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Dual objective multimodal transportation path optimization based on different carbon tax mechanisms under uncertain demand

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Abstract: By delving into low-carbon transportation research, we can address the imperative for the high-quality development of transportation services, while simultaneously advancing the realization of the dual-carbon objective. This study focuses on optimizing multimodal transport routes under varying carbon tax frameworks, taking into account the demand uncertainty that arises from unforeseen events such as abrupt restocking or seasonal fluctuations. We formulate a dual-objective 0-1 path optimization model under both a unified carbon tax mechanism and a piecewise progressive carbon tax scheme. The model aims to minimize total cost and carbon emissions in the face of stochastic demand. Utilizing Monte Carlo simulation and the laws of large numbers, we convert the model to maximize the expected value of the uncertain objective. An enhanced non-dominated sorting genetic algorithm is then developed to solve this model, yielding solutions that more effectively meet our objectives. This algorithm is designed to expand the search space, mitigating the “"premature convergence” issue and thereby generating superior individuals and solutions. Finally, we assess the applicability of our model and algorithm to transportation challenges within the context of the dual-carbon initiative through a numerical example. We also explore the influence of different carbon tax mechanisms on total cost and emissions, as well as their applicability and efficacy in the face of demand unceraity. The findings indicate that companies can achieve emission reductions with minimal cost increases under dual-target cost scenarios, ideal for dual carbon transportation contexts. Moreover, carbon tax rates significantly impact emission control, with segmented progressive taxes proving more effective, especially in high-demand uncertainty. Decision-makers should consider technological capabilities to set optimal tax rates and thresholds, fostering corporate enthusiasm. This research informs policy and decision-making for authorities and firms.

Keywords: Transport economics; Dual-objective route optimization; Improved non-dominated sorting genetic algorithm; Multimodal transport; Demand uncertainty; Carbon tax mechanism

1 Introduction

With the improvement of people’s awareness of coping with global warming, low-carbon and green related issues have been widely concerned. At the 75th United Nations General Assembly, China put forward the double carbon goals of “carbon neutralization” and “carbon peak”, and defined the carbon emission reduction requirements of various industries. As one of the three major sources of carbon emissions, the transportation industry is the key area of energy conservation and emission reduction at present. Multimodal transport can improve transport efficiency, reduce logistics costs and decrease carbon emissions by optimizing the transport structure, which is a low-carbon and efficient cargo transport mode. Carbon tax is a market-oriented policy tool to control carbon emissions, which guides enterprises’ low-carbon investment and drives low-carbon innovation through the externalities of endogenous enterprises’ carbon emissions [1] , and is used by many countries and regions. The “Special Report on the Framework Design of China’s Carbon Tax System” promulgated by China in 2017 puts forward the implementation framework and launch time of carbon tax [2], but did not specify specific issues such as collection mechanism and tax rate level. Therefore, through path optimization research, this paper analyzes the emission reduction effect and influence of different carbon tax collection mechanisms and their tax rate levels in multimodal transport, which can provide reference for government departments as designers of carbon tax system and cargo enterprises as specific decision makers, and also has important theoretical and practical significance for developing low-carbon transportation and promoting the realization of double carbon goals.

Scholars at home and abroad have made rich research achievements in multimodal transportation path optimization [3-4], and began to pay attention to low-carbon multimodal transport related issues with the proposition of the development concepts of green and low carbon. Specific to the route optimization problem, the existing research can be divided into the following two aspects: first, based on empirical research to analyze the advantages of multimodal transportation path optimization in low-carbon environment, for example: Santos et al. took Belgium as an example to analyze the competitive advantage of railway multimodal transport enterprises under carbon emission control [5]; Jin Lin et al. took container multimodal transport in Southwest China as an example

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to conduct SWOT analysis on single transport and multimodal transport modes to verify the advantages of multimodal transport in environmental protection and economy [6]; Li Xiaodong et al. took container multimodal transport in Northeast China as an example to conduct an empirical study on low-carbon transportation, determined the transportation scheme and proved the advantages of multimodal transportation [7]. The second is to establish multimodal transportation path optimization models based on different carbon emission policies and analyze their impacts. For example, Hua et al. and Zhang Xu et al. studied the problem of path selection under carbon trading policies, and analyzed the impact of carbon emission quota restrictions and carbon trading prices on decision-making [8, 9]; Bouchery et al. built a multi-objective dynamic multimodal transport network model to determine the transportation scheme under mandatory carbon emission control [10]; Wang et al. and Jiang Qiwei et al. optimized multimodal transport routes based on a unified carbon tax mechanism. The former built a dual-objective model with minimum cost and time, while the latter analyzed the impact of different carbon tax rate changes on decision-making [11, 12]; Cui Eying et al. compared the impact of unified carbon tax mechanism and segmented progressive carbon tax mechanism on the optimization decision of multimodal transportation network [13]; Cheng Xingqun et al. and Yuan Xumei et al. discussed the impact of four policies of mandatory carbon emissions, carbon tax, carbon trading and carbon compensation on carbon emissions and costs of multimodal transport through model analysis [14, 15]. Affected by market fluctuation, order lead time and weather conditions, the demand for goods in the actual multimodal transportation process is obviously uncertain, so the academic circles adopt different methods to study it: Sun et al. and Zhang Xu et al. respectively constructed a mixed integer nonlinear model and a stochastic optimization model with regret value constraints for the uncertain demand in the multimodal transport process and solved them [16, 17]; Chen Mili et al. combined the stochastic expected value model and opportunity constrained programming theory to build a path optimization combination model and solve it [18]; Zahra et al. constructed a multi-objective path optimization model considering the uncertainty of demand, and adopted robust optimization method to deal with random fuzzy variables [19].

To sum up, the existing research on low-carbon multimodal transportation path optimization has achieved some results, however, in the uncertain decision-making environment, the multi-objective path optimization research that analyzes the impact of different carbon tax mechanisms at the same time needs to be improved. In view of this, the unpredictable demand caused by unexpected factors such as seasonal changes or sudden replenishment is considered by the study, a dual-objective low-carbon multimodal transportation path optimization model with minimum total cost and total carbon emissions is constructed under uncertain demand, the model is transformed based on stochastic expectation, and an improved non-dominated sequencing genetic algorithm is designed to solve the model. Finally, we analyze the effectiveness of the model and algorithm through an example, calculate the transportation route and scheme, and further discuss the impact of different carbon tax mechanisms on the total cost and total carbon emissions, which provides reference for the policy design of government departments and the decision-making of multimodal transport enterprises.

2 Problem description and hypothesis

2.1 Problem description

This study envisages a transportation enterprise intends to carry a batch of cargo tasks with uncertain demand. This task needs to be transported from the place of supply O to the place of demand D within a specified time, during which it can be transferred through several nodes, and different modes of transportation such as road, railway and waterway can be adopted between two adjacent nodes. The transportation capacity, distance, speed, unit cost and carbon emissions corresponding to each mode of transportation are known. Under the above conditions, the transportation route and mode are determined with the goal of minimizing the total cost and total carbon emissions, and the influence of different carbon tax mechanisms is clarified. The total cost in the model includes direct transportation cost, transit cost, time cost and carbon emission cost based on carbon tax.

The main parameters involved in the study and their meanings are as follows:

N is the collection of transportation nodes; M the collection of transportation modes; Q is the the cargo volume; T the sum of transportation time and transshipment time; R is the number of random variables; T_{E} is the lower limit of the time window required for the total time; T_{L} is the upper limit of the time window required for the total time; C_{s} is the unit warehousing cost for early arrival; C_{d} is the unit penalty cost for late arrival; C is the total cost; E^{e} is the total carbon emissions; C_{ij}^{k} represents the unit transportation cost of transportation mode k between nodes i, j; Q_{r} is the randomly generated freight volume that follows a normal distribution; v^k is the average speed of transportation mode k; d_{ij}^{k} and t_{ij}^{k} are the transport distance and time of the mode k between nodes i, j respectively, which are related to the average speed v^k of the transport mode k; t_i^{kl} and C_i^{kl} are the unit transshipment time and transshipment cost when the mode k is converted to l at i; e_{ij}^{k} is the unit carbon emission between nodes i, j corresponding to mode k; e_i^{kl} is the unit carbon emissions when the mode of transportation k is converted to l at i; μ_i^{kl} represents the transport carbon emission factor when the mode of transportation k is converted to l at i; α_0 represents the carbon tax rate under the unified carbon tax mechanism; α_m is the carbon tax rate of the m grade in the segmented progressive carbon tax mechanism, and its corresponding emission threshold is E_m.

The decision variables involved in the study are as follows:

X_{ij}^{k}: whether the cargos are transported from node i to j by means of transport k; if so, $X_{ij}^{k}=1$, otherwise, $X_{ij}^{k}=0$.

y_i^{kl}: whether to convert from mode k to mode l at node i; if so; y_i^{kl}=1, otherwise, y_i^{kl}=0.

2.2 Hypothesis

In order to facilitate the analysis and consider the actual situation of multimodal transport, the following assumptions are made for the model:

(1) Goods are indivisible during the process of transportation, the same batch of goods can only be transported in one way between two adjacent nodes;

(2) At most one transportation mode change occurs at the same node, and the node has sufficient transit capacity;

(3) The cargo capacity of different modes of transportation can meet the cargo volume requirements of customers;

(4) The influence of waiting time and cost caused by emergencies such as weather, cargo damage and equipment failure during transportation shall not be considered.

3 Modeling

The path optimization problem of low-carbon multimodal transportation studied in this paper should not only consider how to express the uncertainty of demand and add the objective function, but also consider the impact of different carbon tax mechanisms on the total cost and carbon emissions. The model construction idea is as follows: Assume that the demand Q obey the normal distribution of mean value μ and variance σ^2, i.e., $Q \sim N(\mu,\sigma^2)$. Firstly, the basic model of multimodal transportation path optimization based on different carbon tax mechanisms under uncertain demand is constructed. Secondly, the basic model is transformed into a stochastic expected value model with the help of stochastic optimization theory.

3.1 Modeling under different carbon tax mechanisms

Carbon tax is a kind of environmental tax, which is considered as an effective means to control carbon emissions in both practice and academic fields. However, there is no consensus on the specific collection mechanism and tax rate level at present. This part constructs the multimodal transport route optimization model with uncertain demand under the unified carbon tax mechanism and the segmented progressive carbon tax mechanism respectively, as follows.

3.1.1 Path optimization model under unified carbon tax mechanism (Model I)

Under the unified carbon tax mechanism, carbon tax α_0 shall be levied according to the unified carbon tax rate on the carbon emissions in transportation, and the corresponding model I is as follows:

$$\min C = C_1 + C_2 + C_3 + C_4 = \sum_{i,j\in N}\sum_{k\in M} QC_{ij}^k d_{ij}^k x_{ij}^k + \sum_{i\in N}\sum_{k,l\in M} QC_i^{kl} y_i^{kl} + QC_s \max(ET - T, 0) + QC_d \max(T - LT, 0) + \alpha_0 E^e, \tag{1}$$

$$\min E^e = E_1^e + E_2^e = \sum_{i,j\in N}\sum_{k\in M} Q e_{ij}^k d_{ij}^k x_{ij}^k + \sum_{i\in N}\sum_{k,l\in M} Q e_i^{kl} y_i^{kl}, \tag{2}$$

s.t.

$$Q \sim N(\mu, \sigma^2), \tag{3}$$

$$\sum_{k\in M} x_{ij}^k \leqslant 1, \forall i, j \in N, \forall k \in M, \tag{4}$$

$$\sum_{k,l\in M} y_i^{kl} \leqslant 1, \forall i \in N, \forall k, l \in M, \tag{5}$$

$$x_{ij}^k \times x_{jn}^k = y_i^{kl}, \forall i, j, n \in N, \forall k \in M, \tag{6}$$

$$x_{ij}^k \in \{0, 1\}, \tag{7}$$

$$y_i^{kl} \in \{0, 1\}. \tag{8}$$

Among them, Eq. (1) is the goal of minimizing the total cost, including the transportation cost C_1, which is expressed by the product of cargo volume, transportation distance between nodes and unit transportation cost; the transit cost C_2, expressed by the product of cargo volume and unit cost corresponding to the transformation of transportation mode of a certain node; the time cost C_3, which consists of transportation time and transit time, is the storage cost of early arrival or the penalty cost of late arrival; the carbon emission cost C_4 is represented by the product of carbon emission and carbon tax rate. Eq. (2) is the goal of minimizing carbon emissions, including carbon emissions E_1^e during transportation, which is composed of the product of cargo volume, unit carbon emissions between nodes and transportation distance; transshipment carbon emission E_2^e is expressed by the product of cargo volume and carbon emission coefficient corresponding to the transformation of transportation mode at a certain node. Eq. (3) shows that the demand for goods obeys the normal distribution with mean value μ and variance σ^2. Eqs. (4)−(6) are constraints related to hypothetical conditions, where Eq. (4) indicates that at most one mode of transportation is allowed between nodes i, j. Eq. (5) indicates that sat most one transportation mode change is carried out at node i; Eq. (6) restricts the continuity of transportation to prevent conflicts among routes when the mode of transportation is changed. Eqs. (7) and (8) limit the decision variables to 0-1 variables.

3.1.2 Path optimization model under segmented progressive carbon tax mechanism (Model II)

The segmented cumulative carbon tax mechanism is a carbon tax collection mode, which determines different tax rates according to different carbon emissions. The specific method is to divide carbon emissions into several grades and design corresponding carbon tax rates for each grade. In reality, electricity price and water price all adopt this charging mechanism to respond to the national call for energy conservation and curb waste. Generally, the higher the carbon emissions, the higher the tax rate [13]. This part combines the piece wise function form in the existing literature [13] and the concept of quick deduction in personal income tax [17], the carbon emission cost C_4 under the segmented progressive carbon tax mechanism is expressed as Eq. (9).

$$C_4 = \alpha_m E^e - \beta_m \tag{9}$$

where, β_m is the quick deduction, which is the pre-calculated data in advance to solve the complex technical problems when calculating the tax amount by grades of the excessive progressive tax rate. The specific formula is as shown in Eq. (10).

$$\beta_m = E_{m-1}(\alpha_m - \alpha_{m-1}) + \beta_{m-1} \tag{10}$$

According to the characteristics of the research problem, set E_0=0, β_1=0. For example, when m=2, it means that the carbon emission E^e is in the second stage, i.e. $E^e \in (E_1, E_2]$, then $C_4 = \alpha_1 E_1 + (E_2 - E_1)\alpha_2$, it means that the part not exceeding E_1 is levied at the low carbon tax rate α_1, and the part exceeding E_1 is levied at the higher carbon tax rate α_2.

To sum up, in Model II under the segmented progressive carbon tax mechanism, the objective function of minimizing carbon emissions remains unchanged as shown in Eq. (2). The objective function of minimizing the total cost is shown in Eq. (11). Compared with Eq. (1), the calculation of carbon emission cost C_4 has changed.

$$\min C = C_1 + C_2 + C_3 + C_4 = \sum_{i,j\in N}\sum_{k\in M} QC_{ij}^k d_{ij}^k x_{ij}^k + \sum_{i\in N}\sum_{k,l\in M} QC_i^{kl} y_i^{kl} + QC_s \max(ET - T, 0) + QC_d \max(T - LT, 0) + \alpha_m E^e - \beta_m \tag{11}$$

s.t.

$$E^e \in (E_{m-1}, E_m] \tag{12}$$

At the same time, Eqs. (3)−(8) and (10) hold true.

Among them, Eq. (12) represents the carbon emission threshold corresponding to the m-level carbon tax.

3.2 Model: transformation based on stochastic expected value

Based on the stochastic optimization theory, the basic model is transformed into the stochastic expected value model, by maximizing the expected value of the uncertain target. Taking Model I as an example, When $R \to \infty$, the expected value form $E(C_1)$, $E(C_2)$, $E(C_3)$, $E\left(E_1^e\right)$, $E\left(E_2^e\right)$ of transportation cost, transshipment cost, time cost, transportation carbon emission and transshipment carbon emission obtained by Monte Carlo simulation and laws of large numbers can be expressed as Eqs. (13)−(17).

$$\left[\frac{1}{R}\sum_{i,j\in N}\sum_{k\in M}\sum_{r=1}^{R} Q_r C_{ij}^k d_{ij}^k x_{ij}^k\right] \to E(C_1), \tag{13}$$

$$\left[\frac{1}{R}\sum_{i\in N}\sum_{k,l\in M}\sum_{r=1}^{R} Q_r C_i^{kl} y_i^{kl}\right] \to E(C_2), \tag{14}$$

$$\left\{\begin{array}{l} \dfrac{1}{R}\displaystyle\sum_{r=1}^{R} Q_r C_s \max[ET - \left(\sum_{i,j\in N}\sum_{k\in M} x_{ij}^k \frac{d_{ij}^k}{v^k} + \sum_{i\in N}\sum_{k,l\in M} y_i^{kl} t_i^{kl}\right), 0] + \\ \dfrac{1}{R}\displaystyle\sum_{r=1}^{R} Q_r C_d \max[\left(\sum_{i,j\in N}\sum_{k\in M} x_{ij}^k \frac{d_{ij}^k}{v^k} + \sum_{i\in N}\sum_{k,l\in M} y_i^{kl} t_i^{kl}\right) - LT, 0] \end{array}\right\} \to E(C_3), \tag{15}$$

$$\left[\frac{1}{R}\sum_{i,j\in N}\sum_{k\in M}\sum_{r=1}^{R} Q_r e_{ij}^k d_{ij}^k x_{ij}^k\right] \to E\left(E_1^e\right), \tag{16}$$

$$\left[\frac{1}{R}\sum_{i\in N}\sum_{k,l\in M}\sum_{r=1}^{R} Q_r e_i^{kl} y_i^{kl}\right] \to E\left(E_2^e\right). \tag{17}$$

Thus, the transformed Model I is as follows:

$$\min C = E(C_1) + E(C_2) + E(C_3) + C_4, \tag{18}$$

$$\min E^e = E(E_1^e) + E(E_2^e). \tag{19}$$

At the same time, Eq.s (3)−(8) hold true.

Among them, the Eq. (18) represents the expected objective function of the total cost, and the Eq. (19) represents the expected objective function of the total carbon emission.

Similarly, Model II can be transformed into a deterministic model based on the above method.

4 Improved non-dominated sorting genetic algorithm (I-NSGA-II)

Model I and Model II are both dual-objective 0-1 optimization models, each objective is conflicting with each other, so the unique optimal solution usually cannot be obtained, but only the non-inferior solution set, the Pareto optimal solution set can [20]. Compared with traditional genetic algorithm, NSGA-II algorithm introduces fast non-dominated sorting, congestion calculation and elite strategy, which reduces computational complexity and improves search ability. It is a mature algorithm for solving multi-objective problems at present. However, it is easy to fall into “premature”. In order to avoid this defect, an improved non-dominated sorting genetic algorithm (I-NSGA-II) is studied and designed, these specific improvements include: (1) adding topological sorting rules when generating initialized population; (2) Adopting improved cyclic crowding sequencing method to select operation; (3) Introducing proportional method into elite strategy.

4.1 Chromosome coding and population initialization

4.1.1 Chromosome coding

Coding is the first step of genetic algorithm, which directly affects the operation results of genetic algorithm. The route optimization problem of multimodal transport needs to determine the route and mode of transportation, therefore, a two-layer coding structure is adopted: the first layer is the code of transportation route x_{ij}^k, and the second layer is the code of transportation mode y_i^{kl}, as shown in Eq. (20), both are coded in real numbers. Among them, the total length of chromosome is 2N-1, i.e., a total of N nodes adopt N-1 transportation modes.

$$X = [\{x_1, x_2, ..., x_N\} | \{y_1, y_2, ..., y_{N-1}\}]. \tag{20}$$

4.1.2 Population Initialization Based on Topological Sorting

The nodes in the multimodal transportation are arranged in a certain order, in order to ensure the feasibility of the solution, and considering the research characteristics, topological sorting rules are used to generate initialization population, topological sorting sequences are designed based on directed acyclic graphs generated by multimodal transport networks, and chromosome initialization is carried out accordingly to suppress the generation of illegal schemes.

4.2 Fitness Function

Considering the characteristics of genetic operation, the objective function of minimizing total cost and carbon emissions is transformed to maximize, and the fitness function is constructed. If $C(i)$ and $E^e(i)$ are the total cost and carbon emissions corresponding to individual i, the fitness function can be expressed as Eq. (21).

$$F_1(i) = 1/C(i) F_2(i) = 1/E^e(i). \tag{21}$$

4.3 Fast Non-dominated Sequencing and Congestion Calculation

4.3.1 Fast Non-dominated Sequencing

According to the calculated fitness value, the population is sorted by fast non-dominant sorting, and the specific steps are as follows:

Step 1. For each solution p $(p \in R)$ in the population, two variables N_p and S_p are defined, which are the number of dominated solutions p and the set of solutions dominated by solution p respectively;

Step 2. Find out all solutions whose N_p is 0 and form a non-dominant solution set F_1, assume that its non-dominant level is 1, and set the same non-dominant order for all solutions in the set;

Step 3. Let the set of solutions dominated by each solution in the current set F_1 be S_q, traverse each solution in S_q, and execute N_q=N_q-1. If N_q-1=0, the individual q is stored in the set F_2, and take F_2 as the current set;

Step 4. Repeat Step 2- Step 3 to determine the non-dominated rank of each solution set and the non-dominated order of each solution;

Step 5. Sort all the found non dominated solution sets, $\{F_1 > F_2 > \cdots > F_n\}$ indicates that the individual in the set F_1 is the best and the others decrease in turn.

4.3.2 Congestion Calculation

To sum up, in the fast non-dominated ranking, the lower the non-dominated layer the individual is, the better the individual is. However, if individuals are in the same non-dominanted layer, further congestion comparison is needed. Congestion degree represents the density value of individuals in space, which can be expressed by a rectangle around individuals excluding other individuals, as shown in Fig. 1. The greater the congestion of the population,, the greater the relative distance between individual n and surrounding individuals, and the better the diversity of solutions.

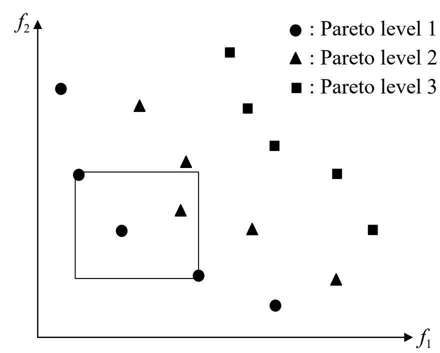

Fig. 1 Schematic diagram of congestion of each individual.

The calculation formula of congestion n_d is as Eq. (22), where $f_h^{\max}$ and $f_h^{\min}$ respectively represent the maximum and minimum values of the *h-th* objective function in the individual set.

$$n_d = \sum_{h=1}^{2} \frac{f_h(n+1) - f_h(n-1)}{f_h^{\max} - f_h^{\min}} \tag{22}$$

4.4 Genetic operation

4.4.1 Selection operator based on cyclic crowding sequencing method

Traditional NSGA-II algorithm generally adopts tournament selection method, i.e., randomly selects two individuals to compare their non-dominant ranking levels, and the lower one enters the next generation population. If the ranking levels are the same, the congestion of the individuals in each non-dominant layer is calculated. But in fact, only using the degree of crowding to maintain population diversity cannot objectively reflect the true degree of crowding among individuals [21]. Therefore, an improved cyclic crowding sequencing method is introduced [22], in which individuals are retained in a way of rejection, and the number of individuals after cyclic rejection is required to be equal to the number of individuals to be selected, so that the final Pareto solution is evenly distributed. The specific steps are as follows:

Step 1. Determine the total number of individuals on the non-inferior frontier level in the population, i.e. the number of non dominant solutions is n, and it is required to screen i individuals from this level.

Step 2. Calculate the congestion of n individuals and eliminate the individual with the smallest congestion.

Step 3. Judge whether the number of eliminated individuals is i, if so, end, otherwise, enter Step 4.

Step 4. The individuals with the smallest congestion are eliminated one by one, and the congestion of the remaining individuals is recalculated every time an individual is eliminated, and the previous step is repeated until the end.

4.4.2 Cross and variation

In this study, the single-point crossover method is used to perform crossover operation on chromosomes, i.e., according to the fixed crossover probability, some genes of two chromosomes in the parent population are randomly crossover operation, and a new coding string is formed, and the feasibility is judged according to the topological sorting rule and fitness function value.

Mutation can produce new individuals through gene mutation. Similarly, single-point mutation method is used for mutation operation, i.e., two mutation points are selected on a chromosome, and the region between the mutation points is reversed according to a certain mutation probability, so as to produce new individuals to ensure the diversity of population.

4.5 Elite strategy based on proportional method

In order to ensure that elite individuals are not missed and reduce the computational complexity, elite strategy is added to NSGA-II. However, the traditional elite strategy may lead to an increase in the rejection probability of offspring individuals in the population with the increase of iteration times, which makes the algorithm fall into local optimum. Therefore, the research designs an elite strategy based on the proportional method [23], i.e., set the maximum number of iterations be NLmax. In the NLmax / 3 generation, the proportion method is adopted and lasts until the NLmax generation. In the other iterations, the traditional elitist strategy is adopted to ensure that the proportion of the parents' individuals decreases linearly with the increase of the number of iterations, which increases the probability of offspring individuals being selected in the process of generating new population.

To sum up, the flow of the improved non-dominated sorting genetic algorithm (I-NSGA-II) designed by the research is shown in Fig. 2.

5 Numerical example

5.1 Basic scenario and data

The numerical scenario considers that a multimodal transport enterprise would transport a batch of cargo from the starting point O to the destination point D through a joint transport network con-

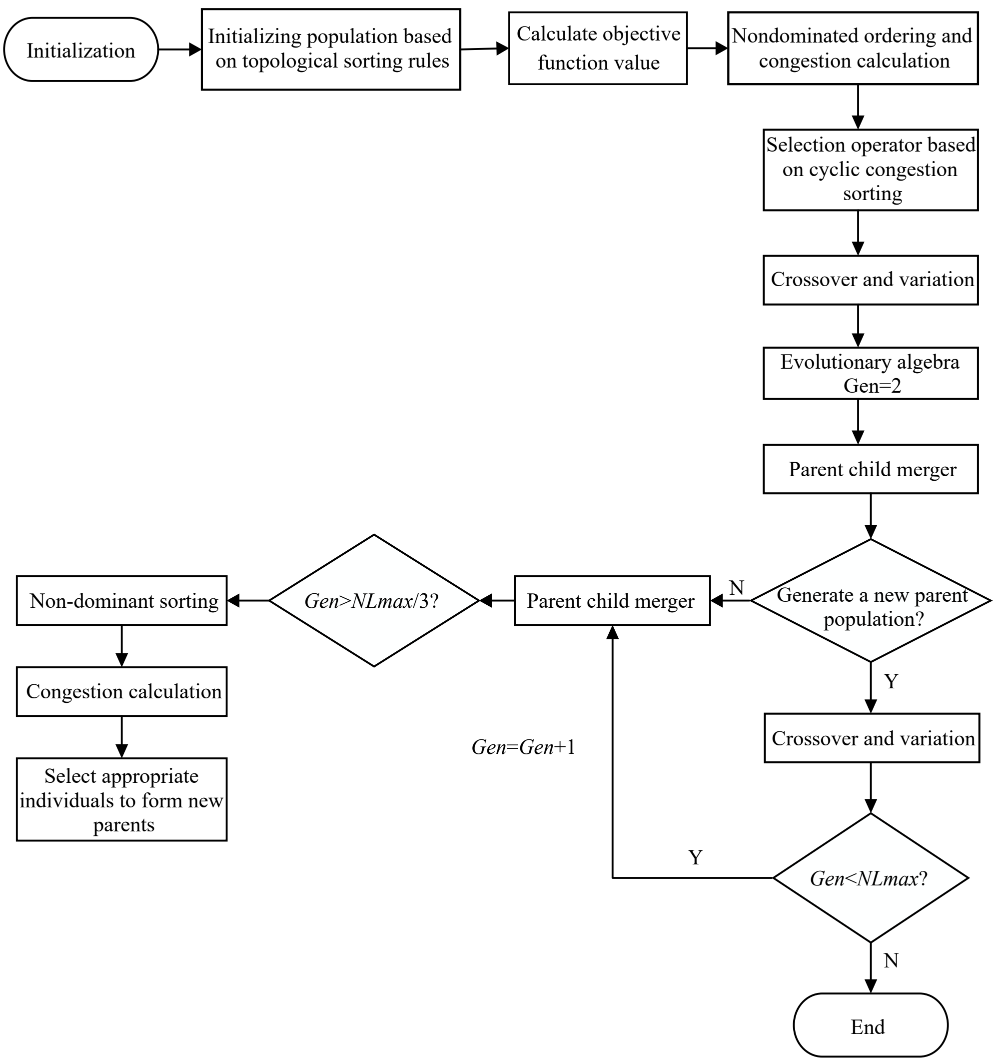

Fig. 2 I-NSGA-II process.

taining 15 nodes. According to the objective reality, this research supposes that the cargo must arrive within the time period [80,90] h. The unit storage fee for early arrival is 18 CNY/(hour·t), and the unit penalty cost for late arrival is 30 CNY/(hour·t). Referring to the carbon tax collection standards of various countries, the carbon tax rate for non-segmentation is 0.2 CNY/kg , the carbon tax rate is (0.2,0.3] CNY/kg when it is divided into two stages, and the lower limit of carbon emission in each stage is (0,4 000) kg.

Different nodes can be transported by road, railway and waterway, and the corresponding transportation distances are shown in Table 1. (a, b and c) respectively indicate the corresponding transportation distances of road, railway and waterway, and "-" indicates that there is no corresponding transportation mode between the two nodes.

Table 1 Transport distances corresponding to different transport modes between transport nodes (unit: km).

Road section	Distance	Road section	Distance	Road section	Distance	Road section	Distance
O-1	(124, 101, 81)	4-7	(156, 143, 198)	7-10	(226, 237, -)	10-D	(212, 172, -)
O-2	(143, 151, 102)	4-8	(206, 197, -)	7-11	(197, 227, -)	11-12	(238, 247, 190)
1-3	(212, 194, 124)	4-9	(204, 221, -)	7-12	(211, 223, -)	11-13	(203, 214, 143)
1-4	(266, 197, -)	5-7	(178, 198, -)	8-10	(201, 202, -)	11-D	(223, 209, -)
2-5	(246, 299, 278)	5-8	(186, 164, 174)	8-11	(199, 200, -)	12-13	(179, 216, 227)
2-6	(224, 212, 170)	5-9	(201, 214, -)	8-12	(221, 233, -)	12-D	(209, 212, -)
3-7	(244, 187, -)	6-7	(256, 179, -)	9-10	(200, 203, -)	13-D	(167, 154, -)
3-8	(276, 249, -)	6-8	(246, 267, -)	9-11	(178, 203, 224)		
3-9	(179, 187, -)	6-9	(243, 257, -)	9-12	(214, 176, 178)		

Consult the cargo rate table of cargo services, IPCC National Greenhouse Gas Inventory Guidelines , China Transportation Yearbook and other materials to determine the average speed, unit transportation cost and unit carbon emission of each mode of transportation, as shown in Table 2. Among them, (a, b and c) in the operating base price respectively represent the unit cargo rate when the distance between transportation nodes is within 500 km, 500-1 000 km and above 1 000 km.

Table 2 Transport parameters of different transport modes.

Transport modes	Average velocity v_n(km/h)	Unit transportation cost C_{ij}^k[CNY/(km·t)]	Unit carbon emission e_{ij}^k[kg/(t·km)]
Highway	80	(0.526, 0.497, 0.361)	0.071
Railway	60	(0.392, 0.340, 0.273)	0.042
Waterway	30	(0.090, 0.073, 0.051)	0.012

By consulting relevant literature and the specific conditions of ports and cargo transfer stations, the unit transshipment cost, time and carbon emission coefficient of different modes of transportation are obtained, as shown in Table 3.

Table 3 Transshipment parameters of different modes of transport.

Transport modes	Transshipment cost C_i^{kl}(CNY/t)	Transit time t_i^{kl}(h /1 000 t)	Transport carbon emission coefficient μ_i^{kl}(kg·t^{-1})
Highway-Railway	8	50	0.128
Railway-Waterway	10	50	0.117
Waterway-Highway	9	50	0.113

Due to the advance of transportation planning, it is difficult to determine the demand of demand enterprises. According to the distribution characteristics of cargo volume in reality and the design in related literature [9,17], set the cargo volume Q obey the normal distribution with the mean value of 100 and the variance of 64, i.e., $Q \sim N(100, 64)$.

5.2 Result Analysis

5.2.1 Algorithm Parameters and Running Results

According to the established model, taking the random number R=100, using the improved non-dominated sorting genetic algorithm (I-NSGA-II), and utilizing the Matlab2019 program to solve the model. The algorithm parameters are set as follows: the population size is 100, the number of iterations is 200, the crossover probability is 0.1, and the mutation probability is 0.8. Taking the fixed carbon tax as an example, the evolution process of Pareto optimal solution set of the objective function is shown in Fig. 3, which gradually decreases and finally converges after reaching a certain number of iterations, and remains unchanged near the optimal solution set.

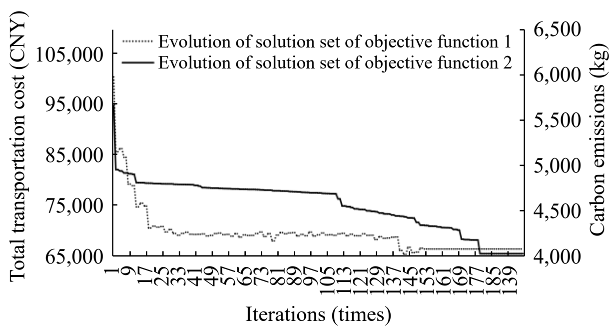

Fig. 3 The evolution process of the objective function Pareto optimal solution set.

In order to analyze the influence of different carbon tax mechanisms on total cost and carbon emissions, Pareto optimal solution set is calculated under fixed carbon tax and segmented progressive carbon tax mechanism, the results are shown in Table 4, and the two solutions for each case correspond to the scheme with the smallest total cost and carbon emission respectively.

In Table 4, under the two carbon tax mechanisms, the total cost of scheme 1 is less than that of scheme 2, but the carbon emission of scheme 1 is greater than that of scheme 2. This phenomenon is caused by the fact that there is no unique optimal solution in the dual-objective optimization problem, which makes two objectives reach the optimal at the same time. Often, when one objective function reaches the optimal, the result of the other objective function will become worse.

Specifically, under the segmented progressive carbon tax mechanism, the total cost and carbon emissions of schemes 1 and 2 are lower than those of the fixed carbon tax. In particular, the total cost of scheme 2 is reduced by 4.75%, and the total carbon emissions

Table 4 Pareto optimal solution set.

	Scheme	Transport route	Mode of transport	Total cost (CNY)	Carbon emissions
Fixed carbon tax 0.2	1	O-2-5-9-11-12-13-D	Railway-Waterway-Railway-Waterway-Railway-Waterway-Railway	66 293.89	4 179.36
	2	O-2-5-8-10-D	Railway-Waterway-Waterway-Railway-Railway	78 787.28	4 021.95
Segmented progressive carbon tax mechanism (0.2,0.3]	1	O-2-5-9-11-12-13-D	Railway-Railway-Waterway-Waterway-Waterway-Railway	66 032.07	3 977.02
	2	O-2-5-8-11-12-13-D	Railway-Waterway-Waterway-Railway-Railway-Waterway-Railway	75 043.33	3 373.26

are reduced by 16.13%. It shows that the segmented progressive carbon tax mechanism has more obvious emission reduction effect.

5.2.2 *Algorithm Effectiveness Test*

In terms of algorithm effectiveness, taking the fixed carbon tax rate as an example, the traditional NSGA-II algorithm and the I-NSGA-II algorithm are used to solve the model respectively, each running 10 times. The running time and solution results of the two algorithms are shown in Table 5. Among them, the running time of I-NSGA-II algorithm is 5“72” , which higher than that of traditional NSGA-II algorithm, but the average optimal cost corresponding to its running results is reduced by 1.47% and the average optimal carbon emission is reduced by 6.85%. This is because compared with the traditional NSGA-II algorithm, the improved NSGA-II algorithm adopts the selection operator based on cyclic crowding sequencing method and the elite strategy based on proportional method, which expands the search space and scope , as well as can obtain more excellent individuals and schemes.

Table 5 Operation time and solution results of the two algorithms.

Algorithm	Optimal total cost (CNY)		Optimal carbon emission		Running time (*s*)	
	Scheme 1	Scheme 2	Scheme 1	Scheme 2	Average	Optimal
I-NSGA-II	67 038.35	79 025.87	4 177.21	4 001.15	21”23	20”89
NSGA-II	68 038.89	79 275.43	4 572.11	4 295.60	15”51	15”40

5.2.3 *Applicability analysis of model*

Taking the fixed carbon tax as an example, the traditional genetic algorithm is used to solve the single-objective optimization model considering only the total cost, to illustrate the applicability of the above dual objective model considering the total cost and total carbon emissions compared with the single objective model to the dual carbon background. The specific results are shown in Table 6.

Table 6 The optimal solution considering only the total cost.

Transport route	Mode of transport	Total cost (CNY)	Carbon emissions
O-1-3-9-11-12-13-D	Waterway-Railway-Railway-Waterway-Waterway-Railway	64 887.53	4 617.06

Comparing Table 4 and table 6, the total cost in the dual objective optimization is changed from 64 887.53 CNY to 66 293.89 CNY, an increase of 2.17% compared with the single objective model; The carbon emission changed from 4 617.06 kg to 4 021.95 kg, reducing by 9.48%. It can be seen that the reduction of carbon emissions generated by unit cost under the dual-objective function is more obvious. By adopting the dual objective strategy of considering the total cost and the total carbon emissions at the same time, decision makers can more clearly understand that enterprises can achieve certain emission reduction effects only by slightly increasing the cost, which is more suitable for transportation scenarios under the dual-carbon background.

Declaration of competing interest

The authors have no competing interests to declare that are relevant to the content of this article.

Data Availability Statement

Some or all Data, models, or code that support the findings of available from the corresponding author upon reasonable request.

5.3 *Impact analysis of different carbon tax mechanisms*

In Table 4, compared with the fixed carbon tax mechanism, the carbon emissions under the segmented progressive carbon tax mechanism decreased significantly, which was prompted by the aversion of decision makers to high-order carbon tax rate, and the decision-making scheme was adjusted to make the carbon emissions less than the emission threshold corresponding to the low-order carbon tax rate. Therefore, the segmented progressive carbon tax mechanism is an effective means to guide and encourage enterprises to control carbon emissions.

Further, in order to analyze the influence of carbon tax rate change on decision-making, the fixed carbon tax rate and the segmented progressive carbon tax rate are respectively set between 0 and 0.6. By adopting the improved non-dominated sorting genetic algorithm proposed above, and based on the calculation formulas of total cost and carbon emissions under unified carbon tax mechanism of Model I and the segmented progressive carbon tax mechanism of Model II, the corresponding total costs and carbon emissions under different scenarios can be calculated with the help of Matlab2019 program programming. The results are shown in Table 7.

From Table 7, under the two carbon tax mechanisms, there is no difference between the transportation scheme and carbon emis-

Table 7 Costs and carbon emissions under different carbon tax rates.

Class	Fixed carbon tax			Segmented progressive carbon tax mechanism		
	Carbon tax	Cost (CNY)	Carbon emissions	Carbon tax	Cost (CNY)	Carbon emissions
I	0	60 856.708	4 870.02	0	60 856.708	4 870.02
II	0.1	61 343.71	4 870.02	(0.1,0.2]	61 430.71	4 870.02
III	0.2	66 293.89	4 179.36	(0.2,0.3]	66 032.07	3 977.02
IV	0.3	70 129.77	4 179.36	(0.3,0.4]	68 179.01	3 696.27
V	0.4	71 016.51	3 906.71	(0.4,0.5]	69 562.79	3 696.27
VI	0.5	72 115.60	3 906.71	(0.5,0.6]	70 856.92	3 696.27
VII	0.6	74 016.17	3 906.71			

sions when the carbon tax rate is in Class II and Class I (excluding the cost of carbon emissions, the tax rate is 0), and the binding effect of carbon tax is not obvious,so enterprises will choose to sacrifice the environment to save costs; under the carbon tax rates in Class III to IV, the carbon emissions are reduced, and its performance is more significant under the segmented progressive carbon tax mechanism; starting from the V-level carbon tax rate, the high carbon tax rate only brings about an increase in costs, but the carbon emissions have not changed, and the emission reduction effect is not ideal. To sum up, no matter under the fixed carbon tax or segmented progressive carbon tax mechanism, the carbon emission control effect of enterprises will be affected by the carbon tax rate, and appropriate carbon tax rate should be set to mobilize the enthusiasm of enterprises for emission reduction.

Furthermore, assuming that the carbon tax rate in each stage is still (0.2, 0.3], the upper limit of carbon emissions is reduced from 4 000 to 2000, and the impacts of emission threshold changes corresponding to low-level carbon tax rates in the segmented progressive carbon tax mechanism on decision-making are analyzed. The results are shown in Fig. 4.

From Fig. 4, when the emission threshold is reduced from 4 000 to 2000, the total cost shows a continuous upward trend; when the emission threshold is reduced from 4 000 to 3 000, the total carbon emissions shows a downward trend, but the further reduction of the emission threshold does not bring about a change in carbon emissions, since the carbon emissions of enterprises will be limited by the existing capacity and emission reduction technology, and if the minimum carbon emissions have been reached under the same conditions, even in the face of increasingly stringent emission reduction requirements, enterprises will be helpless and can only passively bear the pressure brought by increased costs. Therefore, the existing capacity and emission reduction technology level of enterprises should be considered to determine the appropriate carbon tax rate and emission threshold.

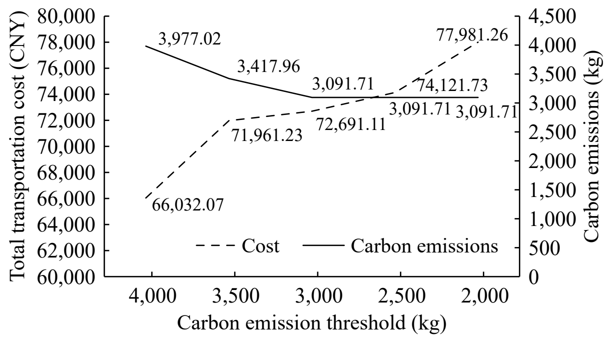

Fig. 4 Changes in cost and carbon emissions under different emission thresholds

5.4 Impact analysis of demand fluctuation under different Carbon tax mechanisms

By considering the daily data of cargo volume in actual transportation tasks and the concern about different cargo volumes, and referring to the setting and calculation methods of cargo parameters in relevant literatures [24], the demand variance is ordered to be 25, 36, 49, 64 and 81 respectively on the premise that the expected value remains unchanged. The transportation scheme, cost and carbon emission under the fixed carbon tax and segmented progressive carbon tax mechanism are calculated respectively, and the influence of demand fluctuation range on decision-making is explored. The results are shown in Table 8.

Table 8 Transportation costs and carbon emissions under different demand changes

Variance (standard deviation)	Fixed carbon tax		Segmented progressive carbon tax mechanism	
	Cost (CNY)	Carbon emissions	Cost (CNY)	Carbon emissions
25(5)	64 171.29	3 889.17	64 163.72	3 880.51
36(6)	64 506.37	3 902.25	64 163.72	3 880.51
49(7)	65 387.21	4 056.42	65 071.27	3 912.26
64(8)	66 793.89	4 179.36	66 032.07	3 977.02
81(9)	67 986.75	4 396.50	66 971.51	3 981.21

From Table 8, the increase of demand variance, i.e., volatility, means the increase of information uncertainty between supply and demand sides, which will have an impact on decision-making. Path optimization system allocates more capacity to cope with the impact of increasing demand uncertainty, which leads to the increase of cost and carbon emissions, whether under fixed carbon tax or segmented progressive carbon tax mechanism. Specifically, When the variance is small, there is little difference between the total cost and carbon emissions under fixed carbon tax and segmented progressive carbon tax mechanism, but with the increase of variance, the advantages of segmented progressive carbon tax mechanism gradually become prominent, and the total cost and carbon emissions are relatively small, which mainly comes from the active pursuit of low carbon emissions driven by the interests of high-order carbon tax rate aversion.

6 Conclusion

This study explores the optimization of multi-modal transport routes within the context of the dual-carbon policy, tackling the challenge of a dual-objective route optimization model subject to uncertain demand. We employ an improved version of the Non-Dominated Sorting Genetic Algorithm (NSGA-II) to solve this model and analyze the impact of diverse carbon tax mechanisms. Through a case example, we evaluate the superiority of the refined NSGA-II algorithm and the relevance of the dual-objective optimization model for low-carbon transportation scenarios. The analysis yields near-optimal solutions that balance minimum total cost and carbon emissions under varying carbon tax regimes. Furthermore, we compare the effectiveness of path optimization strategies under different carbon tax mechanisms. The findings suggest that the segmented progressive carbon tax mechanism exhibits a more pronounced emission reduction effect, particularly when demand uncertainty is high. In light of these results, relevant government agencies are advised to take into account the current capabilities and emission reduction technologies of enterprises when determining appropriate carbon tax rates and emission thresholds. This approach will facilitate the alignment of policy objectives with practical industry needs.

The present research offers valuable policy insights and a decision-making foundation for governmental agencies and multimodal transport enterprises. However, it is important to note that the study focuses on a single transport task. Future work will extend the investigation to address the multi-task low-carbon path optimization challenge. Moreover, achieving the dual carbon goal within the transportation sector is contingent not only on the efforts of governments and multimodal transport enterprises but also on the low-carbon choices made by customers. Consequently, the next phase of research will concentrate on path optimization strategies that incorporate customers' low-carbon behaviors and preferences, aiming to integrate these factors into a more comprehensive solution framework.

Declaration of competing interest

The authors have no competing interests to declare that are relevant to the content of this article.

Data Availability Statement

Some or all Data, models, or code that support the findings of available from the corresponding author upon reasonable request.

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References

[1] Wang MX, Hu Y, Guo DM, et al. Optimal emission implementation and corporate emission reduction investment competition from the perspective of carbon tax. Management Review, 2021, 33(8):17−28.

[2] Yang Y, Xu XY. Research on the evolution of low-carbon behavior of logistics enterprises considering carbon tax policy. Journal of Safety and Environment, 2021, 21(4): 1750−1758.

[3] Ji QK, Hu XP, SUN LJ. Research status and development of empty container scheduling problem. Systems Engineering Theory and Practice, 2014, 34(6): 1578−1586.

[4] Peng Y, Yong PC, Luo YJ. The route problem of multimodal transportation with timetable under uncertainty: multi-objective robust optimization model and heuristic approach. RAIRO - Operations Research, 2021, 55: S3035–S3050.

[5] Santos BF, Limbourg S, Carreira JS. The impact of transport policies on railroad intermodal freight competitiveness–the case of Belgium. Transportation Research Part D: Transport and Environment, 2015, 34: 230−244.

[6] JIN L, WANG XF. Low-carbon optimization of container multimodal transport from southwest china to shanghai: decision-making based on fuzzy, grey and matter-element space. China Circulation Economy, 2015, 29(11): 36−41.

[7] Li XD, Kuang HB, Zhao YZ, et al. An empirical study of low-carbon transportation in northeast china under multimodal transportation. Management Review, 2021, 33(3): 282−291.

[8] Hua GW, Cheng TCE, Wang SY. Managing carbon footprints in inventory management. International Journal of Production Economics, 2011, 132(2): 178–185.

[9] ZHANG X, YUAN XM, JIANG YD. Route Optimization of Multi-modal Transport under Uncertain Demand and Carbon Trading Prices. Systems Engineering Theory and Practice, 2021, 41(10): 2609–2620.

[10] Bouchery Y, Fransoo J. Cost, carbon emissions and modal shift in intermodal network design decisions . International Journal of Production Economics, 2015, 164: 388−399.

[11] Wang LY, Liao ZG, Zhu Q. Research of the Multimodal Transportation Path Optimization Problem Under the Carbon Tax Policy. Statistic Application in Modern Society, 2015: 293−298.

[12] Jiang QW, Lin Y, Feng FL. Research on multimodal transport route optimization problem considering changes in carbon tax value under fuzzy time. Industrial Technology and Economics, 2020, 39(4): 81−88.

[13] Cui EY, Luo JH, Ji JH. Research on the optimization of low-carbon logistics network considering segmented progressive carbon tax mechanism. Computer Application Research, 2016, 33(7): 1978−1982.

[14] Cheng XQ, Jin C. Route selection problem in multimodal transportation with traffic congestion considered under low-carbon policies. Operations Research and Management Science, 2019, 28(4): 67−77.

[15] Yuan XM, Jiang YD, Zhang X. Research on robust optimization of interval-based fuzzy multimodal transport path under low-carbon policy. Industrial Engineering and Management, 2021, 26(4): 134−141.

[16] Sun Y, Liang X, Li XY, et al. A fuzzy programming method for modeling demand uncertainty in the capacitated roa–rail multimodal routing problem with time windows[J]. . Symmetry, 2019, 11(1): 91.

[17] Zhang X, Jiang YD, Yuan XM. Route optimization of low-carbon multimodal transport under uncertain demand. Fuzzy Systems and Mathematics, 2020,34(5): 163−174.

[18] CHEN ML, ZHAO XJ, Deng XG, et al. Optimization of multimodal transport path under uncertain conditions. Highway Traffic Technology, 2021, 315 (1): 143−150, 158.

[19] Ziaei Z, Jabbarzadeh A. A multi-objective robust optimization approach for green location-routing planning of multi-modal transportation systems under uncertainty. Journal of Cleaner Production, 2021, 291: 125293. https://doi.org/10.1016/j.jclepro.2020.125293.

[20] Li SJ, Chen HL. Route optimization of fresh food distribution with time window based on NSGA II. Journal of Shanghai Maritime University, 2020, 41(2): 58−64.

[21] Geng HT, Li HJ, Zhao YG, et al. Improved NSGA-II algorithm based on adaptive mixed non-dominated individual ranking strategy. Computer Applications, 2016, 36(5): 1319−1324, 1340.

[22] Zhao YX. Research and application of improved adaptive non-dominated sorting genetic algorithm in multi-objective workshop scheduling. Dalian: Dalian Jiaotong University, 2017.

[23] Yuan MH, Li YD, Zhang LZ, et al. Research on intelligent workshop resource scheduling method based on improved NSGA-II algorithm. Robotics and Computer-Integrated Manufacturing, 2021, 71: 102141.

[24] Yan YC. Research on the impact of economic development on regional comprehensive transportation structure. Chengdu: Southwest Jiaotong University, 2019: 40−46.