Multiobjective Optimization of Multimodal Transportation Route Problem Under Uncertainty

Youpeng Lu, Fan Chen, and Ping Zhang

***Abstract*—This paper purposes an optimal organization of route and transportation mode in a multimodal transportation network. It considers the uncertainties of freight volumes, expenses, time, and carbon emissions. Considering the above factors comprehensively, it establishes a multiobjective chance-constrained model which aims to minimize total transportation cost. Base on this, the corresponding NSGAⅢ is introduced to solve the model, and the distribution of the Pareto solutions under different parameters are discussed. Using Monte Carlo simulation techniques, the paper explores the solutions of each objective under different reliabilities, and found them to be in accordance with economic regularity. With an increase in reliability, each objective increases monotonously, and the results that correspond to an 80% reliability are the best choice. The corresponding cost is acceptable, and the transportation process completes with high reliability. The study provides a reference for similar studies.**

***Index Terms*—NSGAⅢ, multimodal transportation, route optimization, uncertainty**

I. Introduction

As an efficient form of transportation organization, multimodal transportation offers unprecedented opportunities with the advancement of the "Belt and Road" strategy in China. Route optimization is one of the key issues in multimodal networks, and its essence is the combined optimization of routes and transportation modes. In the actual process, due to the existence of multiple roles, such as shippers, carriers, and management departments, transportation is full of uncertainties, and academics have produced many studies on managing these uncertainties. Shanma, Gupta and Lala [1] established a fuzzy decision system, that using fuzzy reliability theory to evaluate the programs, all the routes in the network are evaluated, and they chose the most suitable transportation program based on the different situations. In addition, stochastic theory was employed by Li, Yang, and Zhu [2], who treated travel time, transfer time, and customer demand as random variables, and through a sensitivity analysis, they discussed the regularities that the final transportation program changed in sync with the random variables. Demeyer, Pickavet, Demeester *et al.* [3] explored different situations, including static, dynamic and time-varying situations, and designed an improved Dijkstra's algorithm to solve for the optimal solution. Peng, Luo, Jiang *et al.* [4] established a two-objective route optimization model that treated time and cost as random variables, and they also introduced a Monte Carlo simulation to address them. Zhang, Jin, Yuan *et al.* [5] took into account expenditures, time, and carbon emissions, and they also adopted stochastic simulation technology.

The studies above described all the variables in a consistent form, such as the random variables or fuzzy variables, and set a predetermined distribution function in advance. However, in practice, a single representation cannot accurately describe all the factors, and because of a lack of samples or because of the subjectivity of the participants, the distribution function cannot be obtained in most cases. Additionally, in previous studies, different objectives were usually considered separately, and the decision-making approach is giving different weights to different objectives. But it is evident that they should be regard as a whole.

In this paper, we study an uncertain multimodal transportation route problem with three optimization objectives. We elaborate the variables from multiple perspectives, adopt subsection function, stochastic theory, uncertainty theory, and different perspectives based on the emissions and distances. We design the NSGAⅢ to search the Pareto solutions, and then add the Monte Carlo simulation method in the algorithm, in order to research the relationship between the variables and the total cost. The rest of this paper is organized as follows. In Section 2, we investigate the uncertainty of the different factors that influence the decision, and formulate a minimized chance-constraint model with three objectives. In Section 3, the corresponding NSGAⅢ is proposed. In Section 4, the performance of the algorithm and its feasibility are tested, and a numerical example is given to illustrate its behavior. In Section 5, we give a brief summary of this paper.

II. Multiobjective model construction

Suppose $G=(N,E,K)$ is an undirected multimodal transportation network, $i,j\in N$ is the collection of freight

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stations, $(i, j) \in E$ is the collection of transportation routes, and $k,l \in K$ is the collection of transportation modes in the network. There are two transportation modes, railway and highway, which are represented by r and h, respectively. The freight must be transited from the start point O to the destination D, assuming that all the routes and stations meet the capacity constraints.

A. Freight Volume Analysis

The freight volume is usually determined by the shippers, different shippers offer different freight volumes, and even the same shipper will generate different freight volumes at different time periods. Hang *et al.* [6] weighed road vehicles according to the axle type classification, found that the loading volume of each vehicle basically obeyed the normal distribution. Wang *et al.* [7] fitted the daily freight volume of the railways according to actual data and found that it obeys a log-normal distribution. As the log-normal distribution has more upwardly distributed values, we assume the freight volume is a random variable ξ that obeys the log-normal distribution.

B. Transportation Expend

The price of highway transportation obeys the “economies of scale” effect, including a fixed price and a variable price, and the relationship between them is represented by a non-convex linear piecewise function that is shown in Fig. 1. The fixed unit price f is the intercept of the vertical axis, the horizontal axis is divided into B stages, and it represents the freight volume ξ. Each stage has an upper limit m^b and a lower limit m^{b-1}. The corresponding slope is the variable unit price c and satisfies $c^1 > c^2 > \cdots > c^b$. Defining the fixed price of road transportation as f^h and the variable price as c^h, gives the price of highway transportation as $F_{ij}^h(\xi) = \left(f^h + c^h\right) \bullet \xi \bullet l_{ij}$, where l_{ij} is the length of the route. The price of railway transportation is only related to the freight volume. The base price 2 (0.138 yuan/ton·km) is adopted for all vehicle transportation and is published on the 95306 website as the unit price f^r, then the price of railway transportation is $F_{ij}^r(\xi) = f^r \bullet \xi \bullet l_{ij}$.

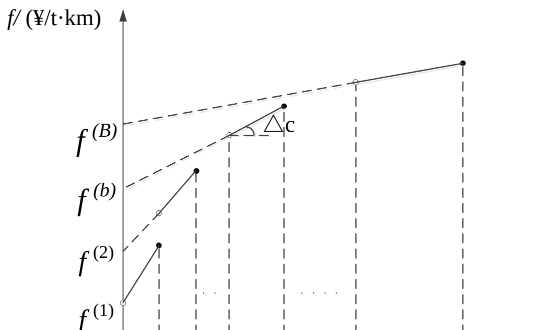

Fig. 1. Relationship of highway prices.

The process of transfer includes storage and loading operations. Assuming that the storage capacity is sufficient, the transfer price is linearly correlated with the freight volume. Defining the coefficient of loading price as α_1, we obtain the transfer price $M_i^{kl}(\xi) = \alpha_1 \xi$, and then, the total price of transportation is:

$$C(\xi) = \sum_{i,j \in N} \sum_{k \in K} F_{ij}^k(\xi) \bullet x_{ij}^k + \sum_{i \in N} \sum_{k,l \in K} M_i^{kl}(\xi) \bullet y_i^{kl} \quad (1)$$

where x_{ij}^k, y_i^{kl} are 0-1 variables, x_{ij}^k indicates whether the freight passes through route (i, j) by the *k*th transportation mode, and y_i^{kl} indicates whether the transportation mode transfers from *k* to *l* at Station *i*. Taking the confidence level ρ_1 and the upper price limit $\overline{C}$, a chance-constrained programming model is established:

$$\min Z_1 = \min \left\{ \overline{C} \middle| \Pr\left\{ \left[\sum_{i,j \in N} \sum_{k \in K} F_{ij}^k(\xi) \bullet x_{ij}^k + \sum_{i \in N} \sum_{k,l \in K} M_i^{kl}(\xi) \bullet y_i^{kl} \right] \le \overline{C} \right\} > \rho_1 \right\} \quad (2)$$

C. Transportation Time

The transportation time of the railway can be expressed by $T_{ij}^r = l_{ij} / \beta$, where β is the average speed of the train; however, a train operation must follow the rail working diagram. Its initial premise is that the train must start from the station in a given time; thus, we set a planned departure time d_i for each station [8].

The transportation time of the highway will be affected by many factors, such as road conditions, weather, and even the personal preferences of the drivers, and its distribution function cannot be accurately obtained. Assuming the arrival time of Station *i* is a_i, it is easily known that the upper and lower limits of the transit time between (i, j) are a_i and d_j. Liu [9] proposed uncertainty theory in 2007, which provides a tool for solving the problem that the distribution function is unknown. According to the definition of uncertain variables, we treat the transportation time of highways as a zigzag uncertain variable, and its measure is shown in (3):

$$\Phi(T_{ij}^h) = \begin{cases} 0, \ if \ T_{ij}^h \le a_i \\ \dfrac{T_{ij}^h - a_i}{2(T_{ij}^r - a_i)}, \ if \ a_i \le T_{ij}^h \le T_{ij}^r \\ \dfrac{T_{ij}^h + d_j - 2T_{ij}^r}{2(d_j - T_{ij}^r)}, \ if \ T_{ij}^r \le T_{ij}^h \le d_j \\ 1, \ if \ d_j \le T_{ij}^h \end{cases} \quad (3)$$

Defining the coefficient of loading time as α_2, the transfer time is $N_i^{kl}(\xi) = \alpha_2 \xi$, and the total time for transit is

$$T(\xi) = \sum_{i,j \in N} \sum_{k \in K} T_{ij}^k \bullet x_{ij}^k + \sum_{i \in N} \sum_{k,l \in K} N_i^{kl}(\xi) \bullet y_i^{kl} \quad (4)$$

It is subject to a time constraint (5), which means that if the transportation mode transfers from highway to railway in section j, the actual departure time cannot overstep the scheduled time.

$$d_j \ge T_{ij}^h \bullet x_{ij}^h + N_j^{hr}(\xi) \bullet y_i^{hr} \quad (5)$$

Taking the confidence level ρ_2 and the upper limit $\overline{T}$, a chance-constrained programming model for transportation time is established:

$$\min Z_2 = \min \left\{ \overline{T} \middle| \Pr\left\{ \left[\sum_{i,j \in N} \sum_{k \in K} T_{ij}^k \bullet x_{ij}^k + \sum_{i \in N} \sum_{k,l \in K} N_i^{kl}(\xi) \bullet y_i^{kl} \right] \le \overline{T} \right\} > \rho_2 \right\} \quad (6)$$

D. Carbon Emissions

According to the recommendations of the "IPCC National

Greenhouse Gas Emission Guidelines," [10] the carbon emissions of transportation vehicles generally have two calculation methods based on travel distance and fuel consumption. Railway transportation runs normally at the designed speed, and the carbon emissions can be calculated based on the distance, such as (*a*) in (7). Due to congestion, weather, and other conditions, driving at a fixed speed is unrealistic for highway transportation; therefore, it is more appropriate to use a method based on fuel consumption [11], such as (*b*) in (7)

$$car_{ij}^{k}=\begin{cases} o^{k}\bullet p^{k}\bullet l_{ij}\bullet\xi,\ k=r & (a)\\ l_{ij}\bullet e\left(v_{ij}\right)\bullet ceil\left(\frac{\xi}{H^{k}}\right)\bullet 10^{-3},\ k=h & (b)\end{cases} \quad (7)$$

where o^k is the unit fuel consumption (kg/ton·km) of the *k*th transportation mode, p^k is the emission coefficient $(kgCO_2/kg)$ of the fuel, and according to the literature [12], $e(v_{ij})$ is calculated by (8), where v_{ij} is the average speed, and $\{\varepsilon_0, \varepsilon_1, \varepsilon_2, \varepsilon_3, \varepsilon_4, \varepsilon_5, \varepsilon_6\}$ is taken (1576, -17.6, 0, 0.00117, 0, 0.36067, 0). $ceil(\frac{\xi}{H^k})$ means rounding up to calculate the number of vehicles, and H^k is the vehicle loading (t/vehicle).

$$e\left(v_{ij}\right)=\varepsilon_0+\varepsilon_1\bullet v_{ij}+\varepsilon_2\bullet\left(v_{ij}\right)^2+\varepsilon_3\bullet\left(v_{ij}\right)^3+\frac{\varepsilon_4}{v_{ij}}+\frac{\varepsilon_5}{\left(v_{ij}\right)^2}+\frac{\varepsilon_6}{\left(v_{ij}\right)^3} \quad (8)$$

We define the coefficient of transfer carbon emissions as α_3, the transfer carbon emissions as $O_i^{kl}(\xi)=\alpha_3\xi$, and the total carbon emissions of transportation as:

$$D(\xi)=\sum_{i,j\in N}\sum_{k,l\in K}car_{ij}^{k}(\xi)x_{ij}^{k}+\sum_{i\in N}\sum_{k,l\in K}O_i^{kl}(\xi)\bullet y_i^{kl} \quad (9)$$

Taking the confidence level ρ_3 and the upper limit $\overline{D}$, the chance-constrained programming model for carbon emissions is established:

$$\min Z_3=\min\left\{\overline{D}\middle|\Pr\left\{\left(\sum_{i,j\in N}\sum_{k,l\in K}car_{ij}^{k}(\xi)x_{ij}^{k}+\sum_{i\in N}\sum_{k,l\in K}O_i^{kl}(\xi)\bullet y_i^{kl}\right)\le\overline{D}\right\}>\rho_3\right\} \quad (10)$$

E. Optimization Model

According to the above description, we can formulate a multiobjective chance-constrained programming model as shown in Equations (11) to (16):

$$\min\left\{\overline{F}\middle|\Pr\left\{F(\xi)=\left(\min Z_1,\min Z_2,\min Z_3\right)\le\overline{F}\right\}\ge\rho\right\} \quad (11)$$

s.t.

$$\sum_{(i,j)\in A}\sum_{k\in K}x_{ij}^{k}-\sum_{(i,j)\in A}\sum_{k\in K}x_{ji}^{k}=\begin{cases}1 & \text{if } i=O\\ -1 & \text{if } i=D\\ 0 & \text{otherwise}\end{cases} \quad (12)$$

$$d_j\ge T_{ij}^{h}\bullet x_{ij}^{h}+N_j^{hr}(\xi)\bullet y_i^{hr} \quad (13)$$

$$\sum_{k\in K}x_{ij}^{k}\le 1 \quad \forall(i,j)\in A \quad (14)$$

$$\sum_{k\in K}\sum_{l\in K}y_i^{kl}\le 1 \quad \forall i\in N \quad (15)$$

$$x_{ij}^{k},\ y_j^{kl}\in\{0,1\}\quad\forall(i,j)\in A;\ j\in N;\ k,l\in K \quad (16)$$

where the objective function indicates that the target cost obtained will be less than the fixed cost $\overline{F}$ with a certain confidence level ρ. The constraint condition (12) indicates the flow balance, (13) is the constraint on the transfer time as (5) shows, (14) means that each route can only choose one transportation mode, (15) means that the transfer in each station can only be taken once, and (16) is the 0-1 variable, if a certain route is selected or a transfer occurs, take 1; otherwise, take 0.

III. SOLVING ALGORITHM

The proposed model in the article is a multiobjective, multiweight, multiconstrained shortest route problem between two points, and the problem has been proven to be a NP-hard problem [13]. In view of the characteristics of the problem, we propose an improved multiobjective Genetic Algorithm to solve it [14].

A. Encoding and Decoding

Using a real number coding chromosome representation, suppose the entire transportation network has *n* nodes, the chromosome is divided into two regions, the first region is the priority of each node, its length is *n*, the second region represents the transportation mode, and its length is *n*-1. For the first region, beginning from the start point, the priority of its backward nodes is compared. The node with the highest priority is selected, and then the above operation is repeated until the end point is reached [15]. Operations on the chromosome change the priorities, and as a result, the order of the nodes will be changed. This representation of the chromosome avoids infeasible solutions and greatly improves the efficiency of the algorithm.

B. Crossover and Mutation

The chromosomes that should undergo crossovers are determined by the initial populations and the crossover rate. If the crossover operation occurs, first select one parent with a sequence that contains two genes, and the other parent has its alleles. Make sure the four genes are different from each other, then create a mapping between the genes of each parent, and next, exchange the alleles and replace the genes of each parent through the mapping relationship. The operation mentioned above is named a partial consistent crossing [16].

Similar to the crossover operation, if the mutation operation occurs, randomly generate two numbers $a\le n, b\le n$, and $a\ne b$, then exchange the genes in positions *a* and *b*, the new chromosome is the child, and after the operations, the parent is replaced by the child.

C. Selection Operation

(1) Generate Reference Points [17]

Suppose there are M goals, and each goal is divided into H parts:

Step 1: Select all the combinations of $\{0/H, 1/H, \ldots, H+M\text{-}2/H\}$ in column M-1.

Step 2: For each element x_{ij}, where i represents the *i*th combination and j represents the *j*th element, let $x_{ij}=x_{ij}-(j-1)/H$.

Step 3: Obtain the reference point $s_{ij}=\begin{cases}x_{ij}-0, & j=1\\ x_{ij}-x_{i(j-1)}, & 1<j<M\\ 1-x_{i(j-1)}, & j=M\end{cases}$.

Step 4: Perform the above three steps to generate reference points in the outermost layer, and then generate the inner reference points by $s_{ij}^{'}=s_{ij}/2+1/2M$; then, we can obtain the reference point set $s=s_{ij}\bigcup s_{ij}^{'}$.

(2) Individual Standardization

Step 1: Select the ideal point $z_i^{(\min)}, i=1,2,\ldots,M$, which is the minimum of the current individual in each dimension, and set the ideal point as the origin. Translate the population through $f_i^{'}(x) = f_i(x) - z_i^{(\min)}$ as a whole.

Step 2: Calculate the extreme value points corresponding to each coordinate by using the formula $ASF(x,w)=\max_{i=1}^{(M)} f_i^{'}(x)/w_i \quad x \in S_t$, we can obtain M extreme points, and the extreme points determine a hyperplane.

Step 3: For the equation $ax+by+cz=1$, set the other two values to 0, and substitute z_1, z_2, z_3 into the equation to obtain the intercept $a_i, i=1,2,\cdots M$, which is the intercept of the hyperplane on each coordinate axis.

Step 4: Normalize the objective function through $f_i^{(n)}(x) = \frac{f_i^{'}(x)}{a_i - z_i^{(\min)}} = \frac{f_i(x) - z_i^{(\min)}}{a_i - z_i^{(\min)}}$, $i=1,2,\ldots,M$; obviously, $\sum_{i=1}^{M} f_i^{(n)}(x) = 1$.

(3) Niche Selection Operation

Step 1: Connect the reference point to the translated origin as the reference line, calculate the vertical distance of the individuals in S_t to the origin, and associate the individuals to the reference point in the nearest reference line [18].

Step 2: If the number of individuals in P_t is less than the population size, select individuals to join the next generation from P_{t+1}, and use the proximity principle rule. If there is no individual associated with it in P_{t+1}, then reselect the reference point.

Step 3: Repeat the above operation until the size of P_{t+1} is equal to the population size.

IV. Simulation Calculation and Result Analysis

The effectiveness of the Genetic Algorithm has been verified in the literature [19], it adopts a single objective model, and uses the above coding method and the genetic operations. Here, we take advantage of its efficiency and apply it to multiobjective circumstances.

A. Numerical Examples

The multimodal transportation network consists of 33 nodes and 53 arcs, as Fig. 2 shows, and the corresponding distance of each arc is shown in Table I. Suppose the unit price of railway transportation is 0.138 yuan/ton·km, the average speed of the railway is 80 km/h, the distribution function of the transportation volume obeys $\ln(\xi) \sim N(4, 0.1)$, and the transfer cost and time windows are shown in Table II and Table III, respectively.

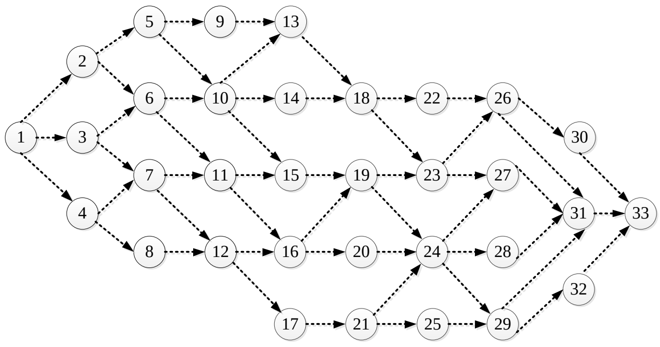

Fig. 2. Multimodal transportation network

B. Result Analysis

As each objective will affect the result, and a single objective also obtains different results under different confidence levels, we first solve the objectives and then calculate the results under different confidence levels through a Monte Carlo simulation. Each confidence runs 10 times and the optimal results are shown in Table IV. The results below the 80% confidence level are more typical, and their convergence process is shown in Fig. 3 - Fig. 5. The process of the results that make changes from the confidence levels is shown in Fig. 6.

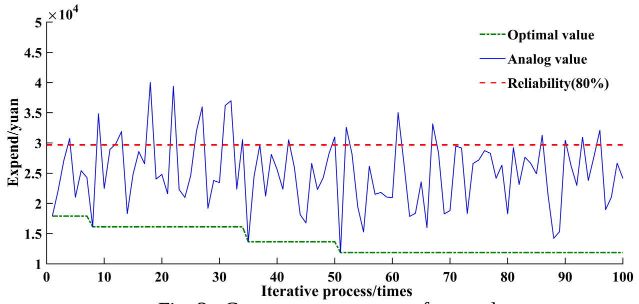

Fig. 3. Convergence process of expend

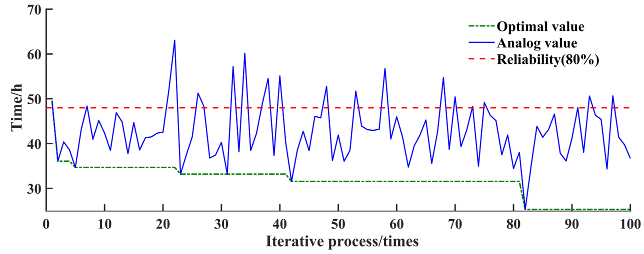

Fig. 4. Convergence process of time

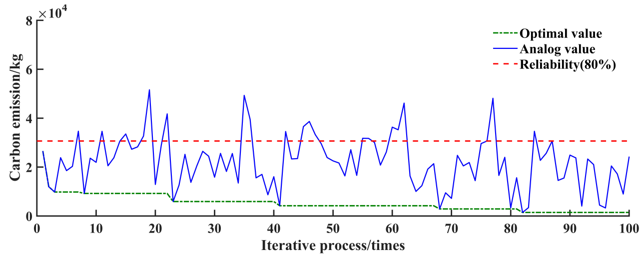

Fig. 5. Convergence process of carbon emission

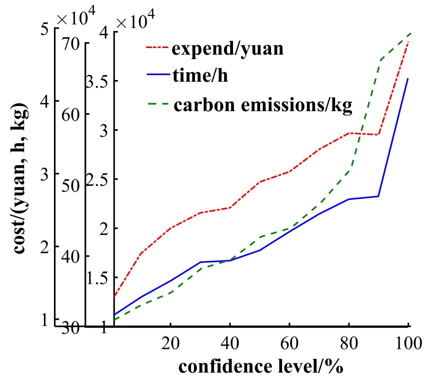

Fig. 6. Process of cost change with reliability

It is easy to see that different perspectives result in different decisions. Taking the case of the 1% confidence level as an example, from the perspective of minimum expense, the best scheme is 1-2-5-9-13-18-22-26-30-33, and the railway is adopted throughout the transportation process. However, from the perspective of minimum carbon emissions, the best scheme is 1-4-8-12-16-19-24-29-31-33, and the entire transportation mode is via the highway. In addition, from the perspective of minimum time, the best scheme is 1-3-6-11-16-20-24-28-31-33, and we also need to convert the transportation mode halfway through the process.

TABLE I
PROPERTIES OF THE NETWORK (UNIT: KM)

Arcs	Railway distance	Highway distance	Arcs	Railway distance	Highway distance	Arcs	Railway distance	Highway distance
(1,2)	254	267	(10,14)	111	117	(21,25)	112	127
(1,3)	278	284	(10,15)	80	75	(22,26)	300	317
(1,4)	321	317	(11,15)	76	80	(23,26)	311	308
(2,5)	245	265	(11,16)	132	123	(23,27)	127	135
(2,6)	304	315	(12,16)	51	43	(24,27)	195	186
(3,6)	110	108	(12,17)	88	91	(24,28)	207	211
(3,7)	194	186	(13,18)	267	274	(24,29)	337	341
(4,7)	246	223	(14,18)	221	231	(25,29)	87	78
(4,8)	338	336	(15,19)	334	321	(26,30)	217	229
(5,9)	147	152	(16,19)	367	375	(26,31)	426	418
(5,10)	164	154	(16,20)	227	210	(27,31)	328	314
(6,10)	98	112	(17,21)	207	216	(28,31)	146	157
(6,11)	134	128	(18,22)	222	234	(29,31)	408	398
(7,11)	254	249	(18,23)	379	312	(29,32)	267	281
(7,12)	357	376	(19,23)	184	176	(30,33)	227	234
(8,12)	200	207	(19,24)	376	381	(31,33)	198	206
(9,13)	114	110	(20,24)	231	224	(32,33)	278	299
(10,13)	317	320	(21,24)	376	364			

TABLE Ⅱ
TRANSFER COST OF TRANSPORTATION

Cost/ten thousand yuan			Time/h			Carbon emission/kg		
	Railway	Highway		Railway	Highway		Railway	Highway
Railway	0	0.5	Railway	0	2.5	Railway	0	2
Highway	0.5	0	Highway	2.5	0	Highway	2	0

TABLE Ⅲ
TIME WINDOWS OF TRANSPORTATION (UNIT: H)

Nodes	Latest departure time	Nodes	Latest departure time	Nodes	Latest departure time
1	0	12	9.5	23	16.5
2	3.5	13	10.5	24	16.5
3	3.5	14	10.5	25	16.5
4	3.5	15	10.5	26	20
5	7	16	10.5	27	20
6	7.5	17	10.5	8	20
7	7.5	18	13.5	29	20
8	8	19	13.5	30	23
9	9.5	20	13.5	31	23
10	9.5	21	13.5	32	23
11	9.5	22	16.5	33	26

For the determined perspective, different confidence levels will also result in different decisions, and regardless of whether the taken perspective is an expenditure, time, or carbon emission, they will monotonically increase with the confidence level. From another point of view, the higher the cost is, the greater the possibility that the transportation process will be completed successfully. If we select the cost corresponding to the 100% level, the transportation process will definitely be accomplished. However, if we select the cost corresponding to the 1% level, transportation is an almost impossible task, consistent with economic rules.

To further discuss the results, we use a computer with a CPU with an AMD Athlon(tm) X4860K Quad Core Processor and a frequency of 3.7 GHz, 8 GB of memory. Set the population size to 50 and 100, and the maximum evolutionary algebra to 100 and 200. The crossover rate is defined as 0.7 and 0.9, and the mutation rate is defined as 0.02 and 0.2. Because uncertainties exist in both the variables and the genetic algorithm, we define the concepts of approximation and dispersion. The approximation represents the average distance between the generated solutions and the optimal solution of each objective, which is expressed by Equation (17), and *nump* in Equation (17) represents the number of Pareto solutions in the frontier. The dispersion represents the deviation degree between the generated solutions and the average value of the solutions, and is expressed by Equation (18). The calculated solutions are shown in Table V.

TABLE Ⅳ
COMPARISON OF THE RESULTS

Conficidence level	Cost		Path	Transportation mode
100%	Expend/yuan	38991	1-2-5-9-13-18-22-26-30-33	R—R—H—H—R—R—H—R—R
	Time/h	65.0	1-2-5-10-15-19-23-26-30-33	H—R—R—R—R—R—R—R—H
	Carbon emission/kg	49319	1-2-5-10-15-19-23-26-30-33	R—H—H—H—H—H—R—H—H
80%	Expend/yuan	29681	1-3-7-11-16-20-24-28-31-33	R—R—H—R—R—R—R—H—R
	Time/h	47.0	1-3-6-10-13-18-23-27-31-33	H—H—R—R—R—R—H—R—R
	Carbon emission/kg	30665	1-3-7-11-16-19-24-28-31-33	H—R—H—H—H—H—H—H—R
60%	Expend/yuan	25749	1-3-6-10-14-18-22-26-31-33	R—R—R—R—H—R—R—R—R
	Time/h	43.4	1-3-6-11-15-19-23-27-31-33	H—H—H—R—R—R—H—R—R
	Carbon emission/kg	22536	1-2-6-11-16-19-23-26-30-33	R—H—H—H—H—H—H—H—H
40%	Expend/yuan	22086	1-4-7-12-17-21-25-29-31-33	R—R—R—H—R—H—R—R—R
	Time/h	39.4	1-2-6-11-16-19-23-26-30-33	H—R—R—R—R—R—R—R—R
	Carbon emission/kg	18192	1-3-6-11-16-20-24-28-31-33	H—R—R—H—H—H—H—H—H
20%	Expend/yuan	20003	1-3-6-11-15-19-23-27-31-33	R—R—R—R—R—H—R—R—R
	Time/h	36.5	1-3-6-11-15-19-23-27-31-33	R—R—H—H—H—H—H—H—H
	Carbon emission/kg	13661	1-4-8-12-17-21-24-28-31-33	H—H—H—H—H—H—H—R—H
10%	Expend/yuan	17419	1-2-6-10-15-19-24-29-32-33	R—R—R—R—R—R—R—R—R
	Time/h	34.2	1-3-6-10-14-18-22-26-30-33	H—R—R—R—R—R—R—R—R
	Carbon emission/kg	11928	1-4-8-12-17-21-25-29-32-33	H—H—H—H—H—H—H—H—H
1%	Expend/yuan	13014	1-2-5-9-13-18-22-26-30-33	R—R—R—R—R—R—R—R—R
	Time/h	31.8	1-3-6-11-16-20-24-28-31-33	H—H—H—H—R—H—H—H—R
	Carbon emission/kg	9896	1-4-8-12-16-19-24-29-31-33	H—H—H—H—H—H—H—H—H

TABLE Ⅴ
SOLUTIONS UNDER DIFFERENT PARAMETERS

Population size	Evolutionary algebra	Crossover rate	Mutation rate	Number of Pareto solutions	Approximation	Dispersion	operation time/s
50	100	0.7	0.02	50	296.9‰	28.4‰	42.8
50	100	0.7	0.2	48	667.3‰	1951.4‰	47.0
50	100	0.9	0.02	46	1012.4‰	6741.9‰	48.8
50	100	0.9	0.2	50	3639.3‰	8628.1‰	55.4
50	200	0.7	0.02	50	491.7‰	56.3‰	84.5
50	200	0.7	0.2	50	382.3‰	33.9‰	97.0
50	200	0.9	0.02	50	334.0‰	99.7‰	96.6
50	200	0.9	0.2	50	451.8‰	45.6‰	109.1
100	100	0.7	0.02	100	207.6‰	53.7‰	121.0
100	100	0.7	0.2	100	276.2‰	20.3‰	139.0
100	100	0.9	0.02	92	997.7‰	2068.0‰	143.5
100	100	0.9	0.2	100	525.5‰	149.3‰	172.1
100	200	0.7	0.02	94	1374.4‰	1910.1‰	250.2
100	200	0.7	0.2	72	368.5‰	49.8‰	289.3
100	200	0.9	0.02	100	282.8‰	92.8‰	293.7
100	200	0.9	0.2	100	421.0‰	33.2‰	327.9

$$Approximation=\left\{\sum_{i=1}^{nump}\left[\left(\frac{x_i-x_{\min}}{x_{\max}-x_{\min}}\right)+\left(\frac{y_i-y_{\min}}{y_{\max}-y_{\min}}\right)+\left(\frac{z_i-z_{\min}}{z_{\max}-z_{\min}}\right)\right]\Big/3\right\}\Big/nump \quad (17)$$

$$Discreteness=\left[\sqrt{\sum_{i=1}^{nump}\left(x_i-\bar{x}\right)^2/nump}+\sqrt{\sum_{i=1}^{nump}\left(y_i-\bar{y}\right)^2/nump}+\sqrt{\sum_{i=1}^{nump}\left(z_i-\bar{x}\right)^2/nump}\right]\Big/3 \quad (18)$$

Table V shows that the size of the initial population has a great impact on the Pareto solutions; it determines the size of the initial search space, and thereby determines the diversity of the Pareto solutions. With the increase in evolutionary algebra, the degree of approximation and dispersion can basically be kept within a certain range, which reflects the uniformity of the solution. A comparison shows that when the initial population is 100, the number of algebra is 200, the crossover rate is 0.9, and the mutation rate is 0.2, the Pareto solutions present a good distribution, as shown in Fig. 7.

V. CONCLUSION

This paper focuses on the route optimization problem in a multimodal transportation network under uncertainty. The proposed NSGAⅢ can effectively meet the multimodal objectives in a multimodal transportation network, and through a Monte Carlo simulation, it found that although many factors will influence the determination of the final selection, they are all monotonically increasing functions of the confidence level, which means that the higher the reliability is, the higher the cost, which is in line with the regularity of the economy. However, the 80% confidence level is a turning point; when the confidence level exceeds 80%, all the costs begin to increase sharply. Therefore, we can conclude that the 80% corresponding route and its relevant transportation mode is the preferred option. This will effectively reduce the cost, and we can reasonably assume the transportation process will be completed efficiently.

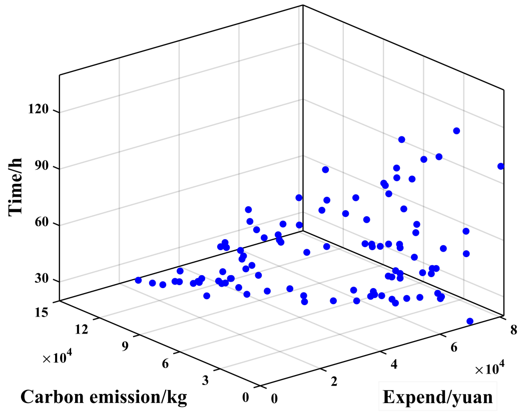

Fig. 7. The Pareto solutions

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