

Optimization of cold chain multimodal transportation routes considering carbon emissions under hybrid uncertainties

Hou, D.N.^{a,b,*}, Liu, S.C.^c

^aDivision of Public Policy, Hong Kong University of Science and Technology, P.R. China

^bShanxi State-owned Capital Operation Co., Ltd, P.R. China

^cSchool of Business Administration, Fujian Business University, P.R. China

ABSTRACT

As the third largest greenhouse gas emission industry across the globe, the transportation industry dominates a major position in the total carbon emission. Multimodal transportation has incomparable advantages over single-modal transportation, and choosing transportation routes and modes under the background of carbon peaking and carbon neutrality is crucial. The uncertainties of demand and transportation time were described using the maximum regret value and Lyapunov central limit theorem, respectively, and a robust optimization model for cold chain multimodal transportation routes considering hybrid uncertainty of carbon emissions was established. Then, a dual-pheromone ant colony algorithm was designed, and the improved niche genetic algorithm was nested into the ant colony algorithm to solve the model. Results showed that the changes in transportation time and node transfer time lead to the changes in transportation cost and transportation scheme, and the robust optimization of the multimodal transportation route under hybrid uncertainties is affected by the regret value constraint and the fluctuation range of uncertain factors, resulting in the increase in transportation cost and carbon emission cost. Therefore, the decision-makers of cold chain multimodal transportation must predict the influence of uncertain factors, choose the appropriate maximum regret value, and pay attention to the mixed time window constraints of transportation time and node transfer time to reduce costs and improve efficiency.

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**Corresponding author:*
denimhou@163.com
(Hou, D.N.)

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1. Introduction

As an important constituent of the comprehensive transportation system, multimodal transportation can integrate various single modes of transportation and scattered transportation resources. Multimodal transportation has become an important way of cargo transportation and an inevitable development trend of the modern comprehensive transportation system by virtue of its efficient, safe, and economical characteristics. In addition, multimodal transportation plays an important role in integrating transportation resources, saving energy and reducing transportation costs [1], and serves as an effective way to realize the unification of transportation efficiency and cost [2]. According to statistics, the multimodal transportation volume in Europe and the United States has developed rapidly, and the overall proportion has increased year by year. Generally, the container multimodal transportation accounts for approximately 20 % interna-

tionally, 40 % in the United States, 35 % in France, 25 % in India, and 2 % in China [3]. Compared with single road transportation, multimodal transportation can reduce transport costs by 20 % and CO₂ emissions by 57 % [4]. The transportation efficiency and cost of cold chain container multimodal transportation are affected by multimodal transportation stations, transportation routes, means of transportation, transportation prices, transportation time and carbon emission restrictions, and different transportation organization schemes must be formulated by catering to the different needs of customers [5]. Cold chain container multimodal transportation involves many subjects, such as shippers, carriers, and consignees, and various modes and means of transportation, accompanied by problems such as the coordination of transportation organizations, the optimization of transportation routes, and the distribution of transportation benefits. In the complex and volatile external environment, multimodal transportation carriers should optimize transportation organization schemes considering multiple uncertain factors; for example, during the COVID-19 epidemic, some key nodes in the multimodal transportation network failed, the transportation demand and time were uncertain, while the goods were required to be delivered within the shortest time. Therefore, a modelling analysis under multifactor uncertainties was performed based on the study on container cold chain multimodal transportation route optimization under single-factor uncertainty. Many uncertain factors, such as transshipment time and uncertain transportation demand in the multimodal transportation network, interact with each other, and during cold chain multimodal transportation, various transportation equipment and refrigerated containers release carbon dioxide, which affects the choice of cold chain multimodal transportation routes. Hence, a cold chain multimodal transportation route optimization model considering carbon emissions under hybrid uncertainties was constructed, aiming to solve the problem of cold chain multimodal transportation route optimization under the hybrid uncertainties of transportation time and demand. Meanwhile, the model also considered the influence of carbon emissions on cold chain container multimodal transportation routes. Studying the intermodal route scheme under parameter changes through sensitivity analysis is of specific theoretical guiding importance for improving the operational capacity of the intermodal network in complicated situations.

2. Literature review

As for the research on the disturbance of uncertain demands, Qiu *et al.* established a robust optimization model of multimodal transportation routes through a scenario analysis among robust optimization methods, in which the objective function was the total cost composed of transportation cost, time value cost of goods and carbon emission cost, and the constraint conditions included the node operation time window [6]. On the basis of demand uncertainty and carbon trading policy, Deng *et al.* (2023) built a robust optimization model of multimodal transportation routes with the minimum economic cost as the objective and solved the model using a genetic algorithm to verify its rationality and effectiveness [7]. Li and Sun (2022) constructed a robust stochastic optimization model for container multimodal transportation considering the uncertainty of demand and the randomness of carbon transaction price and designed a hybrid firework algorithm based on gravity search operator [8]. During uncertainty model transformation, Wang (2024) used the Bertsimas robust optimization method to linearize the demand uncertainty parameter and then transformed the demand uncertainty model into a certainty model [9]. Tang *et al.* (2023) constructed a multi-objective model with the minimum total transportation cost and total transportation time, transformed the multiple objectives into a single objective by using the linear weighting method, and designed a genetic algorithm based on simulated annealing to solve the model [10]. Mainly considering the demand uncertainty in intermodal transportation, Li *et al.* (2017) designed the sequential decision on terminal location and route planning based on a two-stage stochastic programming model to realize an economical and efficient multimodal transportation network [11]. Considering the uncertain demand in multimodal transportation, Hu *et al.* (2017) proposed a two-stage stochastic programming model to determine the terminal location and transportation route under the uncertain customer demand [12]. Zhang *et al.* (2020) established a two-stage nonlinear stochastic programming model consider-

ing the uncertainty of iron ore demand and the economies of scale in port transshipment [13]. In accordance with the above research results, the transportation volume has been set to a specific value for optimization modelling in most of the existing literature while neglecting the uncertainty of customer transportation demands. Moreover, the design of transportation schemes is of certain foresightedness, and the capacity constraints of each transportation route and transshipment node have not been considered.

Regarding the research on the uncertainty of transportation price, Chen (2020) mainly considered the uncertain disturbance relations, such as transportation process price, depicted the uncertainty of transportation price through the interval method, constructed a hybrid integer robust optimization model, and solved the model with an accurate algorithm [14]. Aiming at the uncertainty of transportation cost, Hu *et al.* (2018) built a facility planning model considering the uncertainty of fixed investment, logistics cost, inventory cost and recovery [15]. Zhang *et al.* (2021) established a hybrid robust stochastic optimization model and designed a catastrophic adaptive genetic algorithm based on Monte Carlo sampling [16]. Xie and Cao (2021) explored into the multimodal transportation of dangerous goods under uncertain conditions and proposed an interval 0–1 integer programming model with the transportation risk and transportation cost during the transportation of dangerous goods as the objectives [17]. Li *et al.* (2024) considered the influences of uncertain freight rates and navigation conditions of different route segments, constructed the Yangtze River container multimodal transportation route optimization model under uncertain conditions, and designed Monte Carlo simulation and improved wolf pack algorithm to solve the model [18]. Pian *et al.* (2022) constructed a two-level programming model with the objectives of maximizing the profit of carriers and minimizing the generalized cost of shippers, solved the model by using a sensitivity-based heuristic algorithm, and verified its effectiveness [19]. Aradi (2022) constructed a two-level programming model, a carrier revenue maximization model, and a shipper transportation mode selection model considering the influence of the pricing strategy on shippers [20]. Considering the generalized cost of customers and the revenue of railway operation enterprises, Aghabayk *et al.* (2020) established a pricing model with the minimum generalized cost as the objective and a two-level programming pricing model and concluded that the two-level programming model is better than the model with the minimum generalized cost [21]. The above studies mainly focus on the uncertainty of transportation price, which, however, is affected by market law, transportation cycle, and international environment and strongly influenced by the market policy with marked regional differences. Moreover, the maximum and minimum carbon trading prices vary greatly from region to region; thus, the effect is extremely limited if the minimum value of the objective function is utilized to describe the container multimodal route optimization model considering the uncertainty of transportation price.

Regarding the research on uncertain transportation time, the influence of traffic congestion on multimodal transportation routes has been analysed by some scholars. For instance, Norouzi *et al.* (2015) built a route optimization model with the objectives of maximum reliability and minimum time considering road dynamics [22]. Ehr Gott *et al.* (2012) constructed a hybrid integer optimization model based on fuzzy chance constraints aiming at two uncertain factors, namely, railway capacity and highway passage time, and designed an accurate solution to solve the model by the linearization method [23]. Considering road reliability, Gupta *et al.* (2018) constructed a multi-objective route optimization model with the objectives of maximum reliability, minimum time, and minimum material unsatisfaction degree [24]. Taking the time-dependent nature of disasters, Gupta *et al.* (2020) established an emergency logistics route planning model with maximum reliability and minimum transportation time as the objective functions [25]. Mardanya *et al.* (2021) studied the route selection model for emergency supplies considering the reconfiguration and reliability of routes [26]. Biswas *et al.* (2019) built a multimodal route optimization model carrying time windows in the multimodal network with full consideration of the uncertainties in transportation time and transshipment time [27]. Given the time-dependent nature of the transportation network, Liu (2021) established a cold chain container multimodal transportation route optimization model, designed two scenarios—static optimization and dynamic optimization, and adopted an improved genetic algorithm to solve the model [28]. When

studying multimodal route selection, Das *et al.* (2020) introduced the time window constraint to establish a hybrid integer fuzzy mathematical model with demand assumption as a fuzzy number, aiming to improve customer satisfaction to the greatest extent [29]. Maity *et al.* (2020) probed into the modelling and optimization of the public highway–railway multimodal transportation system based on the central radiation network under uncertain conditions, taking cost and time as objective functions and using the weighted sum method to deal with multi-objective problems [30]. Roy *et al.* (2017) established a multi-objective route decision model for multimodal transportation considering the uncertainties of highway transportation speed and transshipment time in the actual transportation process and solved the model by using the K-shortest route algorithm and nondominated sorting genetic algorithm [31]. All the parameters related to transportation time in most multimodal transportation models studied above are definite values, but in actual transportation, transportation time is also affected by time-varying transportation networks.

In summary, the multimodal route optimization problem that simultaneously considers the hybrid certainties of cold chain container transportation time and demand has been rarely involved in the existing literature, not to mention the research considering carbon emissions and the uncertainty of multimodal links. On this account, the carbon emission cost was imported into the container multimodal route optimization model under the hybrid uncertainties in transportation time and demand to construct a cold chain container multimodal low-carbon route optimization model under the hybrid uncertainties of time and demand. For the NP-hard characteristic of the problem to be solved, a solution strategy combining niche genetic algorithm and ant colony algorithm was designed, followed by the verification of model and algorithm effectiveness through an example. This study is of certain theoretical importance and practical application value.

The remainder of this paper is organized as follows: In Section III, the cold chain container multimodal route optimization problem considering the hybrid uncertainties of time and demand was modelled; in Section IV, a “dual-pheromone matrix” storage method was designed to realize the niche genetic algorithm–ant colony algorithm combined hybrid algorithm guided by the matching and search between target objects; in Section V, analysis was performed by taking the multimodal network in Chinese Circum-Bohai Sea Economic Zone as an example to verify the effectiveness of the proposed model and algorithm; in the final section, the relevant conclusions were drawn.

3. Modelling

3.1 Problem description and model assumptions

It is assumed that there are totally n transportation nodes in the multimodal transportation network in a region, with m modes of transportation between every two nodes. Thus, transportation is conducted using *teu* refrigerated containers. In consideration of the constraint conditions of the transportation network, the minimum cost and the minimum carbon emissions during the transportation process are achieved by selecting the combinations of different modes of transportation.

A batch of cold chain cargoes are transported from city O to city D , where O is the starting point of transportation ($O \in I$), D is the endpoint ($D \in I$) and I represents the transportation set. Several middle nodes are passed in the process of transportation; moreover, between any two nodes in the multimodal network are one or multiple selectable modes of transportation, such as highway, railway, and waterway, and the difference in the mode of transportation selected results in the differences in carbon dioxide emissions, transportation distance, and transportation cost, and transportation time and transshipment time are set to be random numbers. In this study, the minimization of total cost, including carbon emission cost, was solved, the decision on the multimodal transportation route and mode was made, and carriers were required to meet the time window limit of a certain confidence level when delivering goods to the endpoint. The following assumptions were made:

- The driving speed and the total transportation volume demanded under different modes of transportation on each road section follow a probability distribution.
- After transshipment is completed, emergency supplies can be transported to the next node only upon the nearest shift.
- The goods are no special requirements for the mode of transportation. All nodes except the starting point and endpoint can serve as transshipment nodes.
- At transshipment nodes, emergency supplies can only be transshipped to one node instead of split transshipment.

3.2 Model parameters and variables

Based on the problem description and model assumptions, the symbol descriptions are exhibited in Table 1.

Table 1 Symbol descriptions

Parameter	Parameter definition	Unit
I	Transportation node set, representing the locations passed during the transportation of goods, $i \in I$;	—
J	Set of modes of transportation, indicating the type of transportation mode, $j \in J, k \in J$;	—
teu	Number of cold chain transportation containers;	Ea
$x_{i,i+1}^j$	If the j -th mode of transportation is adopted from location i to location $i + 1$, the value is 1, or otherwise, it is 0;	—
$l_{i,i+1}^j$	Transportation distance under the j -th mode of transportation from location i to location $i + 1$;	—
$t_{i,i+1}^j$	Transportation time under the j -th mode of transportation from location i to location $i + 1$;	Min
$e_{i,i+1}^j$	Unit transportation cost under the j -th mode of transportation from location i to location $i + 1$;	yuan
$co_{i,i+1}^j$	Unit carbon emission under the j -th mode of transportation from location i to location $i + 1$;	kg
co_z	Unit carbon emission during the rehandling operation at nodes;	T
$y_i^{j,k}$	If the mode of transportation is changed from j to k at location i , the value is 1, or otherwise, it is 0;	—
$e_i^{j,k}$	Rehandling cost of unit goods if the mode of transportation is changed from j to k at location i . The value is zero if the mode of transportation at this location is unchanged;	—
$t_i^{j,k}$	Rehandling time of unit goods if the mode of transportation is changed from j to k at location i . The value is zero if the mode of transportation at this location is unchanged;	—
e_l	Refrigeration cost of cold chain containers within unit time;	yuan
co_l	Refrigeration-induced carbon emission of cold chain containers within unit time;	t
r_e	Carbon tax value;	yuan
γ_1	Storage management cost to be paid within unit time when the goods arrive at location i in advance;	yuan
γ_2	Penalty cost to be paid within unit time in case of delayed arrival of goods at location i ;	yuan
a_i	Earliest arrival time of goods allowed at location i ;	—
b_i	Latest arrival time of goods allowed at location i ;	—
v_j	The speed of the j -th mode of transportation.	—

3.3 Robust optimization model

Based on the actual operation process of cold chain container multimodal transportation and the above assumptions, the objective function of the model consists of the following parts:

- Transportation process cost C_1 , including internode transportation cost, cold chain equipment refrigeration cost, and rehandling cost at nodes, and each cost during the transportation process is expressed as follows:

$$\begin{aligned}
 C_1 = & \sum_{i=1}^n \sum_{j=1}^m e_{i,i+1}^j x_{i,i+1}^j l_{i,i+1}^j + \sum_{i=1}^n \sum_{j=1}^m \sum_{k=1}^m y_i^{j,k} e_i^{j,k} + e_l \left(\sum_{i=1}^n \sum_{j=1}^m t_{i,i+1}^j x_{i,i+1}^j \right. \\
 & \left. + \sum_{i=1}^n \sum_{j=1}^m \sum_{k=1}^m y_i^{j,k} t_i^{j,k} \right)
 \end{aligned} \quad (1)$$

- Carbon emission cost C_2 during transportation, including carbon emission cost during inter-node transportation, carbon emission cost induced by cold chain equipment refrigeration, and carbon emission cost induced by rehandling at nodes. The carbon emission cost during transportation is expressed as follows:

$$C_2 = \left(\sum_{i=1}^n \sum_{j=1}^m co_{i,i+1}^j x_{i,i+1}^j l_{i,i+1}^j + \sum_{i=1}^n \sum_{j=1}^m \sum_{k=1}^m y_i^{j,k} co_z \right. \\ \left. + co_l \left(\sum_{i=1}^n \sum_{j=1}^m t_{i,i+1}^j x_{i,i+1}^j \sum_{i=1}^n \sum_{j=1}^m \sum_{k=1}^m y_i^{j,k} t_i^{j,k} \right) \right) r_e \quad (2)$$

- Time window cost C_3 , including the storage cost because of advanced arrival and the penalty cost because of delayed arrival, specifically as follows:

$$C_3 = \gamma_1 \sum_{i=1}^n \max(a_i - t_i, 0) + \gamma_2 \sum_{i=1}^n \max(t_i - b_i, 0) \quad (3)$$

- Cargo damage cost C_4 . Cold chain goods are sensitive to environmental changes, and time and temperature changes probably lead to the deterioration of goods. In this study, the cargo damage cost was calculated via Arrhenius equation as follows:

$$C_4 = P_{teu} [1 - e^{-\mu \frac{l_{i,i+1}^j}{v_j}}] \quad (4)$$

where μ represents the sensitivity coefficient.

The objective functions of the model are displayed as follows:

$$\min C = teu(C_1 + C_2 + C_3 + C_4) \quad (5)$$

s. t.

$$x_{i,i+1}^j + x_{i-1,i}^j \geq 2y_i^{j,k} \quad \forall i \in I, \forall j, k \in J \quad (6)$$

$$t_{i,i+1}^j \geq 0, t_i^{j,k} \geq 0, l_{i,i+1}^j \geq 0, teu \geq 0 \quad (7)$$

$$t_{i,i+1}^j = \frac{l_{i,i+1}^j}{v_j} \quad \forall i \in I, \forall j \in J \quad (8)$$

$$\sum_{j=1}^m \sum_{k=1}^m y_i^{j,k} = 1 \quad \forall i \in I, \forall j, k \in J \quad (9)$$

$$x_{i,i+1}^j (t_{i+1} - t_i) \geq 0 \quad \forall i \in I \quad (10)$$

$$\sum_{j=1}^m x_{i,i+1}^j = 1 \quad \forall i \in I, \forall j \in J \quad (11)$$

$$t_i^{j,k} \sim N(\mu_i^{j,k}, (\sigma_i^{j,k})^2) \quad (12)$$

$$t_{i,i+1}^j \sim N(\mu_{i,i+1}^j, (\sigma_{i,i+1}^j)^2) \quad (13)$$

$$x_{i,i+1}^j = \begin{cases} 1, & \text{transportation mode } j \text{ is selected between node } i \text{ and } i+1 \\ 0, & \text{otherwise} \end{cases} \quad (14)$$

$$y_i^{j,k} = \begin{cases} 1, & \text{transportation mode is changed from } j \text{ to } k \text{ at the node } i \\ 0, & \text{otherwise} \end{cases} \quad (15)$$

Eq. 5 is the objective function, which consists of four parts: transportation cost, time window cost, carbon emission cost, and damage cost of cold chain products. Eq. 6 aims to ensure the continuity and accuracy of the conversion between various modes of transportation in the process of cold chain multimodal transportation. Eq. 7 ensures that the transportation time, transshipment time, transportation distance, and transportation volume are positive values. Eq. 8 is the transportation time of goods between two adjacent nodes (i and $i+1$), which is related to the speed. Eq. 9 means that the cold chain container can only be converted from the current mode of transportation to another mode of transportation at transshipment nodes. Eq. 10 indicates the

continuity of cargo transportation time, and the time when the cold chain container arrives at the back node ($i + 1$) is later than the time when the cargo arrives at the previous node (i). Eq. 11 indicates that only one mode of transportation can be selected between adjacent nodes. Eqs. 12 and 13 mean that transshipment time and transportation time obey a normal distribution. Eq. 14 is a value constraint of the decision variable, representing whether a certain mode of transportation is used between two nodes. Eq. 15 is also a value constraint for decision variables, representing whether to change the mode of transportation at a certain node.

4. Algorithm design

4.1 Description of hybrid algorithm

In accordance with the characteristics of the problem, the “dual-pheromone matrix” storage method was designed to realize the “interactive selection” of routes and modes of transportation. Next, a hybrid algorithm combining genetic algorithm and ant colony algorithm was designed. First, the similarity between schemes was reduced through the niche technology based on genetic algorithm, and multiple groups of feasible solutions that contained more representative solution spaces were obtained; second, each optimal route and mode of transportation were combined, and the dual-pheromone heuristic matrix in ant colony algorithm was updated so that the initial ant colony possessed an improved matching basis for the route and mode of transportation to guide and accelerate the route optimization process of ants and further enhance the solution accuracy and convergence rate of the hybrid algorithm.

4.2 Niche genetic algorithm

In this study, the niche genetic algorithm was introduced into the ant colony algorithm. To prevent the algorithm from sampling the fixed area of the target space [16], two-point mutation and mask crossover were designed as genetic operators, and the diversity of the population was guaranteed, as shown in Fig. 1.

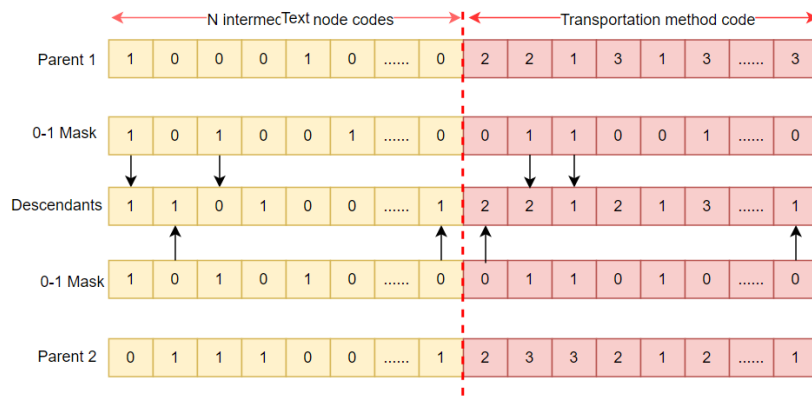


Fig. 1 Schematic of chromosome coding

4.3 Dynamic dual-pheromone ant colony algorithm

In this study, the “dual-pheromone matrix” storage method was designed, aiming to eliminate the blindness of route mode of transportation matching. As for the dual-pheromone storage structure, the heuristic information $\eta_{ij}(t)$ at time t indicates the probability of route selection, pheromone concentration $\tau_{ij}(t)$ denotes the probability for the selection of modes of transportation, $p_{ij}^a(t)$ is the probability for ant a to transfer from node i to node j at time t , and the probability for the selectable mode of transportation that matches with the selected arc segment (i, j) can be solved in a similar way.

$$p_{ij}^a(t) = \begin{cases} \frac{[\tau_{ij}(t)]^\alpha [\eta_{ij}(t)]^\beta}{\sum_{r \in allowed_a} [\tau_{ir}(t)]^\alpha [\eta_{ir}(t)]^\beta} & j \in allowed_a \\ 0 & j \notin allowed_a \end{cases} \quad (16)$$

Where the set of nodes or modes of transportation that can be selected by ant a is expressed as $\tau_{ij}(t+1) = (1-\rho) \times \tau_{ij}(t) + \Delta\tau_{best}$; $\tau_{ij}(t)$ stands for the pheromone intensity of route (i, j) at time t ; $\tau_{ij}(t+1) = (1-\rho) \times \tau_{ij}(t) + \Delta\tau_{best}$ is the influencing factor, indicating the reliance on the pheromone matrix and heuristic matrix during node selection by ants; $\tau_{ij}(t+1) = (1-\rho) \times \tau_{ij}(t) + \Delta\tau_{best}$ is the influencing factor, reflecting the reliance of the mode of transportation on the pheromone matrix and heuristic matrix [26].

The max-min ant strategy is adopted to avoid the stagnation of algorithm search in the later stage, and the pheromone value of each arc and each mode of transportation must be within the interval of (τ_{min}, τ_{max}) , where $L(S_{best})$ is the favourable solution of each niche or the best solution of the ant colony algorithm in the current iteration. The range of initial pheromone and the solution obtained from the niche genetic algorithm are determined as per Eqs. 17 and 18 [29].

$$\tau_{max}(t) = \frac{1}{2(1-\rho)} \times \frac{1}{L(S_{best})} \quad (17)$$

$$\tau_{min}(t) = \frac{\tau_{max}(t)}{20} \quad (18)$$

After the niche genetic algorithm ends, τ_{min} is determined via Eq. 18 and τ_{max} via Eq. 19.

$$\tau_{max}(t) = \frac{1}{2(1-\rho)} \times \frac{1}{L(S_{best})} + \frac{1}{L(S_{best})} \quad (19)$$

4.4 Improved time-varying pheromone evaporation operator

By analysing the factors influencing the algorithm search space and algorithm convergence, the importance of the pheromone evaporation factor in the selection of route or mode of transportation is found to be directly proportional [32]. In the niche genetic algorithm and ant colony algorithm mechanism designed in this study, therefore, the pheromone evaporation factor ρ increases with the increase in the number of iterations during algorithm operation [31].

$$\rho = \rho_0(1 - \mu_0^{-\lambda}) \quad (20)$$

where μ_0 is the pheromone evaporation speed; λ denotes the number of iterations performed by the ant colony algorithm; ρ_0 is the initial pheromone evaporation factor. μ_0 controls the pheromone evaporation factor to finally converge to ρ_0 , and the value of μ_0 is directly proportional to the increase rate of the pheromone evaporation factor with the increase in the number of algorithm iterations [33].

4.5 Dual-pheromone hybrid algorithm flow

The dual-pheromone hybrid algorithm flow is displayed in Fig. 2.

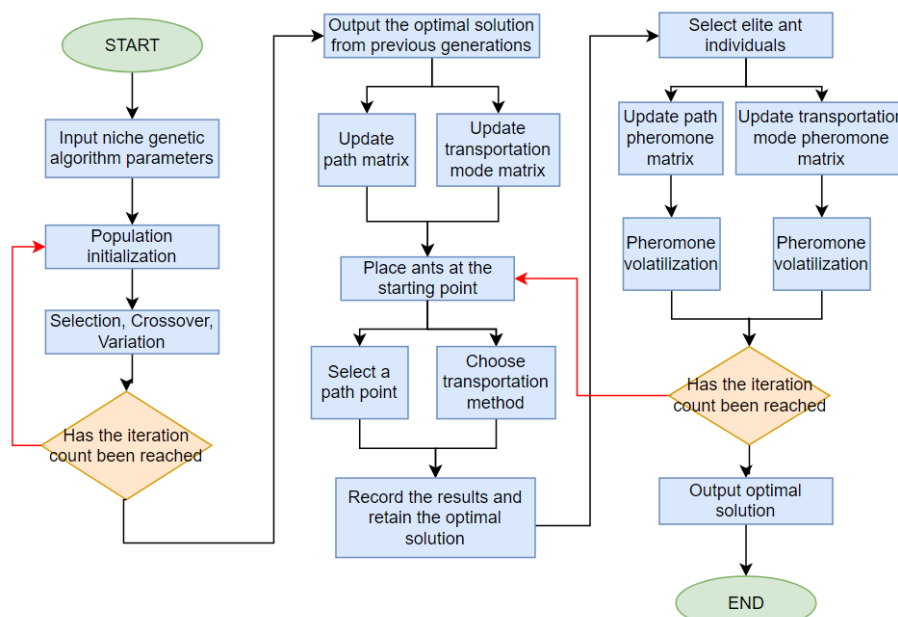


Fig. 2 Flowchart for solving the multimodal route optimization problem based on an improved genetic algorithm

5. Example analysis

5.1 Data description

With the Chinese Circum-Bohai Sea Economic Zone taken as the study object, the most important dense extravert and multifunctional urban agglomerations in Northern China were constituted with Beijing and Tianjin as the center, coastal cities such as Dalian, Qingdao, Yantai and Weihai as the sector, and provincial cities such as Shenyang, Jinan, and Shijiazhuang as the regional pivots. These urban agglomerations exerted the agglomerating, radiating, serving, and driving effects in nationwide and regional economy, powerfully facilitating the development of their characteristic economic zones. The location map of the Circum-Bohai Sea Economic Zone is shown in Fig. 3. The shortest route mileages among 35 main nodes under such modes of transportation as highway, railway, and waterway were acquired in accordance with the China railway information network, Baidu Map, and relevant electronic maps. Among the 35 cities, transportation could be realized between any two cities by means of highway and railway, and no waterway transportation existed between some cities. The multimodal network with 35 nodes was simulated to investigate the feasibility of the model and algorithm. The basic data tables were omitted due to the limitations on the length of the paper.

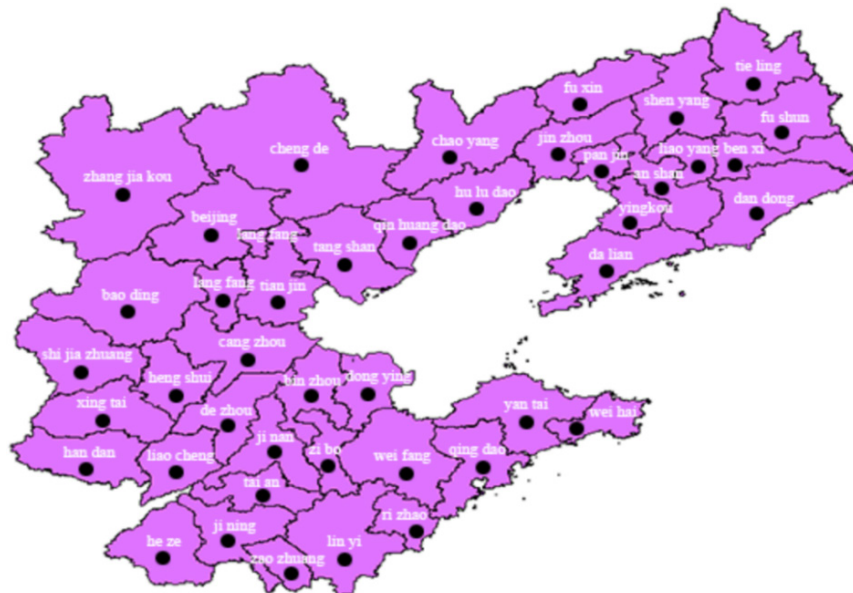


Fig. 3 Multimodal transportation network

5.2 Example design

Table 2 shows three transportation tasks undertaken by a transportation company. The unit warehousing cost and penalty cost induced by the advanced and delayed arrival of goods at the endpoint relative to the customer-expected arrival time are 60 and 100 yuan/teu*h, respectively. In reference to the actual transportation speed under each mode of transportation in China, the highway, railway, and waterway transportation speeds were respectively taken as 90, 65, and 35 km/h. The ratio of transportation time to transportation speed is the reference transportation time T , and the reference volume of goods transported is $Q = 28$.

Table 2 Table of transportation tasks

Transportation task	Starting point	Endpoint	Quanty (teu)	Cargo value
Task 1	Qingdao	Chengde	5	150,000/teu
Task 2	Qingdao	Beijing	5	150,000/teu
Task 3	Qingdao	Shenyang	8	150,000/teu

Four possible demand scenarios for the transportation volume in the current transportation task were assumed, and the probability for their occurrence was 0.1, 0.2, 0.3, and 0.4, respectively. The robust optimization model based on scenario sets was proposed by Mulvey *et al.* [34],

which divided scenario sets according to data characteristics so that they could cover all the possible occurrence conditions of events. The customer demand under each scenario is listed in Table 3.

Table 3 Customer demand under each scenario

Transportation task	Scenario I	Scenario II	Scenario III	Scenario IV	Cargo value	
Task 1	5	6	4	4	150,000/teu	5.3
Task 2	8	4	5	4	150,000/teu	5.5
Task 3	7	10	7	6	150,000/teu	8.4

The total value of each teu of cold chain goods is 150000 yuan, with a weight of 20 tons. A total of 33 node cities were chosen as the possible transshipment nodes and numbered as 1, 2...33 for the convenience of expression. The average data of transportation time between two nodes under different modes of transportation are difficult to obtain; thus, the ratio of transportation distance to transportation speed was assumed to be the average value of transportation time, and the variance of highway transportation, railway transportation, and waterway transportation was taken as 0.52, 0.22, and 0.752, respectively. Table 4 shows the relevant parameters of three transportation modes.

Table 4 Profiles of three modes of transportation

Mode of transportation	Highway	Railway	Waterway
Unit freight charge (yuan/teu*km)	8.5	2.025	0.5
Transportation speed (km/h)	(100, 0.52)	(60, 0.22)	(30, 0.752)
Carbon emission (teu/tkm)	1.4	0.412	0.332

For the railway line existing between nodes, a nonstop train can be started between some nodes, and this train does not perform unloading or transshipment operation at the middle node, and it is not affected by the departure time of other trains at the transshipment node. In this case, the transportation time of the nonstop train is the sum of transportation time on each section of the railway line, and the unit cargo transportation cost is the average value of the unit cargo transportation cost on each section of the railway line. The transshipment cost between different modes of transportation, the carbon emission, and the transshipment time are exhibited in Table 5.

Table 5 Rehandling circumstances between different modes of transportation

Mode of transportation	Highway			Railway			Waterway		
	Cost (yuan)	Carbon emission (kg)	Time (h)	Cost (yuan)	Carbon emission (kg)	Time (h)	Cost (yuan)	Carbon emission (kg)	Time (h)
Highway	0	0	0	30	1.4	(0.1, 12)	50	3.5	(0.3, 12)
Railway	30	1.4	(0.1, 12)	0	0	0	60	4.2	(0.4, 12)
Waterway	50	3.5	(0.3, 12)	60	4.2	(0.4, 12)	0	0	0

5.3 Model solving

Certainty model solving

For the certainty model, the influence of transportation volume on the cold chain container multimodal route is not considered. Under the certainty model, it takes 11.10 s to solve three tasks via MATLAB2014b, and the optimal multimodal route is displayed in Fig. 4. The convergence curve of the multimodal transportation cost for the three tasks under the certainty model is exhibited in Fig. 5, and the minimum total cost for the three tasks is 79,789 yuan.

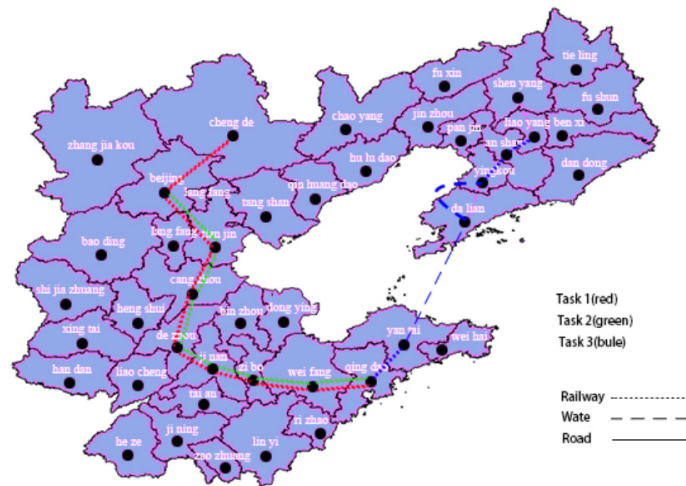


Fig. 4 Multimodal route with the minimum total cost under certainty model

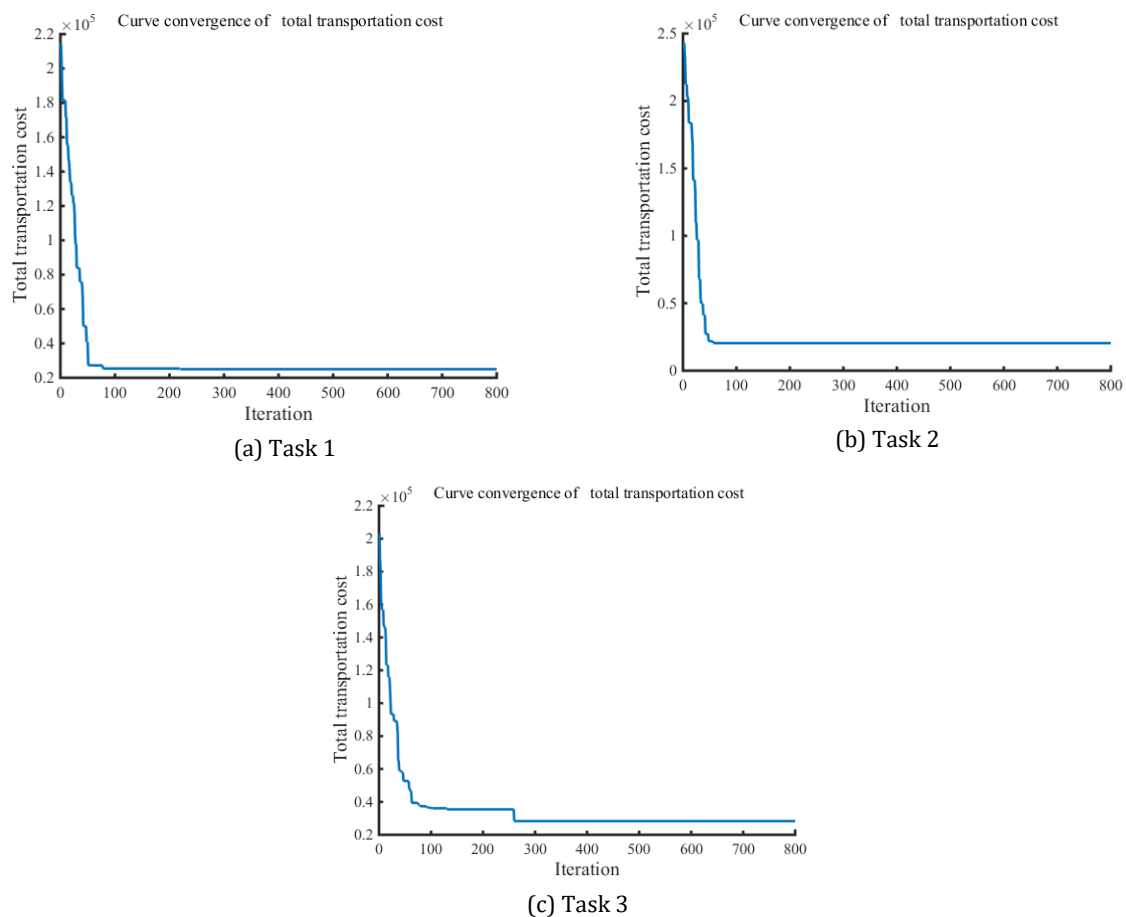


Fig. 5 Convergence curve of the multimodal transportation cost for three tasks under the static model

Time uncertainty model solving

The influence of different transportation task characteristics on the transportation scheme was compared by designing three different types of examples according to the different transportation tasks and transportation scales, that is, according to the number of transportation tasks and the size of transportation batches. To simulate the uncertainty of transportation time and re-handling time, transportation time and rehandling time were processed using fuzzy time, the average value of transportation time was the ratio of transportation distance to transportation speed, and the variance of highway transportation, railway transportation, and waterway transportation was 0.52, 0.22, and 0.752, respectively. The average value of transportation time was

changed by adjusting the average value of transportation speed according to the transportation time. The average transshipment time and variance were acquired by analysing the statistical data on container multimodal transshipment time at one transshipment node. At the confidence level of 90 %, the transportation time and transshipment time were lengthened to solve the time uncertainty mode, and the total cost of the three tasks was 82,672 yuan, as shown in Fig. 6. The convergence curve of each task is displayed in Fig. 7.

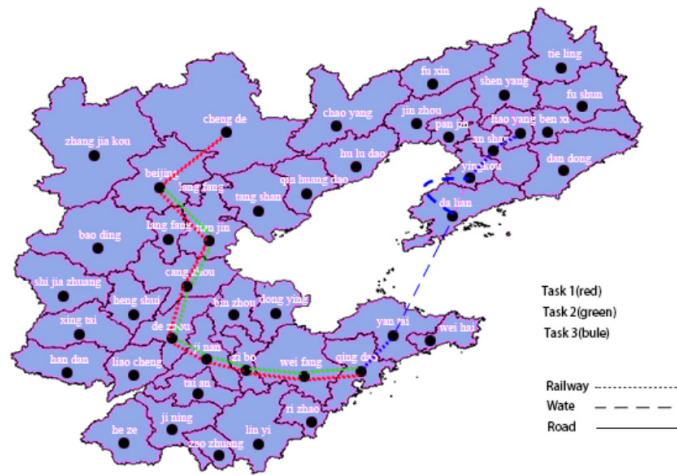


Fig. 6 Multimodal route with the minimum total cost under fuzzy time model

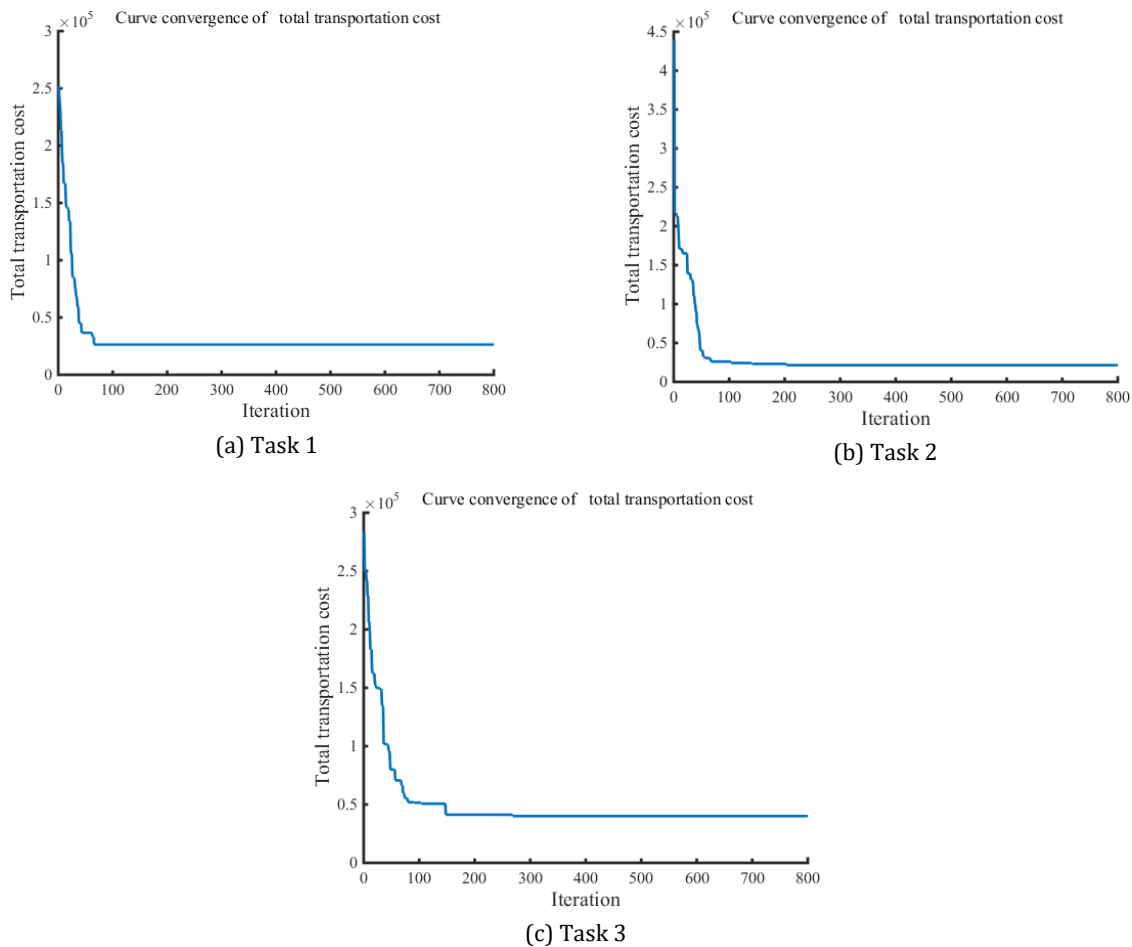


Fig. 7 Convergence curve of multimodal transportation cost for three tasks under the static model

Demand uncertainty model solving

In case of any change in the transportation volume, the optimal multimodal route changes if the optimization scheme under static environments is continuously executed. Under the dynamic model, it takes 10.094210 s to solve the three tasks via MATLAB2014b. The optimal multimodal route is as shown in Fig. 8, and the minimum total cost of the three tasks is 88,663 yuan. The convergence curve of the total multimodal transportation cost for the three tasks under the dynamic model is exhibited in Fig. 9.

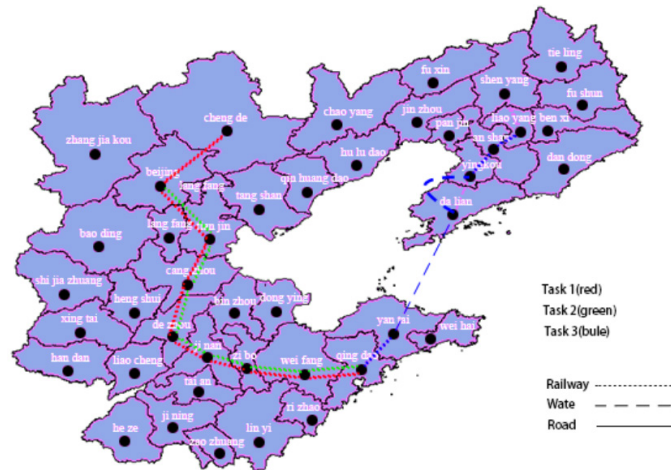


Fig. 8 Cold chain multimodal route considering demand uncertainty

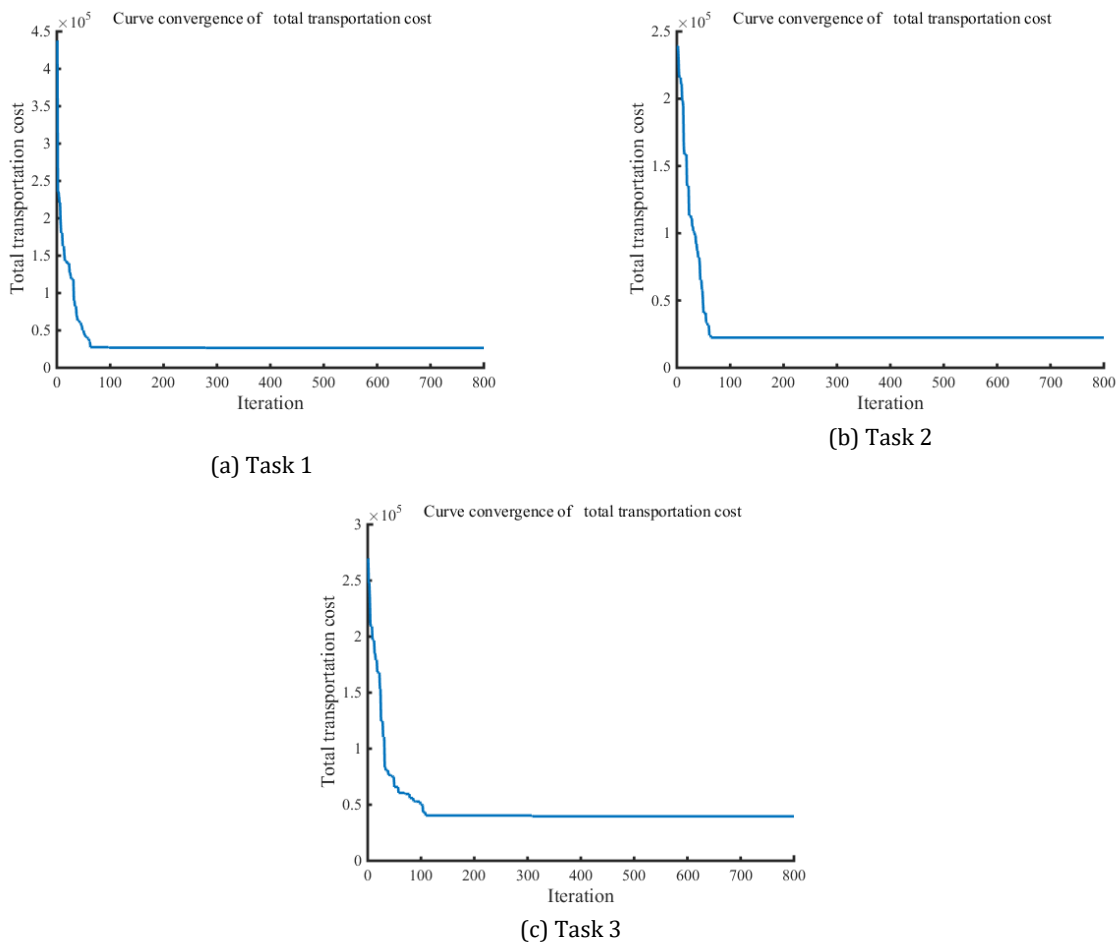


Fig. 9 Convergence curve of multimodal transportation cost for three tasks under the dynamic model

The solution that is feasible in all transportation scenarios and satisfies the regret coefficient constraint is referred to as a robust feasible solution, while the robust optimal solution is that with the lowest expected cost in all transportation scenarios. The robust feasible solution and the robust optimal solution are related to the regret coefficient, and the robust solution changes under different regret value coefficients but the same transportation scenario. In case of a too small regret value coefficient, if the regret constraint for the solution is too strict, then the model has no solution. As the regret value coefficient gradually increases, the robustness constraint for the solution is loosened, the number of robust feasible solutions grows, and the robust optimal solution changes accordingly. Four transportation scenario sets were respectively substituted into the certainty model to calculate the corresponding optimal value and compared with the robust optimization model to determine the advantages of robust models; the results are exhibited in Fig. 10.

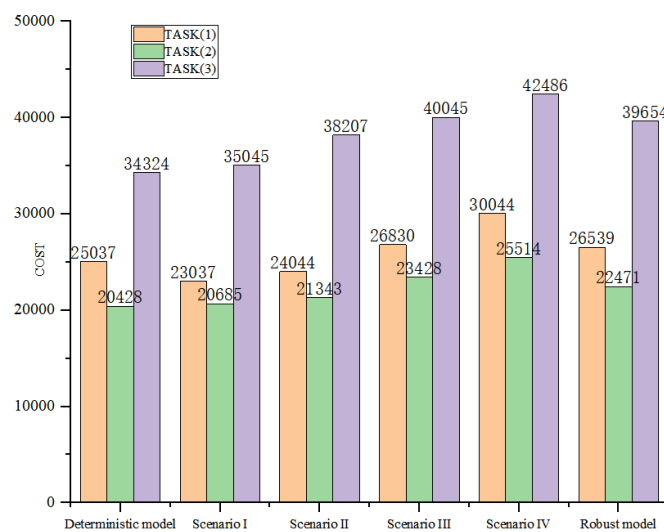


Fig. 10 Comparison of robust optimization results

Hybrid uncertainty model solving

To explore the influences of demand uncertainty and time uncertainty on the cold chain container multimodal route, it takes 13.50 s to solve the three tasks in MATLAB2014b through the hybrid algorithm designed in the previous part, the optimal multimodal route for the three tasks under the hybrid uncertainty model is as shown in Fig. 11, and the minimum total cost of the three tasks is 88,664 yuan. The convergence curve of the multimodal transportation cost for the three tasks under the hybrid uncertainty model is displayed in Fig. 12.

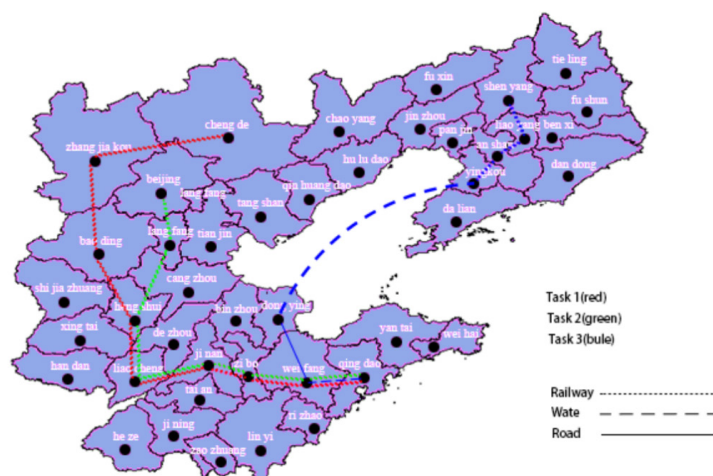


Fig. 11 Cold chain multimodal route considering hybrid uncertainties

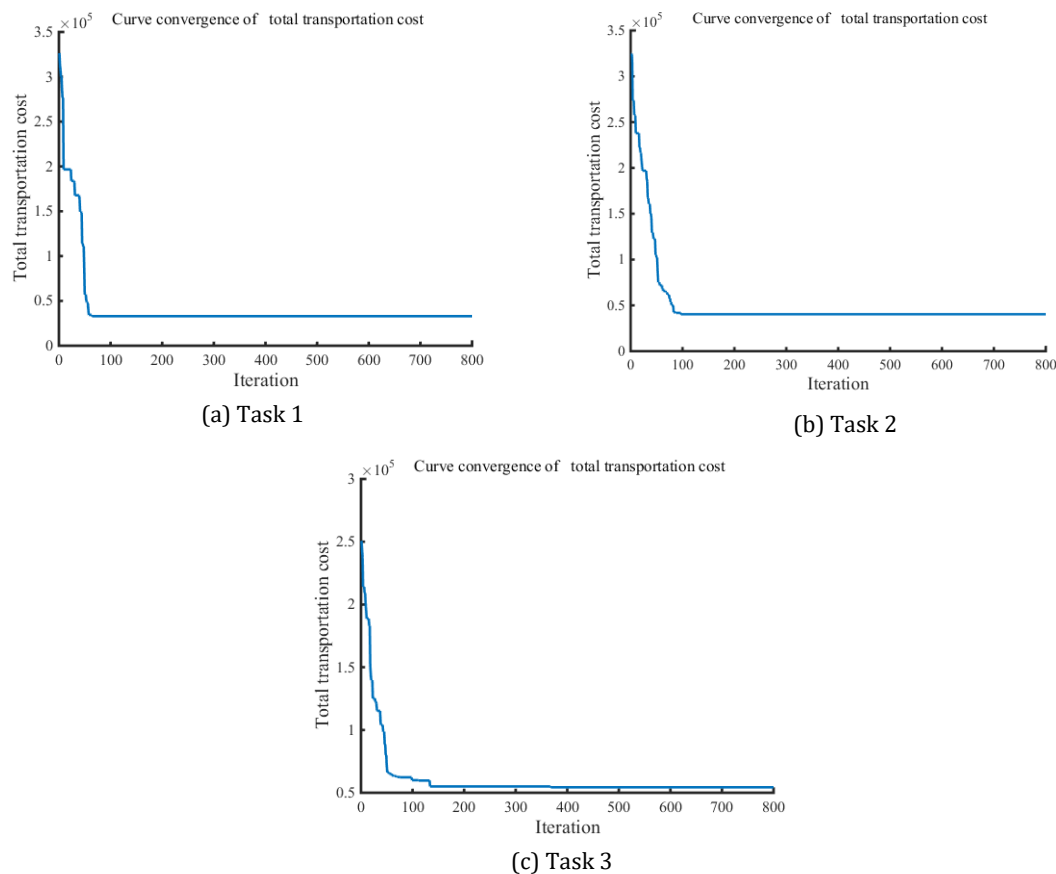


Fig. 12 Convergence curve of multimodal transportation cost for three tasks under hybrid uncertainties

Result analysis and comparison of examples

In this study, various costs involved in the multimodal network were analysed when dual hybrid uncertain factors followed a random distribution, and the different results acquired are displayed in Fig. 13. Three transportation tasks were compared by comparatively analysing the changes in the multimodal route programming with time uncertainty and demand uncertainty under four scenarios. When the transportation time and transshipment time changes, the total multimodal transportation cost under the time uncertainty model increased slightly. In case of demand changes, the total multimodal transportation cost under the demand uncertainty model also grew slightly. When time uncertainty or demand uncertainty was independently considered, the transportation route and the corresponding mode of transportation did not change mainly for two reasons: the transportation volume under each mode of transportation in the multimodal network was not constrained during model design; the transportation time and transshipment time under each mode of transportation changed inconsequentially. When time uncertainty and demand uncertainty were simultaneously considered, the total multimodal transportation cost grew remarkably under the hybrid uncertainty model, and the transportation route and the corresponding mode of transportation also changed evidently under the hybrid uncertainty scenario. The reasons were explained as follows: the comprehensive transportation volume for cold chain container multimodal transportation tasks was acquired by fully considering all scenarios of the robust model; the increasing demand led to the increase in the total cost of cold chain container multimodal transportation. Therefore, the gap in the total cost of cold chain container multimodal transportation under all scenarios in the robust model is stable, being always acceptable, and this verifies the interference immunity and high-cost characteristic of the robust model.

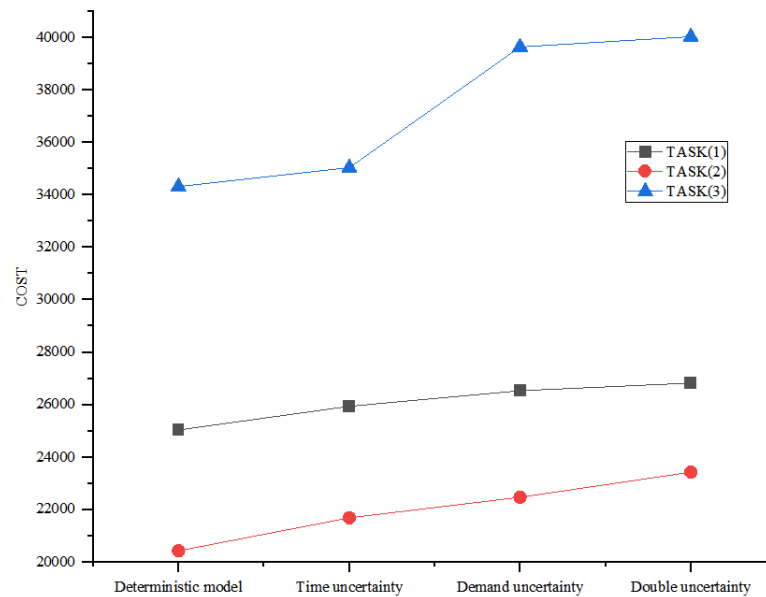


Fig. 13 Comparison of costs under four scenarios

6. Conclusions

The problem of cold chain container multimodal route optimization considering carbon emissions under the hybrid uncertainties of transportation time and demand was explored in this study. Then, a robust optimization model for the low-carbon cold chain container multimodal route under hybrid uncertainties was constructed on the basis of the robust optimization theory and solved by designing a hybrid algorithm based on the niche genetic algorithm and the dynamic dual-pheromone ant colony algorithm. Finally, the following conclusions were drawn:

- The uncertainties in transportation time and transshipment time result in the changes in transportation cost, carbon emission cost, and transportation scheme.
- When the problem of cold chain container multimodal route optimization under demand uncertainty is solved using a robust model, the decision-maker must predict the fluctuation range of demand uncertainty: the smaller the fluctuation range, the easier it is to obtain the robust optimal solution under a small regret coefficient value, thus enhancing the quality of the robust optimal solution.
- Studying the problem of cold chain container multimodal route optimization considering carbon emissions under the hybrid uncertainties of time and demand reveals that the carbon emission cost and total cost of cold chain multimodal transportation under hybrid uncertainties increase remarkably, accompanied by the evident changes in the transportation route and the corresponding mode of transportation.

Therefore, when formulating the intermodal transportation scheme, the decision-maker must consider the hybrid time windows at nodes and the endpoint according to the actual situation. Given the different influences of different factors on the robustness of the solution, the decision-maker should respectively determine the fluctuation range of different uncertain factors when using a robust optimization model. The study results can be used as reference to solve the problem of multimodal route optimization under uncertain environments. However, in a cold chain multimodal network, the cold chain multimodal route is affected by such factors as risk uncertainty, transportation price uncertainty, and customer satisfaction in addition to time and demand uncertainties. In a follow-up study, this problem remains to be further analysed and studied by combining the queuing, disassembly, and marshalling situations of trains at nodes.

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