Optimization of Traveler Intermodal Transport Routes Considering Carbon Emissions

Zongfang Wang, Changfeng Zhu, and Jinhao Fang

***Abstract*—Optimization of the travel paths is necessary to shorten travel time and reduce travel costs. This paper proposes the analysis theory of the travelers' low carbon route choice behavior based on improved prospect theory by analyzing the punctuality rate of travel time, the travelers' comfort level on the travelers' intermodal transport route optimization. Dual reference points are set according to the whether travelers have the prior experience as the judgment basis, constructing an optimization model of travelers' intermodal transport under bounded rationality. The results show that, in the travelers' intermodal transport route considering carbon emissions, the travel route selected by travelers will change with the road state. In this problem, the gain sensitivity coefficient α and the loss sensitivity coefficient β have influence on the decision. When traffic crowding or bad weather occurs, travelers tend to be more sensitive to time. The setting of each parameter has an important impact on the comprehensive prospect values.**

***Index Terms*—Travelers' intermodal transport, travel behavior, carbon emissions, bounded rationality, improved quantum genetic algorithm**

I. Introduction

TRAVELERS' intermodal transport route selection plays a significant role in making a relatively reliable and reasonable travel plan. Travelers' intermodal transport can reduce travel costs and promote the coordinated development of various transportation modes. However, this problem is affected by complex factors such as travelers' psychology and the external environment.

Compared with a single mode of transportation, travelers' intermodal transport can better describe the actual travel demand of travelers. In the early period, some scholars conducted research on trip distribution and transportation mode distribution [1][2][3][4][5][6][7], a combined trip traffic allocation model under fixed demand is proposed, it has important theoretical significance for optimizing trip path. Some scholars have studied the choice of travel mode by discrete choice models. [8] by analyzing the relationship between the travelers' characteristics and the travel mode, the discrete choice model is used to construct the functional relationship between travelers' personal characteristics and travel characteristics. Multinomial logit models were used to analyze the potential psychological factors of travelers and the influence of bus users' groups on trip modes [9] [10]. The hierarchical mixed logit model was established to explore the influence of the sense of individual observation period correlation and age on travel mode [11][12][13]. [14][15] analyzed the influence of traffic information on travelers' path choice behavior, and established the multidimensional relationships between residents' choice behaviors and travel patterns. [16] by considering the absolute cost difference and relative cost difference in travelers' route choice decision, a hybrid closed route selection model and the corresponding stochastic user equilibrium (SUE) were established to alleviate the shortcomings of the logit model and weibit model. [17] compared different route choice behaviors of travelers under risky road network conditions and studied the impact of travel information on route choice behavior.

However, carried out the above research in deterministic networks and has not considered the transportation networks' uncertainty. To understand the path selection model under the uncertain conditions, [18] established a network equilibrium model in a random road network. Considering the impact of risk perception on route selection, [19] proposed a discrete choice model based on risk perception. But, in addition to the uncertainty of the transportation network, travelers are also affected by habits, cognition, and environment, and it is difficult for travelers to make entirely rational decisions [20] [21]. [22] found that prospect theory could well describe path choice behavior of travelers under uncertain environments and applied it to path optimization problems [23]. Based on the theory of bounded rationality, [24] established a route selection model with the continuous random distribution of the travel utility and revealed travelers bounded rational decision-making process. By introducing the cumulative prospect theory, [25] considered uncertainty of the route selection and constructed a multi-mode stochastic traffic allocation model based on bounded rationality. [26] [27] established a multi-modal bounded rational hierarchical logit model to describe the travel choice behavior of travelers by considering bounded rational satisfaction decision criterion. [28] compared the optimal selection results of cumulative prospect theory and expected utility theory in different scenarios by considering three travel modes. [29] discussed the formation and evolution process of reference points by analyzing travelers' risk attitudes and explored the formation and evolution of reference points. For this reason, some scholars set reference points when establishing the path selection model. [30] chose positive and negative ideal travel

Manuscript received April 4, 2023; revised July 19, 2023.

This work was supported in part by the National Natural Science Foundation of China (No. 71961016, 72161024), the Natural Science Foundation of Gansu Province (No. 20JR10RA212, 20JR10R10RA214), and "Double-First Class" Major Research Programs, Educational Department of Gansu Province (No. GSSYLXM-04).

Zongfang Wang is a Postgraduate student at School of Traffic and Transportation, Lanzhou Jiaotong University, Lanzhou 730070, China. (e-mail: 1781116144@qq. com).

Changfeng Zhu is a Professor at School of Traffic and Transportation, Lanzhou Jiaotong University, Lanzhou 730070, China. (Corresponding author, phone: +86 18919891566, e-mail: cfzhu003@163. com).

Jinhao Fang is a doctoral candidate at School of Traffic and Transportation, Lanzhou Jiaotong University, Lanzhou 730070, China. (e-mail: fangjin_hao@163. com).

modes as the reference points in the travel decision-making process, and found the sharing rates model of travel modes. [31][32] introduced travel time cost and monetary travel cost as double reference points by establishing the perceived cost function. [33][34] established the route selection model of commuters and selected the earliest and latest arrival times as pseudo reference points. [35] established a perceptual utility model and selected expected arrival time as multi-reference points. It is necessary to set multiple reference points in the path optimization.

To sum up, relevant scholars have conducted some studies on route optimization of travelers' intermodal transport, but there are still the following deficiencies. First of all, most existing scholars mainly study the path optimization of a single transport mode in the city and lack the consideration of the combination optimization of multiple transport modes. Secondly, a few scholars have studied the route optimization problem based on the prospect theory without considering the impact of traveler heterogeneity on the route optimization problem. Thirdly, most studies lack consideration of the travelers' existing travel experience, which makes the conclusions slightly inconsistent with reality. Finally, few scholars have studied the combination optimization of the multiple transportation modes under low carbon background.

Based on the analysis of the complexity of travelers' intermodal transport, through the study of travel behavior characteristics under the bounded rationality, considering the weather, road crowding, low carbon emissions, and other factors affect the travelers' intermodal transport. Taking the expected travel time, travel cost, and carbon emissions as multiple objectives and constructing a path optimization model under bounded rationality conditions.

The rest of this paper is summarized as follows: In Section II, we introduce the travelers' intermodal transport problems. and reference points are selected to analyze the path selection behavior of travelers based on improved prospect theory. In Section III, we establish the trip path optimization model. In Section V, we verify the rationality of the model built in Section III, Section VI is a discussion mainly analyzing the effect of some parameter changes on the results and Section VII concludes.

II. Analysis of Route Choice Behavior

The process of the travelers' intermodal transport mainly includes travelers short-distance transportation before the long-distance travel phase, the long-distance travel phase, and the short-distance transportation after the long-distance travel phase.

Assume that $G(E,N,M)$ is travelers' intermodal transport network, where E is the set of nodes, and N is the set of transport arc segments. M is the set of transport modes. For travelers' intermodal transport network, each node represents the transfer decision point for the passenger. In the actual travel process, the travelers simplify a complex intermodal network into a single subnetwork, as shown in Fig. 1.

The transfer of transportation modes between different networks can only occur at nodes, meaning it is impossible to transfer to another mode midway, and only some hubs have all modes of transportation.

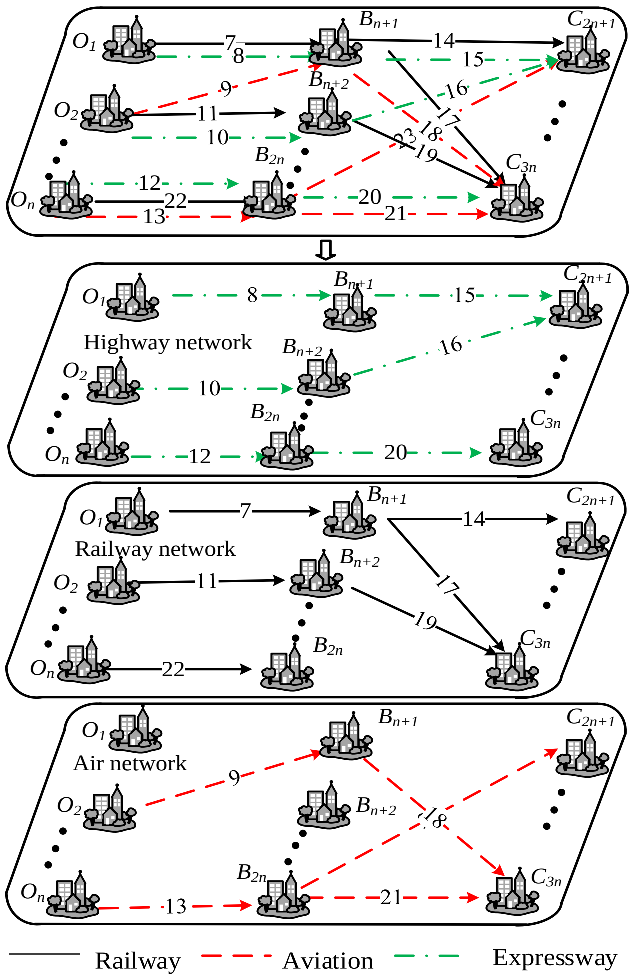

Fig. 1. Intermodal transport network

Combined with the evaluation results of travel choice behavior, if travelers are satisfied with the evaluation results of the first n-1 trips, the n-1 times before trips will be adopted, and the time and cost of the n-1 times before trips will be taken as the reference point. If the travelers are not satisfied with the evaluation result or there is no evaluation result, the traveler will re-select the path, the selection process is shown in Fig. 2.

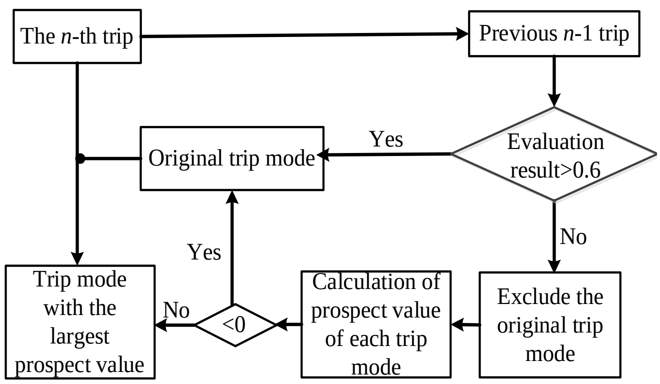

Fig. 2. Traveler route selection process

A. Selection of Double Reference Points

Set double reference points of the time expectation and the cost expectation to analyze the travelers' intermodal transport path selection behavior, travelers decide the travel mode from node i to node j before departure.

$$T_{ij}^{M_n}=\left(\frac{d_{ij}^{M_n}}{v_{ij}^{M_n}\cdot\eta\cdot\lambda^{*}}\right)\cdot r_{ij}^{M_n}+t_{ij}^{d_n}+(1-\sigma)\sum_{H=1}^{n}t_{ij}^{M^{n}{}_{H}} \tag{1}$$

Where, $T_{ij}^{m_n}$ represents the total time of transportation mode M from node i to node j for the n times trip; $d_{ij}^{M_n}$ represents the distance of transportation mode M from node i to node j for the n times trip; $v_{ij}^{M_n}$ represents average travel speed of transportation mode M from node i to node j for the n times trip, km/h; η represents road crowding coefficient, $\eta\in(0,1)$, when $\eta=1$, the road condition is excellent; λ^{*} represents the weather reduction coefficient, $\lambda^{*}\in(0,1)$, when $\lambda^{*}=1$, it indicates that the weather is very excellent; $t_{ij}^{d_n}$ represents the additional time for the travelers to travel for the n times trip, including the time for picking up tickets, and waiting according to the schedule, min; $t_{ij}^{M^{n}{}_{H}}$ represents the transfer time between transportation mode M and another transportation mode, which is a 0-1 variable, H is the number of transfers, when $H<1$, $\sigma=1$, otherwise, $\sigma=0$; $r_{ij}^{M_n}$ represents the travel time reliability coefficient from node i to node j for the n times trip.

$$r_{ij}^{m_n}=\frac{1}{n}\sum_{i=1}^{n}\frac{t_{ij}^{m_n^s}}{t_{ij}^{m_n^p}} \tag{2}$$

Where, $t_{ij}^{m_n^s}$ represents the actual time of choosing transportation mode M from node i to node j for the n times trip, min; $t_{ij}^{m_n^p}$ represents the estimated time of choosing transportation mode M from node i to node j for the n times trip, min.

$$C_{ij}^{M_n}=[c_{ij}^{M_n}+\sigma c_{ij,0}^{M_n}]\cdot d_{ij}^{M_n}-z_{ij}^{M_n}E_{ij}^{M_n} \tag{3}$$

Where, $C_{ij}^{M_n}$ represents the total cost of transportation mode M from node i to node j for the n times trip, yuan; σ is a 0-1 variable, and H is the number of transfers, when H<1, $\sigma=1$, otherwise $\sigma=0$; $c_{ij}^{M_n}$ represents the unit travel cost of transportation mode M from node i to node j for the n times trip, yuan; $c_{ij,0}^{M_n}$ represents the transfer cost from node i to node j for the n times trip, yuan; $E_{ij}^{M_n}$ represents the comfort level when travelers choose transportation mode M from node i to node j for the n times trip, yuan; $z_{ij}^{M_n}$ represents the cost value coefficient of transportation mode M chosen by travelers from node i to node j for the n times trip.

To accurately describe the travelers' travel situation, this paper introduces the fuzzy evaluation model to evaluate travelers' satisfaction, establishes a factor set to represent comfort, reliability, safety, timeliness, cost acceptability, and carbon emissions, and obtains the evaluation result [36].

When travelers prepare for the n times trip, the accumulated travel evaluation results of the previous n-1 trips are used as the preliminary information for the *n-th* trip. If the evaluation result is "satisfactory", then continue to choose the original travel mode. if evaluation result is "unsatisfactory", travelers choose the average unit time and average travel cost of this trip as reference points.

B. Improved Prospect Theory Value Function

Influenced by cultural differences, education levels and other factors, different travelers have different cognition, which makes parameters in prospect theory and cumulative the prospect theory incompatible. Therefore, introduced the utility curve to improve the value function in prospect theory [37].

$$v(T_{ij})=\begin{cases}\varsigma\left((1-\psi)(T_{ij}^{M_n}-\frac{1}{g}\sum_{M=1}^{g}T_{ij}^{M_n})+\psi(T_{ij}^{M_n}-T_{ij}^{M_{n-1}})\right)^{\alpha}, \\ T_{ij}^{M_n}<\frac{1}{g}\sum_{M=1}^{g}T_{ij}^{M_n},T_{ij}^{M_n}<T_{ij}^{M_{n-1}},\psi\in\{0,\quad 1\} \\ -\lambda\left((1-\psi)(\frac{1}{g}\sum_{m=1}^{g}T_{ij}^{M_n}-T_{ij}^{M_n})+\psi(T_{ij}^{M_{n-1}}-T_{ij}^{M_n})\right)^{\beta}, \\ T_{ij}^{M_n}\geq\frac{1}{g}\sum_{M=1}^{g}T_{ij}^{M_n},T_{ij}^{M_n}\geq T_{ij}^{M_{n-1}},\psi\in\{0,\quad 1\}\end{cases} \tag{4}$$

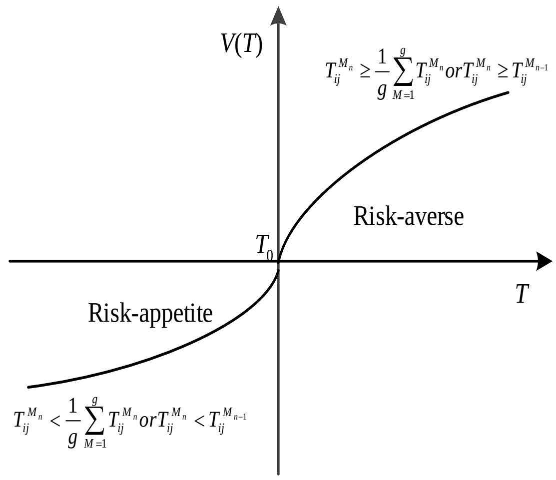

Fig. 3. Value function curve of the time expectation value

$$v(C_{ij})=\begin{cases}\varsigma\left((1-\psi)(C_{ij}^{M_n}-\frac{1}{g}\sum_{M=1}^{g}C_{ij}^{M_n})+\psi(C_{ij}^{M_n}-C_{ij}^{M_{n-1}})\right)^{\alpha}, \\ C_{ij}^{M_n}<\frac{1}{g}\sum_{M=1}^{g}C_{ij}^{M_n},C_{ij}^{M_n}<C_{ij}^{M_{n-1}},\psi\in\{0,\quad 1\} \\ -\lambda\left((1-\psi)(\frac{1}{g}\sum_{m=1}^{g}C_{ij}^{M_n}-C_{ij}^{M_n})+\psi(C_{ij}^{M_{n-1}}-C_{ij}^{M_n})\right)^{\beta}, \\ C_{ij}^{M_n}\geq\frac{1}{g}\sum_{M=1}^{g}C_{ij}^{M_n},C_{ij}^{M_n}\geq C_{ij}^{M_{n-1}},\psi\in\{0,\quad 1\}\end{cases} \tag{5}$$

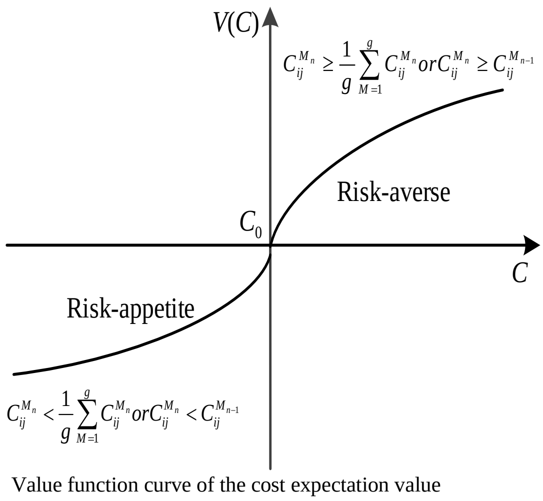

Fig. 4. Value function curve of the cost expectation value

Where, ψ is a 0-1 variable, $\psi=0$ means the evaluation result is unsatisfactory, and $\psi=1$ means the evaluation result is satisfactory; α,β represents risk sensitivity coefficient; ς represents the travelers sensitivity to the gain, λ represents the travelers sensitivity to loss, $\varsigma=1$, $\lambda>1$ represents travelers are more sensitive to losses, $\varsigma>1$, $\lambda=1$ represents travelers are more sensitive to gain; when $0<\alpha\ ,\beta<1$, the travelers tend to adventurous; when $\alpha=\beta=1$, the travelers tend to the middle type; when $\alpha>1$, $\beta>1$ travelers tend to conservative.

C. Subjective Probability Function

The subjective probability function is used to simulate the psychological effect of the travelers. When travelers face losses, they hold the risk preference attitude, while when travelers face the gain, they hold the risk aversion attitude.

$$\varpi(p)=\begin{cases}\varpi^{+}(p)=\dfrac{p^{\gamma}}{\left[p^{\gamma}+(1-p)^{\gamma}\right]^{1/\gamma}}\\ \varpi^{-}(p)=\dfrac{p^{\delta}}{\left[p^{\delta}+(1-p)^{\delta}\right]^{1/\delta}}\end{cases} \tag{6}$$

Where, $\varpi(p)$ represents perceived probability of an event occurring; p represents the actual probability of the trip mode chosen by the travelers; in the case of gain, γ is 0.61, and in the case of loss, δ is 0.69.the subjective probability function curve is shown in Fig. 5.

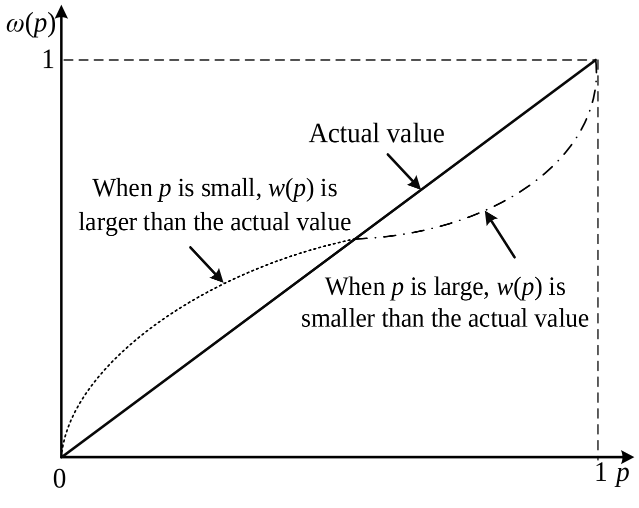

Fig. 5. Subjective probability function curve

III. Model Building

Set dual reference points based on time expectation values and cost expectation values, analyze the behavior theory of the travelers' intermodal transport route selection, and consider the influence of weather, the road crowding and other factors, and use the travelers' expectation trip time and the expectation trip cost as dual objectives, constructing a travelers' intermodal transport route optimization model for travelers under bounded rationality.

$$\max \quad p_1=\sum_{i\in E}\sum_{j\in E}\omega_{ij}\cdot v(T_{ij}) \tag{7}$$

$$\max \quad p_2=\sum_{i\in E}\sum_{j\in E}\omega_{ij}\cdot v(C_{ij}) \tag{8}$$

$$\min \quad p_3=\sum_{i=1}^{n}C_{co_2}=\sum_{m\in M}\sum_{i\in E}\sum_{j\in E}e_{ij}^{M}\cdot d_{ij}^{M}\cdot N\cdot x_{ij}^{M}\cdot S_{ij}^{M} \tag{9}$$

s.t.

$$\sum_{M}x_{ij}^{M}\le 1,\forall i,j \tag{10}$$

$$\sum_{M}\sum_{h}y_{ij}^{Mh}\le 1,\forall i,j \tag{11}$$

$$\sum_{i\in E}\sum_{j\in E}\sum_{m\in M}x_{ij}^{M}-\sum_{i\in E}\sum_{j\in E}\sum_{m\in M}x_{ij}^{M}=1,\forall i=o \tag{12}$$

$$\sum_{i\in E}\sum_{j\in E}\sum_{m\in M}x_{ij}^{M}-\sum_{i\in E}\sum_{j\in E}\sum_{m\in M}x_{ij}^{M}=0 \tag{13}$$

$$\sum_{i\in E}\sum_{j\in E}\sum_{m\in M}x_{ij}^{M}-\sum_{i\in E}\sum_{j\in E}\sum_{m\in M}x_{ij}^{M}=-1,\forall i=d \tag{14}$$

$$\sum_{h}\sum_{M}\sum_{i}\sum_{j}r_{ij}^{hM}\le K \tag{15}$$

Where, e_{ij}^{M} represents the carbon emissions factor of transportation mode M, kg/（per·km) ; N represents the total travel volume of travelers; S_{ij}^{M} represents the share rate of m transportation mode. Constraint (10) represents that travelers can only use one transportation method from node i to node j. Constraint (11) represents that travelers can only make one transfer in the travel process from node i to node j. Constraint (12)-(14) to ensure the continuity of the transportation process, travelers only have a complete route to each destination, and travelers cannot generate an entire route at intermediate nodes. Constraint (15) to prevent travelers from making too many transfers during the trip, set a specified maximum number of transfers.

IV. Algorithm Design

Since the travelers' intermodal transport path optimization problem involves the transformation of several of transportation modes, therefore, a multi-objective hybrid quantum evolutionary algorithm is proposed to solve this problem.

A. Hybrid Quantum Code

The individual in hybrid quantum evolutionary algorithm consists of two parts: binary code and quantum probability vector code. The binary code is used as the current target of the quantum probability vector to participate in the update of the probability vector [38], the first m terms represent the transportation node, and the latter terms represent different modes of transportation.

$$p_i=\Bigg[\underbrace{\begin{vmatrix}\overset{0}{\alpha_{i,1}}\\ \beta_{i,1}\end{vmatrix}\cdots\begin{vmatrix}\overset{1}{\alpha_{i,m}}\\ \beta_{i,m}\end{vmatrix}}_{\text{transport node}}\;\underbrace{\begin{vmatrix}\overset{0}{\alpha_{i,m+1}}\\ \beta_{i,m+1}\end{vmatrix}\cdots\begin{vmatrix}\overset{0}{\alpha_{i,2m}}\\ \beta_{i,2m}\end{vmatrix}}_{\text{mode of transportation 1}}\;\cdots\underbrace{\begin{vmatrix}\overset{0}{\alpha_{i,(n-1)m+1}}\\ \beta_{i,(n-1)m+1}\end{vmatrix}\cdots\begin{vmatrix}\overset{1}{\alpha_{i,nm}}\\ \beta_{i,nm}\end{vmatrix}}_{\text{mode of transportation n}}\Bigg]$$

$$=\Bigg[\underbrace{\begin{vmatrix}\overset{0}{\cos(t_{i,1})}\\ \sin(t_{i,1})\end{vmatrix}\cdots\begin{vmatrix}\overset{1}{\cos(t_{i,m})}\\ \sin(t_{i,m})\end{vmatrix}}_{\text{transport node}}\underbrace{\begin{vmatrix}\overset{0}{\cos(t_{i,m+1})}\\ \sin(t_{i,m+1})\end{vmatrix}\cdots\begin{vmatrix}\overset{0}{\cos(t_{i,2m})}\\ \sin(t_{i,2m})\end{vmatrix}}_{\text{mode of transportation 1}} \tag{16}$$

$$\cdots\underbrace{\begin{vmatrix}\overset{0}{\cos(t_{i,(n-1)m+1})}\\ \sin(t_{i,(n-1)m+1})\end{vmatrix}\cdots\begin{vmatrix}\overset{1}{\cos(t_{i,nm})}\\ \sin(t_{i,nm})\end{vmatrix}}_{\text{mode of transportation n}}\Bigg]$$

Where, α and β satisfy the normalization condition, $t_{i,j}=2\pi r$, r is a random number between (0,1), k is the population size, and n is the quantum number.

B. Qubit Update Strategy

By changing the probability amplitude of the qubit encoding, the chromosome is updated to realize the population evolution, which is updated as follows.

$$U(\theta_i)=\begin{bmatrix}\cos t_{ij}\\ \sin t_{ij}\end{bmatrix}=\begin{bmatrix}\cos\theta_i & -\sin\theta_i\\ \sin\theta_i & \cos\theta\end{bmatrix}\begin{bmatrix}\cos t_{ij}\\ \sin t_{ij}\end{bmatrix}=\begin{bmatrix}\cos(t_{ij}+\theta_i)\\ \sin(t_{ij}+\theta_i)\end{bmatrix} \tag{17}$$

Where, U represents quantum rotation gate; θ represents quantum rotation angle.

The value of θ affects the convergence rate of the population. Too large a deal will lead to premature maturity. The value of θ is generally, to make the convergence rate of the population smoother, designed an adaptive adjustment of θ:

$$\theta_i=\frac{p_n-p_{\min}}{p_{\max}-p_{\min}}\times\Delta\theta \tag{18}$$

Where, p_n represents the fitness value of individual n, the binary coded objective function value is taken as the individual fitness value; $p_{\min}$ represents the minimum fitness value in the population; $p_{\max}$ represents the maximum fitness value in the population, $\Delta\theta=0.05\pi$.

C. Quantum Crossover and Mutation

In order to ensure the diversification of the population, the chromosomes are crossed and mutated, using a single-point mutation strategy. The binary code of the point changes from 1 to 0 or from 0 to 1, the corresponding quantum probability codes α and β exchange the positions. This form of cross-mutation makes trip paths diverse, and only the nodes that travelers pass will mark the mode of transportation.

D. Choice of Solution

The solution obtained by the algorithm is a pareto solution set composed of several non-dominated solutions, which form many alternative schemes. The fuzzy logic method proposed by [39] to select the optimal compromise solution from pareto solution set assists travelers in decision-making and improves the efficiency of route selection.

a. The Score of Each Candidate Solution in Each Target Space in the Pareto Solution Set is Calculated

$$\mu_i=\begin{cases}1 & if \quad p_i\le p_i^{\min}\\ \dfrac{p_i^{\max}-p_i}{p_i^{\max}-p_i^{\min}} & if \quad p_i^{\min}<p_i<p_i^{\max}\\ 0 & if \quad p_i\ge p_i^{\max}\end{cases} \tag{19}$$

Where, $p_i^{\min}$ represents the corresponding minimum value of the *i-th* objective function in all pareto solution sets; $p_i^{\max}$ represents the corresponding maximum value of the *i-th* objective function in all pareto solution sets.

b. The Score of Each Candidate Solution in the Pareto Solution Set is Calculated in the Whole Objective Space

$$\mu[k]=\sum_{i=1}^{N}\mu_i[k]/\sum_{j=1}^{N_{Pareto}}\sum_{i=1}^{N}\mu_i[j] \tag{20}$$

Where, N represents the number of optimization goals; N_{Pareto} represents the number of pareto solution sets; $\mu[k]$ represents score the entire target space, the candidate solution with the highest score is the best compromise solution.

First, judge whether the travelers have prior experience. If yes, consider the satisfaction from the previous experience. If not, follow the following steps:

Step 1: The initial population Q_t was randomly generated to select the trip path and mode.

Step 2: Update by quantum bits, crossover produces offspring population P_t .

Step 3: The parent and offspring populations are merged into a new population $I_t=Q_t\cap P_t$.

Step 4: Non-dominated sorting generates a non-inferior solution set and calculates the crowding degree.

Step 5: According to the crowding degree comparison operator, suitable individuals are selected to enter the next generation until the number of new populations equals the number of initial populations.

Step 6: Let t=t+1 to determine whether the iteration termination condition is met. If it is, the iteration will end. Otherwise, offspring population P_{t+1} will be generated through quantum bits update, crossover, and mutation, and go to step 3.

V. CASE STUDY

The road network of a certain urban agglomeration is shown in Fig. 6 below. It assumed that the main long-distance transportation modes in urban agglomeration are airplanes, high-speed railways, and high-speed buses, and the main short-distance transportation modes are subways, taxis, and buses. Suppose a passenger is ready to depart from the starting point O_1 and arrive at the destination J_{35} .

The fuzzy relation matrix is obtained according to the actual situation when the traveler is known n-1 times before the trip, as shown in Table I.

TABLE I
THE EVALUATION RESULTS OF N-1 TRIPS BEFORE THE TRAVELER

Node	K	Node	K
(O_1, O_2)	0.78	(J_{32}, J_{35})	0.60
(O_1, O_3)	0.63	(J_{33}, J_{35})	0.44
(O_1, O_4)	0.88	(J_{34}, J_{35})	0.60

The corresponding distance, time and transportation arc of each transportation path are shown in Table II, per unit distance transport costs and per unit distance transport speeds are shown in Table III.

TABLE III
TRANSPORTATION COST AND TRANSPORTATION SPEED PER UNIT DISTANCE

Serial number	Mode of transportation	Unit transport cost (yuan/km)	Transportation speed(km/h)
1	Highway	0.2394	100
2	High speed railway	0.3100	250
3	Aviation	0.5569	800
4	Subway	0.5000	80
5	Bus	0.1000	35
6	Taxi	1.3000	60

Carbon emissions and the travel share of various transport modes are the main influencing factors. The carbon emissions of urban transport are estimated according to the number of travelers, travel mode selection, travel share of different travel modes, and other factors.

TABLE II
THE DISTANCE OF THE TRANSPORT PATH

Node	t_{ij} / h	d_{ij}^M / km	Node	t_{ij} / h	d_{ij}^M / km
(O_1, O_2)	0.52	22	(F_{20}, F_{21})	0.5	22
(O_1, O_3)	0.68	27	(F_{20}, F_{22})	0.42	24
(O_1, O_4)	0.35	29	(F_{21}, F_{22})	0.48	20
(B_8, B_9)	0.45	21	(G_{24}, G_{25})	0.43	13
(B_8, B_{10})	0.50	25	(G_{23}, G_{24})	0.50	17
(B_9, B_{10})	0.48	23	(G_{23}, G_{25})	0.48	16
(C_{11}, C_{12})	0.57	19	(H_{26}, H_{27})	0.41	21
(C_{11}, C_{13})	0.43	17	(H_{26}, H_{28})	0.52	22
(C_{12}, C_{13})	0.65	21	(H_{27}, H_{28})	0.38	14
(A_5, A_6)	0.47	17	(I_{30}, I_{31})	0.48	18
(A_5, A_7)	0.47	21	(I_{29}, I_{30})	0.43	13
(A_6, A_7)	0.55	22	(I_{29}, I_{31})	0.51	21
(D_{14}, D_{15})	0.35	19	(J_{32}, J_{35})	0.44	14
(D_{14}, D_{16})	0.33	13	(J_{33}, J_{35})	0.46	16
(D_{15}, D_{16})	0.32	12	(E_{17}, E_{19})	0.47	21
(E_{17}, E_{18})	0.35	15	(E_{18}, E_{19})	0.51	17

C++ language implementation algorithm based on the visual studio 2017 development environment. Due to the heterogeneity of travelers, travelers are divided into three categories: adventurous, intermediate, and conservative. Different types of travelers have other decision-making options in the face of losses and benefits, as shown in Table III and Table IV.

TABLE IV
CARBON EMISSION FACTORS AND TRAVEL SHARING RATES OF VARIOUS TRANSPORTATION MODES

Transportation mode	Bus	Metro	Taxi	Highway	Rail	Air
e_{ij}^M	0.0693	0.0424	0.2000	0.1264	0.0269	0.0986
The share rate	0.21	0.31	0.18	0.15	0.11	0.04

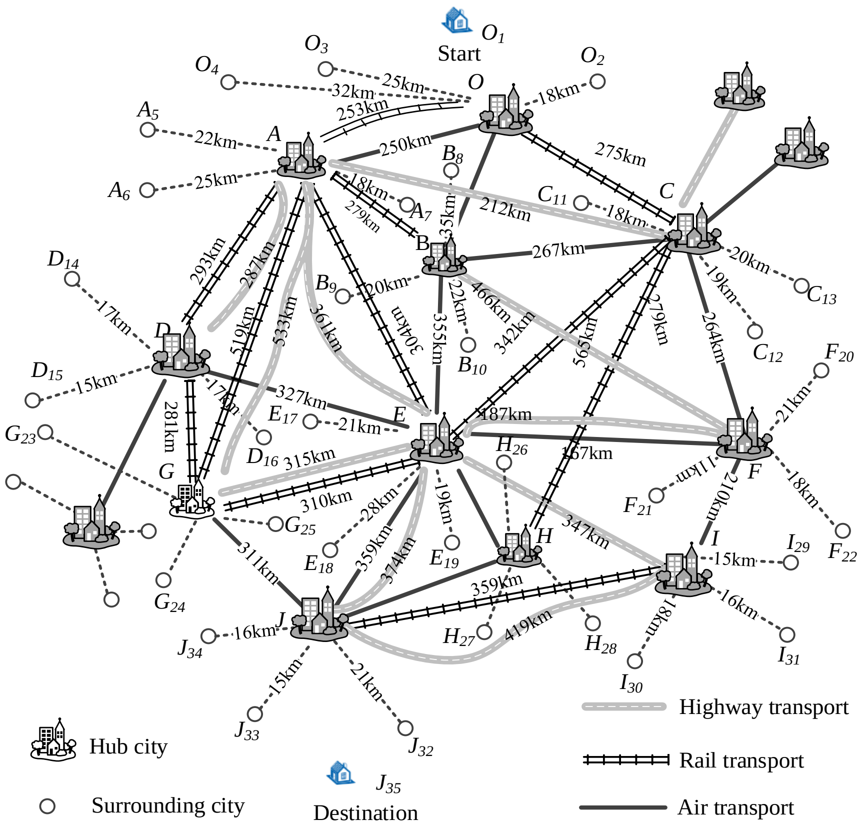

Fig. 6. Virtual transport network

TABLE V
DIFFERENT TYPES OF TRAVELERS PAY MORE ATTENTION TO PATH OPTIMIZATION AT LOSS

	(α，β)	Travel path	Mode of transportation
Adventurous	(0.88，0.88)	1-4-13-19-28-34-35	Bus-Railway-Railway-Railway-Railway-Subway
Intermediate	(1，1)	1-4-10-19-28-32-35	Bus-Railway-Railway-Railway-Railway-Bus
Conservative	(1.12，1.12)	1-4-13-19-28-34-35	Bus-Railway-Railway-Railway-Highway-Bus

Select adventurous travelers who are more sensitive to losses for further analysis. Set the gene mutation probability to 0.75, assuming the total number of travelers traveling that day is 10 million. The generated pareto solution set is shown in Fig. 7.

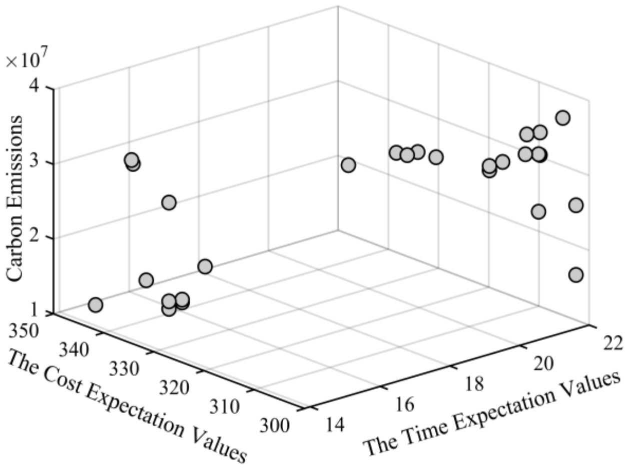

Fig. 7. Distribution of the Pareto solution set

It can be seen from Fig.8, the algorithm is feasible for the travel path optimization problem, and the time expectation values are negatively correlated with the cost expectation values: as the time expectation value increases, the cost expectation value decreases, and carbon emissions are related to the mode and route of travel.

Determine the travelers' sensitivity to expectation time and expectation cost based on the particular scenario. This is shown in Fig. 8.

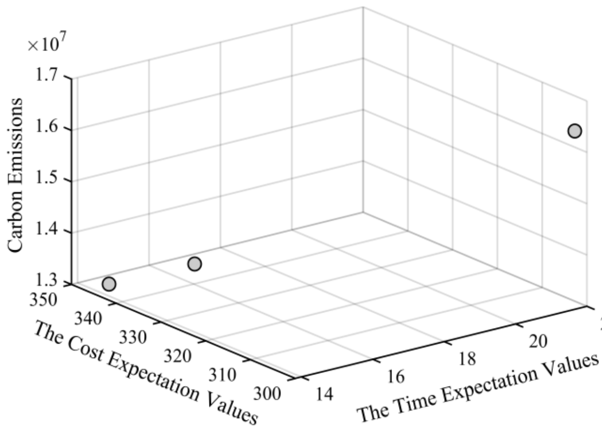

Fig. 8. Objective function values for three special solutions

As can be seen from Fig. 8, for the particular case of the expected time values, that is, when the travelers pay more attention to the time value, the prospect value of the cost will decrease rapidly. For the particular case of the expected cost values, when travelers pay more attention to the cost values, they will spend a lot of time, but relatively speaking, time values are more sensitive.

VI. DISCUSSION AND ANALYSIS

Since travelers are bounded rationality, as shown in Fig. 9 and Fig. 10, the gain sensitivity coefficient and the loss sensitivity coefficient have an impact on the travel time expectation values and travel cost expectation values.

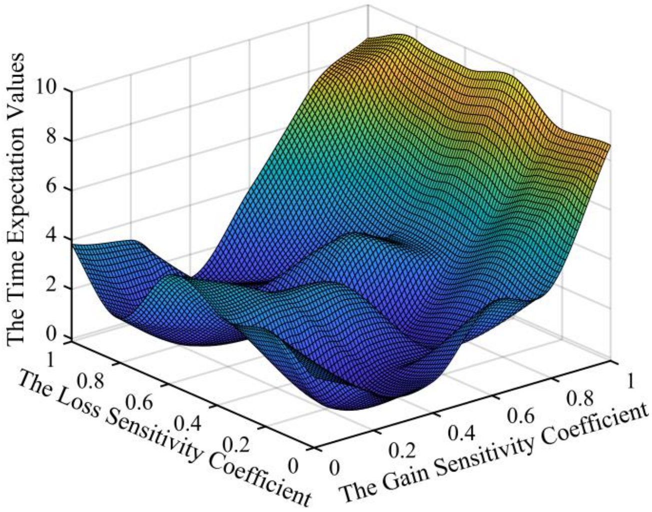

Fig. 9. The effect of value sensitivity coefficient on p_1

As can be seen in Fig. 9, the gain sensitivity coefficient and the loss sensitivity coefficient jointly affect the time expectation values. The impact of the gain sensitivity coefficient on the prospect value is much more significant than that of the loss sensitivity coefficient. The time and cost expectation values are more important than 0, indicating that the travelers' perception of time and cost are beneficial under bounded rationality. The path chosen by the travelers under bounded rationality is more realistic.

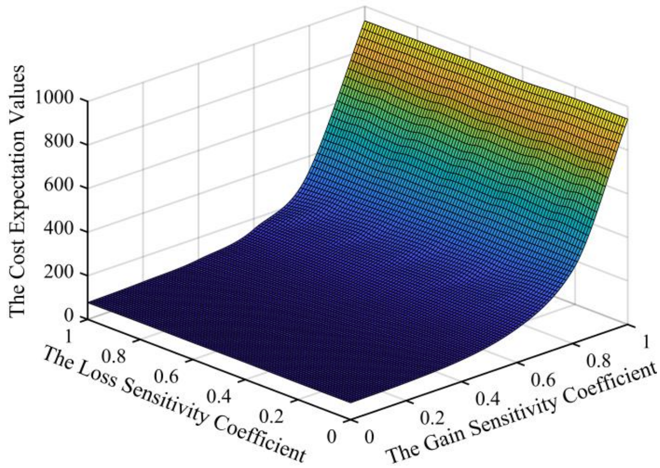

Fig. 10. The effect of value sensitivity coefficient on p_2

TABLE VI
DIFFERENT TYPES OF TRAVELERS MORE ATTENTION TO PATH OPTIMIZATION AT REVENUE

	(α, β)	Travel path	Mode of transportation
Adventurous	(0.88, 0.88)	1-4-13-16-25-34-35	Bus-Railway-Railway-Railway-Highway-Bus
Intermediate	(1, 1)	1-4-10-19-25-32-35	Bus-Railway-Railway-Railway-Railway-Bus
Conservative	(1.12, 1.12)	1-4-13-16-22-25-34-35	Bus-Railway-Railway-Railway-Highway-Bus

It can be seen from Fig. 10 that the time expectation values increase with the gain sensitivity coefficient increase and are not affected by the loss sensitivity coefficient. Both the time and cost expectation values are more significant than 0, indicating that the travelers' perception of time and cost are beneficial under bounded rationality.

As shown in Fig. 11 and Fig. 12, the effect of the weight loss coefficient and the weight gain coefficient on the objective function is shown.

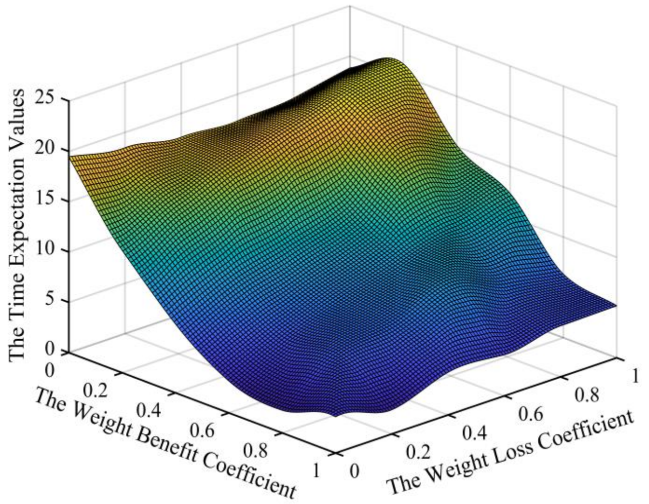

Fig. 11. The effect of weight coefficient on p_1

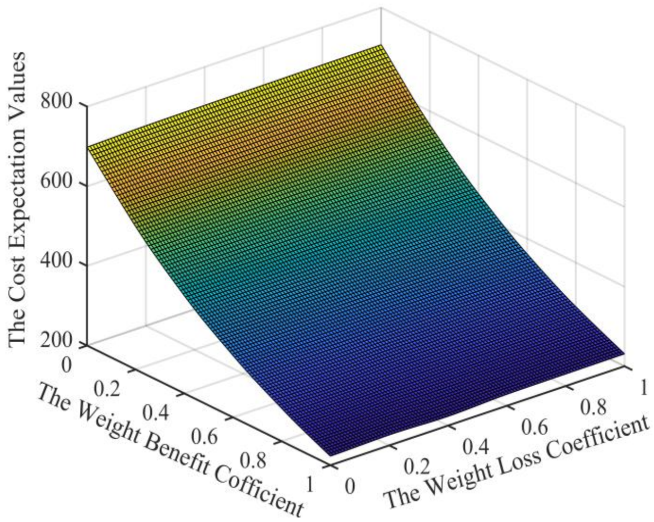

Fig. 12. The effect of weight coefficient on p_2

As can be seen in Fig. 11, the weight loss coefficient and the weight gain coefficient jointly affect the expectation values, with the increase of the weight gain coefficient, the expectation time values fluctuate, and with the increase of the weight loss coefficient, the expectation time values show an upward trend. As can be seen from Fig. 12, the weight loss coefficient is more sensitive than the weight gain coefficient, the cost expectation values decrease with the increase of the weight loss coefficient and increases with the increase of the weight gain coefficient. It can be seen that the travelers' path chosen under bounded rationality is more consistent with the travelers' actual choice.

The weather reduction coefficient, the road crowding coefficient, and the travel time reliability coefficient jointly affect the time expectation values. Fig. 13 to Fig. 16 depict the effect of these three parameters on the time expectation values.

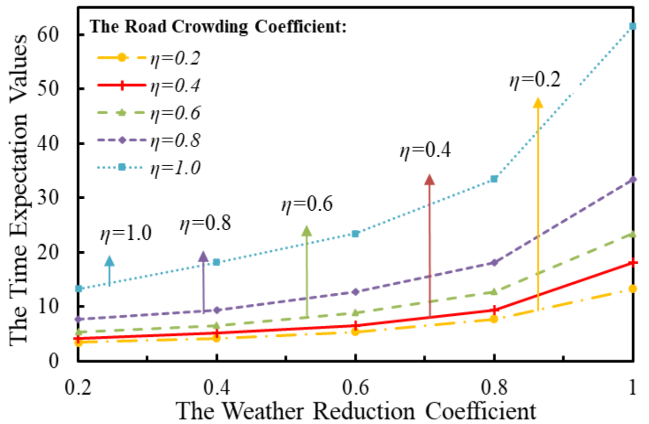

Fig. 13. The effect of the road crowding coefficient and the weather reduction coefficient on p_1

As can be seen from Fig. 13, when the road crowding coefficient is 0.2, and the weather reduction coefficient is 0.2, the road crowding coefficient and the weather reduction coefficient has the most significant influence on the objective function P_1. With the continuous increase of the road crowding coefficient and the weather reduction coefficient, the road traffic is gradually smooth, the weather is gradually better, and the objective function P_1 slowly tends to be stable.

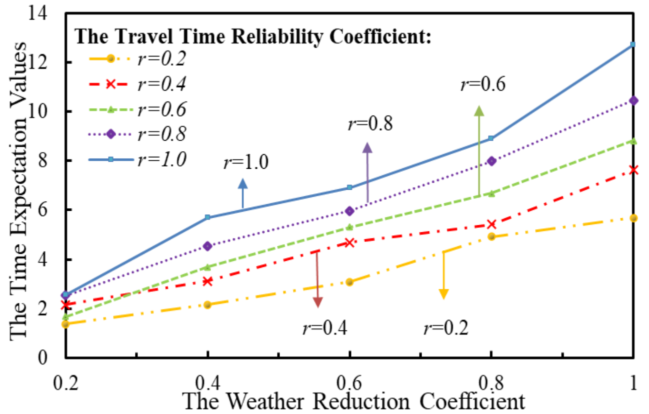

Fig. 14. The effect of the weather reduction coefficient and the travel time reliability coefficient on p_1

As can be seen from Fig. 14, when the weather conditions gradually improve and the punctuality rate of transportation vehicles gradually increases, the time expectation values gradually increase, and both parameters are positively correlated with the time foreground value.

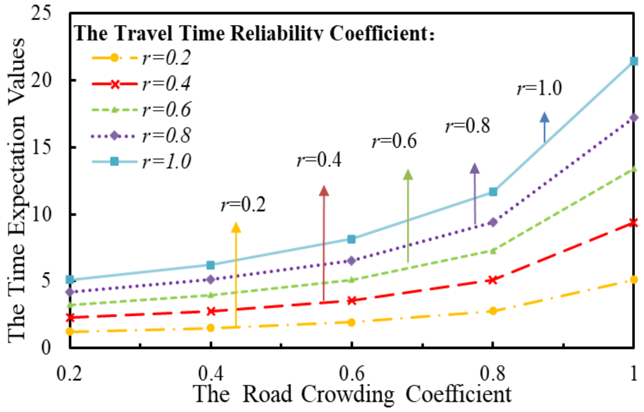

Fig. 15. The effect of the road congestion coefficient and the travel time reliability coefficient on p_1

As shown from Fig. 15, both the road crowding coefficient and the travel time reliability coefficient influences the time expectation values. The time expectation values are more significant than 0, indicating that the travelers' perception of time is beneficial under the road crowding and travel time reliability coefficients.

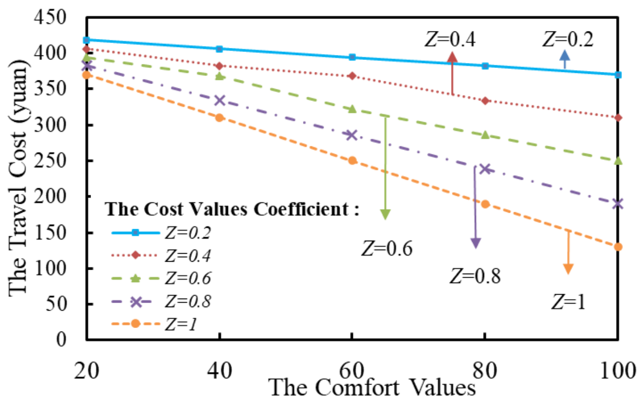

Fig. 16 The effect of the cost values coefficient and the comfort level on the travel cost

As shown in Fig. 16 above, the cost values coefficient and the comfort level impact the travel cost. The cost values coefficient is proportional to the travel cost. In contrast, the cost values coefficient is inversely proportional to the travel cost, which confirms that the more crowded travel tools are, the higher the travel cost.

VII. Concluding

Considering the travelers' bounded rational behavior, the travelers' intermodal transport optimization model is established, and the multi-objective hybrid quantum evolution algorithm is designed to solve the model. The fuzzy logic method is used to find a compromise solution from the pareto solution set, which is used as the travelers' decision scheme. The simulation results show that:

When travelers have prior experience, they can judge their travel paths and modes according to the satisfaction of prior knowledge, which is more realistic than the scheme without previous experience.

Based on considering the time expectation values and the cost expectation values, combined with the carbon emissions of travel, it provides a reference scheme for travelers' travel paths.

Further discussion and analysis are shown road crowding coefficient, the weather reduction coefficient, and the travel time reliability coefficient all affect the time expectation values, but the weather reduction coefficient has a more significant effect on the time expectation values. The road crowding coefficient, the weather reduction coefficient, and the cost value coefficient all influence cost expectation values, but the weather reduction coefficient and the cost value coefficient have a more significant influence on cost prospect value.

In this paper, the heterogeneity of travelers is only considered from the degree of risk of travelers, and the travelers are not refined into specific groups, which will be the content of our subsequent research.

References

[1] T.L. Friesz, "An equivalent optimization problem for combined multiclass distribution, assignment and modal split which obviates symmetry restrictions," *Transportation Research Part B: Methodological*, vol.15, no.5, pp.361-369, 1981.

[2] W.H. Lam, and H.J. Huang, "A combined trip distribution and assignment model for multiple user classes," *Transportation Research Part B: Methodological*, vol.26, no.4, pp.275-287, 1992.

[3] E. Fernández, J. De Cea, M. Florian, and E. Cabrera, "Network equilibrium models with combined modes," *Transportation Science*, vol.28, no.3, pp.182-192, 1994.

[4] H.J. Huang, "Urban Transportation Network Equilibrium Analysis: Theory Practice," *Beijing: China Communications Press*, 1994.

[5] K.N. Ali Safwat, and T.L. Magnanti, "A combined trip generation, trip distribution, modal split, and trip assignment model," *Transportation Science*, vol.22, no.1, pp.14-30, 1988.

[6] M. Florian, J.H. Wu, and S. He, "A multi-class multi-mode variable demand network equilibrium model with hierarchical logit structures," *Springer US*, 119-133, 2002.

[7] H. Yang, and J.Y. Wang, "Park-and-ride location and price optimization in a linear monocentric city with logit-based mode choice," *Transportation in the Information Age: Proceedings of the 7th Conference of Hong Kong Society for Transportation Studies*, pp.345, 2002.

[8] G. Ren, Z.P. Zhou, and H.R. Zhang, "Application of discrete choice model in trip mode structure forecast: a case study of Bengbu," *Journal of Southeast University (English Edition)*, vol.27, no.1, pp.83-87, 2011.

[9] C. Domarchi, A. Tudela, and A. González, "Effect of Attitudes, Habit and Affective Appraisal on Mode Choice: An Application to University Workers," *Transportation*, vol.35, no.5, pp.585-599, 2008.

[10] Z.H. Zhang, H.Z. Guan, H.M. Qin, and Y.Q. Xue, "A traffic mode choice model for the bus user groups based on sp and RP data," *Procedia-Social and Behavioral Sciences*, vol.96, no.6, pp.382-389, 2013.

[11] M. Paulssen, D. Temme, A. Vij, and J.L. Walker, "Values, Attitudes and Travel Behavior: A Hierarchical Latent Variable Mixed Logit Model of Travel Mode Choice," *Transportation*, vol.41, no.4, pp.873-888, 2014.

[12] E. Cherchi, C. Cirillo, J.D. Ortzar, "Modelling Correlation Patterns in Mode Choice Models Estimated on Multiday Travel Data," *Transportation Research Part A: Policy and Practice*, vol.96, pp.146-153, 2017.

[13] C. Thrane, "Examining tourists' long-distance transportation mode choices using a multinomial logit regression model," *Tourism Management Perspectives*, vol.15, pp.115-121, 2015.

[14] K. Liu, and J. Zhou, "Study on the mixed user equilibrium model under the influence of traffic guidance information," *Syst. Eng. Theory Pract*, vol.40, no.2, pp.415-425, 2020.

[15] S. Nurlaela, C. Curtis, "Modeling household residential location choice and travel behavior and its relationship with public transport accessibility," *Procedia-Social and Behavioral Sciences*, vol.54, no.4, pp.56-64, 2012.
[16] X. Xu, A. Chen, S. Kitthamkesorn, H. Yang, and H.K. Lo, "Modeling absolute and relative cost differences in stochastic user equilibrium problem," *Transportation Research Part B: Methodological*, vol.7, pp. 686-703, 2015.
[17] S. Gao, E. Frejinger, M. Ben-Akiva, "Adaptive route choices in risky traffic networks: A prospect theory approach," *Transportation Research Part C: Emerging Technologies*, vol.18, no.5, pp.727-740, 2010.
[18] R.D. Connors, and A. Sumalee, "A network equilibrium model with travelers' perception of stochastic travel times," *Transportation Research Part B: Methodological*, vol.43, no.6, pp.614-624, 2009.
[19] B. LI, and D.A. Hensher, "Risky weighting in discrete choice," *Transportation Research Part B: Methodological*, vol.102, pp.1-21, 2017.
[20] Mahmassani, and S. Hani, "Dynamic network traffic assignment and simulation methodology for advanced system management applications," *Networks and Spatial Economics*, vol.1, no.3, pp.267-292, 2001.
[21] C. Sun, L. Cheng, and J. Ma, "Travel time reliability with boundedly rational travelers," *Transportmetrica A Transport Science*, vol.14, no.3, pp.210-229, 2018.
[22] A. Tversky, and D. Kahneman, "Advances in prospect the ory: Cumulative representation of uncertainty," *Journal of Risk and Uncertainty*, vol.5, no.4, pp.297-323, 1992.
[23] X.F. Pan, and Z. Zuo, "Investigating travelers' heterogeneous attitudes toward losses: insights from a stated preference experiment," *Transportation Letters*, vol.12, no.8, pp.559-569, 2020.
[24] X.Q. Long, J.Q. Song, J.J. Wang, and H.Z. Guan, "Study on traveler's behavior for bounded-rational decision-making," *Highway Transp. Res. Dev*, vol.33, no.5, pp.105-110, 2016.
[25] Z. Zuo, X. Pan, L. Wang, and Feng T., "Stochastic traffic-assignment with multi-modes based on bounded rationality," *In International Symposium for Intelligent Transportation and Smart City. Springer*, Singapore, pp.49-62, 2019.
[26] X.J. Zhang, H.Z. Guan, L. Zhao, and F. Bian, "Nested Logit Model on Travel Mode Choice under boundedly Rational View," *Journal of Transportation Systems Engineering and Information Technology*, vol.18, no.6, pp.110-116, 2018.
[27] W.J. Sun, C.F. Zhu, and K.R. Liu, "Prospect Selection Decisions for Emergency Logistics Paths in Fuzzy Environments," *IAENG International Journal of Applied Mathematics*, vol.53, no.1, pp. 183-193, 2023.
[28] L.J. Tian, Y. Qian, H.J. Huang, and C.R. Lu, "The cumulative prospect theory-based travel mode choice model and its empirical verification," *Systems Engineering-Theory ＆ Practice*, vol.36, no.7, pp.1778-1785, 2016.
[29] H. Xu, Y. Lou, Y. Yin, and J. Zhou, "A prospect-based user equilibrium model with endogenous reference points and its application in congestion pricing," *Transportation Research Part B: Methodological*, vol.45, no.2, pp.311-328, 2011.
[30] H.J. Guo, X.F. Yang, and C.X. Ma, "A Study of travel mode choice of transport corridor based on prospect theory," *Journal of Transport Information and Safety*, vol.37, no.4, pp.120-127, 2019.
[31] J.F. Yang, and G.Y. Jiang, "Development of an enhanced route choice model based on cumulative prospect theory," *Transportation Research Part C: Emerging Technologies*, vol.47, pp.168-178,2014.
[32] J. Mi, and Y. Zhang, "Research of Travel Mode Choice Based on Prospect Theory," *Journal of Transportation Engineering and Information*, vol.13, no.3, pp.81-87, 2015.
[33] X.J. Li, and L.Z. Liu, "Route Choice Model for Commuters Based on Cumulative Prospect Theory," *Journal of Transportation Systems Engineering and Information Technology*, vol.15, no.1, 173-178, 2015.
[34] J.J. Xia, Z.C. Juan, and J.X. Gao, "Travel Routing Behaviors Based on Prospect Theory," *Journal of Highway and Transportation Research and Development*, vol.29, no.4, pp.126-131, 2012.
[35] T. Schwanen, and D.F. Ettema, "Coping with unreliable transportation when collecting children: Examining parents' behavior with cumulative prospect theory," *Transportation Research Part A*, vol.43, no.5, pp.511-525, 2009.
[36] X.L. Shi, "Travel Mode Choice Based on Prospect Theory and Fuzzy Comprehensive evaluation," *Journal of Transportation Engineering and Information*, vol.16, no.3, pp.119-124, 2018.
[37] J. Ma, and X.X. Sun, "Modified Value Function in Prospect Theory Based on Utility Curve," *Information and Control*, vol.40, no.4, pp.501-506, 2011.
[38] P. Xie, B. Li, and Z.Q. Zhuang, "A New Hybrid Quantum Evolutionary Algorithm," *Computer Science*, vol.2, pp.166-170, 2008.
[39] M.A. Abido, "Environmental /economic Power Dispatch Using Multi-Objective Evolutionary Algorithms: A Comparative Study," *Power Systems, IEEE Transactions on Power System*, vol.18, no.4, pp.1529-1537, 2003.

Zongfang Wang was born in Gansu, China, in 1996. She obtained her bachelor degree in Traffic and Transportation from Lanzhou Jiaotong University, Lanzhou, China, in the year 2021. She is currently pursuing her master degree in Traffic and Transportation (the Planning and Management of Traffic and Transportation) in Lanzhou Jiaotong University. Her research interests include route optimization of travelers' intermodal transport and the planning and management of traffic and transportation.