed value of 0.25, which leads to local optimal and poor global search ability, and unacceptable performance.

(3) *Analysis of transfer points location and quantity.* By adding the number of transfer station constraints, cases are designed as shown in Table 13. Case 1 refers to all goods delivered solely by trucks. It shows that the more metro exits, the smaller the total cost within limits. But when the transfer point is set too high, the cost advantage decreases slightly due to the increase in the transfer cost. In addition, the reduction of truck mileage contributes to higher distribution efficiency. When only two metro exits are set up, few courier stations use subway delivery, which is near to that of case 1. The more metro exits, the wider the distribution range of the subway, and the greater the volume of freight transported. Therefore, metro exits can be allocated appropriately to give full play to the timeliness and economic benefit of subway delivery.
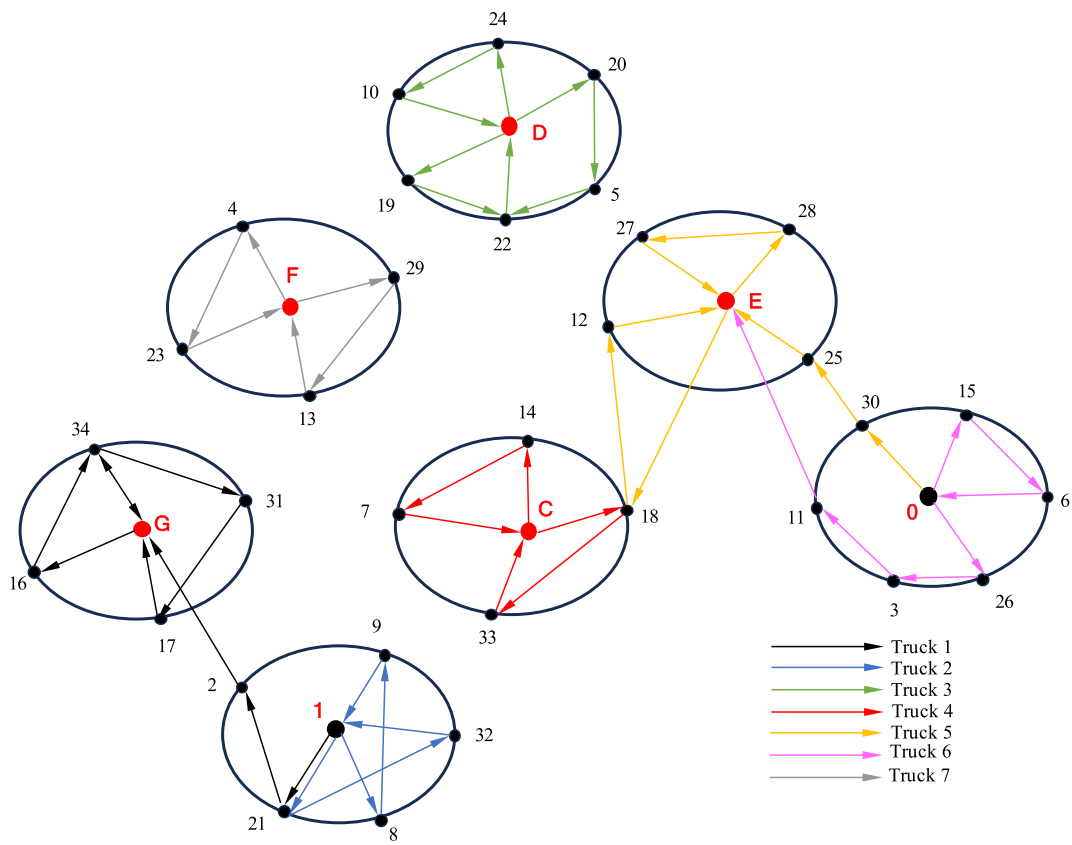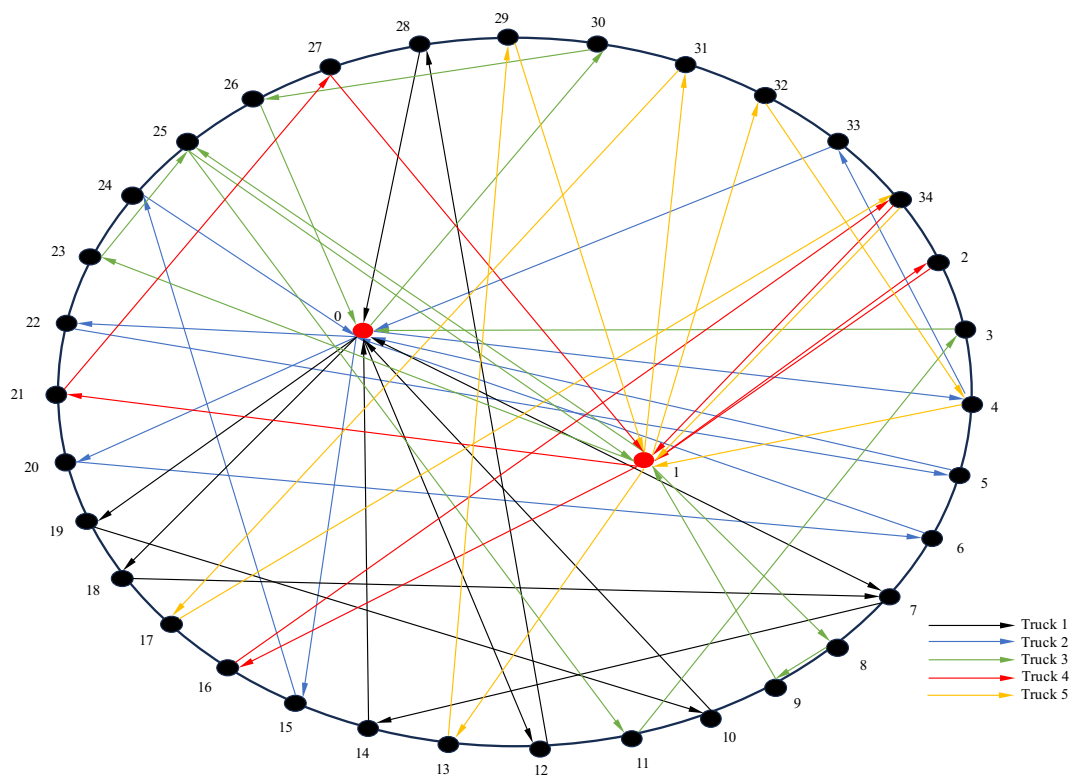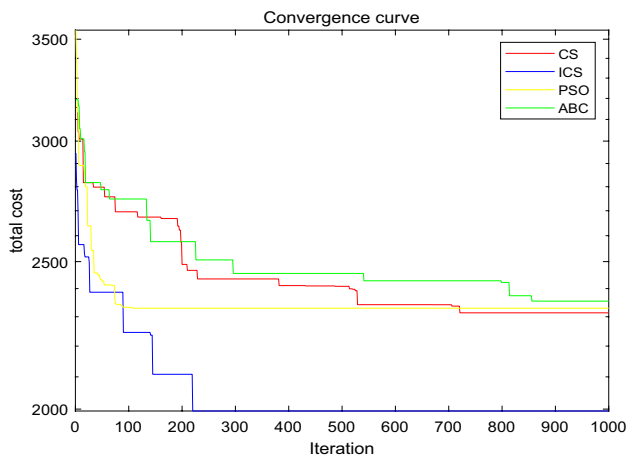
Fig. 6 Schematic diagram of MTC distribution routes

Fig. 7 Schematic diagram of truck distribution routes

Table 12 Comparison of different algorithms

Name	Running time (s)	Truck mileage (km)	Total cost (yuan)
ABC	57.03 (20.5%↑)	382.63 (7.4%↑)	2355.0 (15.3%↑)
PSO	50.25 (9.7%↑)	377.61 (6.1%↑)	2329.9 (14.4%↑)
CS	53.58 (15.3%↑)	374.35 (5.3%↑)	2313.6 (13.8%↑)
ICS	45.36	354.49	1994.3

Fig. 8 Comparison of convergence curves

Table 13 The comparison of cases

Case	Open metro exits	Measurement of performance		
		Truck mileage (km)	Unit delivery time (min t^{-1})	Total cost (yuan)
1	–	514.40	8.11	2572.0
2	D, G	482.04	8.01	2360.2
3	D, E, G	434.62	7.87	2190.4
4	C, D, E, G	409.56	7.34	2047.8
5	C, D, E, F, G	342.49	6.97	1994.3
6	C, D, E, F, G, H	398.14	7.25	2026.8

(4) *Split demand necessity analysis*. The daily delivery volume of each courier station is relatively stable. In order to verify the rationality of the split demand, the truck mileage and distribution cost without split demand under the MTC distribution mode are calculated, which are 388.92 km and 2166.45 yuan, respectively. This reduced truck mileage by 8.8% and saved distribution costs by 7.9% compared to split demand. It follows that the split is reasonable and necessary.

5 Conclusions

In this paper, an MTC considering time windows is constructed, and an ICS is designed to solve it. The MTC mode is less time-consuming and provides effective utilization of space. Considering the capacity limit of subways and trucks, and the joint distribution of multiple subway lines, these achievements are more practical and implemented more easily using MTC.

(1) Compared with the traditional surface delivery mode, the MTC reduces the delivery cost by 22.5% and the truck mileage by 31.1%. It would also increase metro enterprise's extra income, utilize the existing subway network fully, relieve the congestion of surface transportation, and improve the distribution efficiency and service quality.
(2) Considering the influence of the number of transfer stations on the distribution cost, the transfer point allocation strategy can be a reference to the optimization of the urban distribution network, which has both theoretical and practical significance.
(3) The ICS obtains the high-quality solution faster, which is more efficient and stable.

This paper only considers the use of certain metro lines and one shift to transport express, which covers a limited number of courier stations. If the entire existing metro network of the city were organized to carry out the MTC with multiple express companies, the proportion of underground logistics in urban logistics would be larger, and economies of scale would be more significant. Future research will consider adjusting the train schedule after classifying the goods according to the time limit in order to provide on-time service.

Data Availability The data used to support the findings of this study are available from the corresponding author upon request.

Declarations

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