Hindawi
Wireless Communications and Mobile Computing
Volume 2022, Article ID 1288624, 10 pages
https://doi.org/10.1155/2022/1288624

Research Article

Modeling of Mobility as a Service (MaaS) Collaborative Dispatching System of Railway Passenger Transport Hub Based on Neural Network Algorithm

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Received 2 June 2022; Revised 12 July 2022; Accepted 18 July 2022; Published 5 October 2022

Academic Editor: Chia-Huei Wu

In order to solve the modeling problem of travel as a service (MaaS) collaborative dispatching system of railway passenger transport hub based on neural network algorithm, meet people's needs, make up for the lack of high traffic travel pressure, and improve people's living standards, through 30 random questionnaires, it is found that 28 people think that travel convenience improves their quality of life, and 2 people think that owning a car has little effect on travel convenience. Travel has always been people's basic living needs. In recent years, with the improvement of people's living standards, there are more and more urban vehicles. At the same time, the increase of vehicles also directly leads to the increasing pressure of urban traffic travel, and the problems of vehicle emission pollution and traffic congestion are becoming more and more obvious. With the national low-carbon environmental protection policies, green transportation has become the theme of the times. With the continuous development of shared transportation mode and intelligent information technology, the new transportation concept of "Mobility as a Service" based on this technical mode will highly integrate the existing transportation modes and travel services. With the support of MaaS system, people's travel modes will change greatly. Starting with the MaaS cooperative dispatching system of railway passenger transport hub, a multiparameter fuzzy neural network control system dispatching algorithm is proposed to better help the modeling of MaaS cooperative dispatching system of railway passenger transport hub.

1. Introduction

In recent years, with the deepening development of the concept of low-carbon green travel, the field of modern urban transportation has put forward a new transportation concept, MaaS, that is, the concept of Mobility as a Service transportation, with the support of shared transportation mode and intelligent technology. With the help of this concept and system, people will regard travel as a special service, and with the help of this concept, people will no longer need to buy vehicles and other means of transportation in the future, but buy travel services provided by different operators according to their travel destination, distance, location, and other needs. It can be said that the purpose of this concept is to provide corresponding travel solutions based on the travel needs of users [1]. The realization of MaaS collaborative dispatching system of railway passenger transport hub must require the railway passenger transport hub to have good connectivity and provide more convenient services for passengers. Therefore, the collaborative dispatching system is required to provide more reasonable travel choices according to the travel needs of users to the greatest extent. Therefore, based on the neural network algorithm technology, a multiparameter fuzzy neural network algorithm control scheduling algorithm is proposed to better improve the implementation of MaaS collaborative scheduling system of railway passenger transport hub [2].

The scheduler is used to determine the priority of data transmitted by each control loop. The priority of the loop is determined by simultaneous interpreting the network demand parameters obtained from the system error and error rate and the network emergency parameters determined by the idle time. The dynamic weight algorithm is used to optimize the parameter weight to determine the priority, comprehensively considering the impact of various parameters on the loop priority, so as to ensure that the loop with large network demand parameters and small idle parameters has higher priority, and the priority of each loop is adjusted online with the change of parameters [3], as shown in Figure 1.

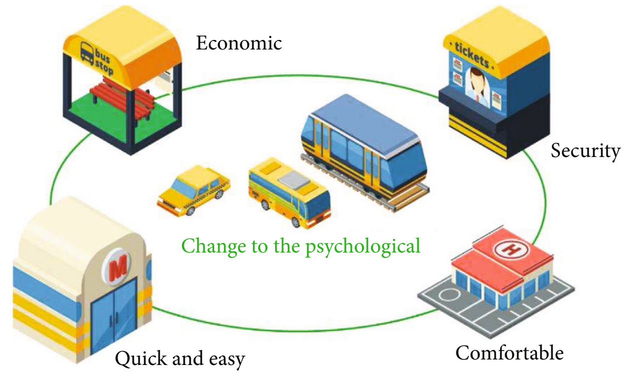

Figure 1: Structure block diagram of multiloop network control system.

2. Literature Review

Marques, B. and others said that in the research of transfer path search algorithm, the k-short circuit algorithm is mainly studied [4]. Chen, Z. believes that in physical networks, the shortest path algorithm is the research hotspot of operations research, automation, computer science and other disciplines, and the core content of resource allocation and traffic network analysis [5]. However, Coles, N. A. said that in the practical application of railway passenger transfer path search, sometimes the shortest path is not the optimal choice of passengers due to its transfer times or arrival time. It is still necessary to solve the second shortest path or the third shortest path and arrange the order of its length increase, which is the k-short circuit algorithm [6]. K-short circuit algorithm is a higher-level search algorithm based on the shortest path search algorithm, which can solve the K-shortest paths from the original point to the target point in the physical network. Compared with the shortest path algorithm, the k-short circuit algorithm is more difficult and complex.

Chalamala, S. R. mentioned that the double sweep algorithm is an effective algorithm for calculating the k-th shortest path, which can calculate the k-th shortest path from a specific vertex to all other vertices in the graph. A fuzzy route selection model based on traveler preference is established, and a mathematical model for counting the number of travelers who do not choose the optimal route is also established. The path generation is based on a selective multistandard method [7]. Ftab, C. describes the route selection behavior of passengers through a random fuzzy utility model. An algorithm is given for the existence of path admissible rings on directed graphs. On the basis of path replacement, a new effective algorithm for simple path is given [8]. Verma, A. A. considers this problem from the perspective of DNA computing. The K-shortest path algorithm of simple path close to the shortest path is given. An algorithm satisfying multiple constraints is given. MacGregor considers the k-shortest path problem in communication networks [9].

Bowers, S. proposed a new k-short circuit algorithm. The algorithm idea is similar to the offset method. Based on the calculation results of the shortest circuit, the required K paths are obtained [10]. Zhang, L. faced with the defects of the traditional Dijkstra algorithm, improved it so that the time complexity of the algorithm is, and everyone reduced its complexity, which is convenient to be realized by program in the computer [11]. Palermos, S. O. based on the directed transfer service network reflecting the passenger travel chain, a k-shortest path algorithm combining splicing and de redundancy is adopted to design and implement the path search system of passenger service network. An algorithm with a complexity of based on dynamic programming is proposed. An improved multilabel K-short path algorithm based on Dijkstra algorithm is proposed [12]. The improved Dijkstra algorithm for solving k-short path with multiple labels is improved, which avoids the emergence of ring in the process of finding k-short circuit, and only needs less additional calculation. The ellipse algorithm is used to limit the path search range for multipath solution, and a path solution algorithm is designed, which is suitable for multiple directed edge complex networks, has low algorithm complexity, has no loop, and is easy to be realized by computer programming. Combined with the characteristics of railway passenger transport network, a hierarchical model of railway network is established, and a K-optimal transfer planning algorithm applied to railway passenger transfer is designed. An automatic reasoning algorithm based on path search is proposed, which turns the search of most paths into the search of one path. The algorithm designed by Li Yinzhen and others uses the threshold as the search constraint, which can greatly improve the calculation speed.

3. Method

3.1. System Structure. Neural network simulates the operation mode of human brain nervous system from the perspective of bionics. It has the functions of self-organization, self-adaptive, and self-learning. In recent years, the fuzzy neural network generated by the cross synthesis of fuzzy control and neural network has become a research hotspot and has been widely used in the field of modeling and control of complex industrial objects [13]. The fuzzy logic rules and membership function in the fuzzy inference system are adjusted by neural network self-learning, which solves the problems of lack of self-learning ability of fuzzy rules and low control accuracy in the fuzzy control system. A traffic flow state prediction algorithm based on Sugeno neuro fuzzy system is designed. The membership function and fuzzy rules of fuzzy inference system are optimized and adjusted by neural network. It is verified that this prediction system has better state prediction performance than conventional fuzzy system. The designed control system is composed of neuro fuzzy predictor and neuro fuzzy controller [14]. A neuro fuzzy control system based on reinforcement learning and the corresponding learning algorithm are proposed, and the online learning of neuro fuzzy controller based on non-training data is realized. The above algorithms are mostly used in controller design, predictive control, model establishment, and parameter optimization, but they are not perfect in the optimal scheduling of networked control system [15].

3.2. Implementation of Network Scheduling Algorithm. Combined with the network demand and network urgency of each control loop, the priority of each loop is determined by dynamic weight algorithm. The processing process of fuzzy neural network scheduling parameters is shown in Figure 2.

For the processing of network demand, the author uses the learning function, associative memory function, and distributed parallel processing function of neural network to realize the expression of fuzzy control rules and knowledge acquisition [16]. The control loop error and the error change rate are used as the input of the fuzzy neural network module, and the network demand is used as the output. When the error and error change rate are large, more network resources need to be allocated. On the contrary, if the error and error change rate are small, less network resources will be allocated. The larger the priority series, the higher the demand of the corresponding control loop network [17]. The fuzzy rules determined according to expert experience are used as the initial training samples of neural network for network training and finally realize the solution of network demand based on fuzzy neural network reasoning [18]. The function curves are shown in Figures 3, 4, and 5, respectively.

Before using the input and output parameter samples of fuzzy control decision table to train the neural network, the training samples should be normalized; that is, all data should be scaled down to a range of no more than 1. After normalization, the control decision is obtained, as shown in Table 1.

The neural network adopts double input and single output BP network with hidden layer of 5 neurons [19]. The training and storage of fuzzy neural network rules need to be realized by programming. The network is trained by function train, and the fitting sampling period is 50 weight adjustment periods. The maximum number of online learning is 20, 000. The network error limit is 0.01. The learning rate is 0.9. After network training and curve fitting, the mapping of fuzzy control rules is completed. The fuzzy rules are stored in the neural network and packaged into a neural network module for the calculation of network demand [20].

In addition to the impact of travel purpose on passengers' transfer behavior, passengers' transfer psychology will also affect their transfer behavior. The transfer psychology of passengers in the transfer process can be summarized as "safe, fast, economical, convenient and comfortable," as shown in Figure 6.

3.3. Network Urgency Parameter Processing. The idle time γ of the task is used as the characterization parameter of network urgency. Since the idle time is an uncertain parameter, the relative deadline is set here to be equal to the cycle of the task, as shown in

$$\gamma_i = T_i - C_i. \tag{1}$$

The network emergency degree of each circuit is shown in

$$R_i = \frac{\gamma_{\max} - \gamma_i}{\gamma_{\max} - \gamma_{\min}}. \tag{2}$$

Considering the control performance of the task and the idle time of the task job, the priority is dynamically adjusted. The author uses the dynamic weight algorithm to determine the dynamic priority of each control loop. If the weight $\omega_i(k)$ is divided into fixed weight $\omega_{0i}(k)$ and compensation weight $\Delta\omega_i(k)$, the weight value of any circuit is shown in the following formulas:

$$\omega_i(k) = \omega_{0i}(k) + \Delta\omega_i(k), \tag{3}$$

$$\omega_{0i}(k) = \{\omega_{01}(k), \omega_{02}(k), \cdots, \omega_{0n}(k)\}, \omega_{0i}(k) \in (0, \max \omega), \tag{4}$$

$$\Delta\omega_i(k) = \{\Delta\omega_1(k), \Delta\omega_2(k), \cdots, \Delta\omega_n(k)\}, \tag{5}$$

$$\Delta\omega_i(k) = [\Delta\omega_{\min}, \max \omega - \omega_{0i}(k)], \tag{6}$$

where $\max \omega$ is the maximum weight coefficient in the system and $\Delta\omega_{\min}$ is the minimum compensation weight coefficient. To sum up, the scheduling algorithm of multiparameter fuzzy neural network is as follows:

(a) The input parameters of fuzzy reasoning are error and error change rate, and the output parameters are network demand. The fuzzy rules are established according to expert experience

(b) The normalization program is used to normalize the fuzzy rules, the BP neural network is used to write the program to realize the training and storage of fuzzy neural rules, and the network demand simulation module is used to solve the network demand parameter VI

(c) Determine the network urgency PI. Substitute the idle time γi and constraints into Equation (1) to calculate the network emergency RI

(d) Determine the priority P_i of each circuit. The weight algorithm is determined according to Equation (2),

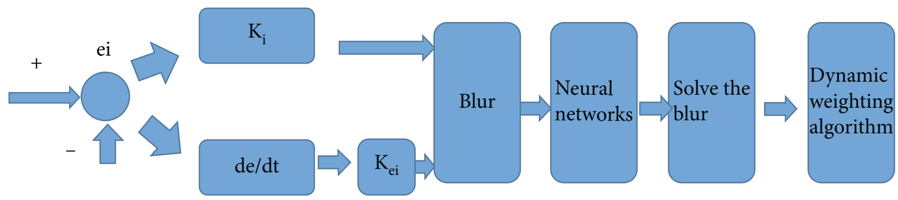

Figure 2: Fuzzy neural network scheduling parameter processing process.

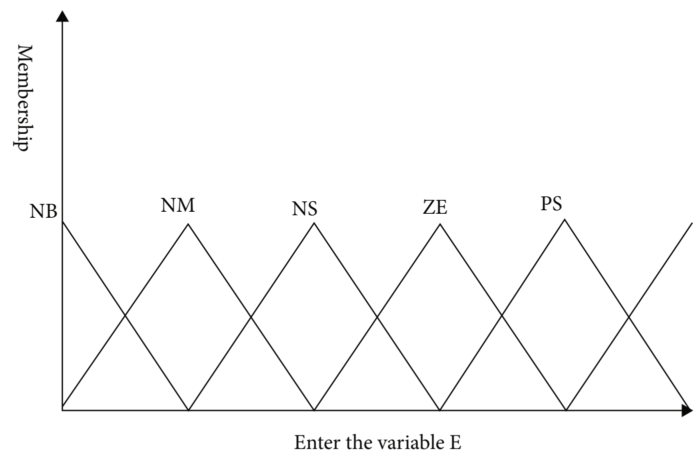

Figure 3: Membership function of input variable e.

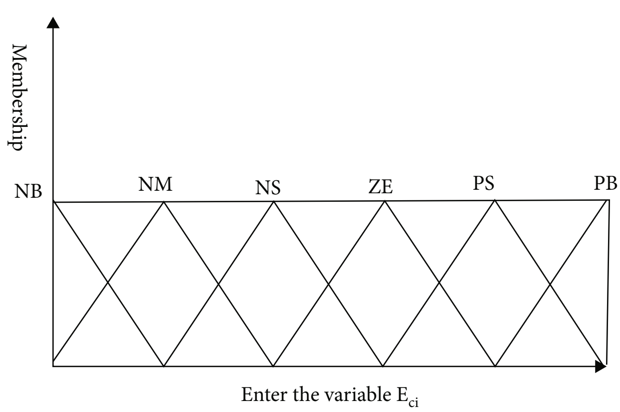

Figure 4: Membership function of input variable E_{ci}.

and the parameter weight value of the priority series is calculated and determined according to Equation (4), and the priority of each circuit is obtained by substituting into Equation (5).

(e) Compare the priority of each circuit and determine the scheduling order of each circuit. If the priority is high, schedule first

4. Results and Analysis

4.1. Elastic Analysis Method. In this paper, point elasticity is used to describe the influence of the change of attribute on the choice of cohesion [21]. The elasticity can be divided into direct elasticity and cross elasticity according to whether the change influencing factors belong to the selection branch of the investigation. Direct elasticity measures the influence of every 1% change in the value of the influencing factor (attribute) in a selection branch of the selection set on the selection probability percentage of the selection branch. The calculation formula is shown in (7) [22]. Cross elasticity is to measure the influence of every 1% change in the value of an influencing factor (attribute) in other selection branches outside the selection branch on the selection probability percentage of a selection branch in the selection set. The calculation formula is shown in the following formulas:

$$E_{X_{\text{ikns}}}^{P_{\text{ins}}} = \frac{\Delta P_{\text{ins}}/P_{\text{ins}}}{\Delta X_{\text{ikns}}/X_{\text{ikns}}} = \frac{\Delta P_{\text{ins}}}{\Delta X_{\text{ikns}}} \cdot \frac{X_{\text{ikns}}}{P_{\text{ins}}}, \tag{7}$$

$$E_{X_{\text{ikns}}}^{P_{\text{jns}}} = \frac{\Delta P_{\text{jns}}/P_{\text{jns}}}{\Delta X_{\text{ikns}}/X_{\text{ikns}}} = \frac{\Delta P_{\text{jns}}}{\Delta X_{\text{ikns}}} \cdot \frac{X_{\text{ikns}}}{P_{\text{jns}}}, \tag{8}$$

where X_{iknx} is the value of the k-th variable of traveler n in selection branch i under scenario s; P_{inx} is the probability of traveler n choosing the i-th branch under scenario s; and P_{jnx} is the probability of traveler n choosing the j-th branch under scenario s.

$$E_{X_{\text{ik}}}^{P_i} = \frac{1}{N}\sum_{n=1}^{N}\sum_{s=1}^{S_n}\frac{P_{\text{ins}}}{\sum_{s=1}^{S_n}P_{\text{ins}}} \cdot \frac{\Delta P_{\text{ins}}/P_{\text{ins}}}{\Delta X_{\text{ikns}}/X_{\text{ikns}}} = \frac{1}{N}\sum_{n=1}^{N}\sum_{s=1}^{S_n}\frac{P_{\text{ins}}}{\sum_{s=1}^{S_n}P_{\text{ins}}} \cdot \frac{\Delta P_{\text{ins}}}{\Delta X_{\text{ikns}}} \cdot \frac{X_{\text{ikns}}}{P_{\text{ins}}}, \tag{9}$$

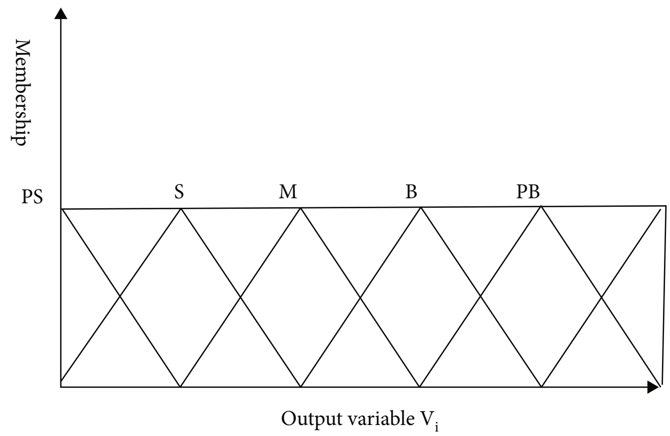

FIGURE 5: Membership function of output variable V_i.

TABLE 1: Normalized fuzzy control decision.

K_{ci}	K_i -1.0	-0.8	-0.6	-0.4	-0.2	0.0
-1.00	1.000	0.981	1.000	0.621	0.386	0.000
-0.75	0.965	0.724	0.697	0.314	0.119	-0.289
-0.50	1.000	0.734	0.584	0.251	-0.251	-0.599
-0.25	0.673	0.495	0.394	-0.117	-0.325	-0.691
0.00	0.584	0.297	0.000	-0.394	-0.684	-1.000

$$E_{X_{\mathrm{ik}}}^{P_j} = \frac{1}{N}\sum_{n=1}^{N}\sum_{s=1}^{S_n}\frac{P_{\mathrm{jns}}}{\sum_{s=1}^{S_n}P_{\mathrm{jns}}}\cdot\frac{\Delta P_{\mathrm{jns}}/P_{\mathrm{jns}}}{\Delta X_{\mathrm{ikns}}/X_{\mathrm{ikns}}} = \frac{1}{N}\sum_{n=1}^{N}\sum_{s=1}^{S_n}\frac{P_{\mathrm{jns}}}{\sum_{s=1}^{S_n}P_{\mathrm{jns}}}\cdot\frac{\Delta P_{\mathrm{jns}}}{\Delta X_{\mathrm{ikns}}}\cdot\frac{X_{\mathrm{ikns}}}{P_{\mathrm{jns}}}. \quad (10)$$

From the definition of elasticity, it can be seen that the calculation results of elasticity value may exist in five states: full elasticity ($E>1$), lack of elasticity ($0<e<1$), single elasticity ($E=1$), complete elasticity ($E=\infty$), and complete inelasticity ($E=0$). When the calculation results of the elasticity value of the adjustment strategy are in different states, the role of the adjustment strategy acting on this way in the coordination process and the specific measures that can be adopted will also be different. In order to more intuitively analyze the impact of different strategies on the choice of passenger connection methods, the elasticity analysis of the above strategies is carried out in combination with the model calibration results in Chapter 5, so as to provide a basis for the selection of system coordination strategies [23].

4.2. Price Adjustment Strategy. In combination with the following two tables, the values in each row, respectively, represent the elasticity results of the cost attribute of a certain mode to the five selected branches, the values on the diagonal of the table represent the direct elasticity, and the rest are the cross elasticity [24]. For example, the first row in Table 2 shows the direct elasticity or cross elasticity of the cost of conventional bus to the connection mode of conventional bus, urban rail transit, taxi, private car, and online car hailing from left to right, as shown in Tables 2 and 3.

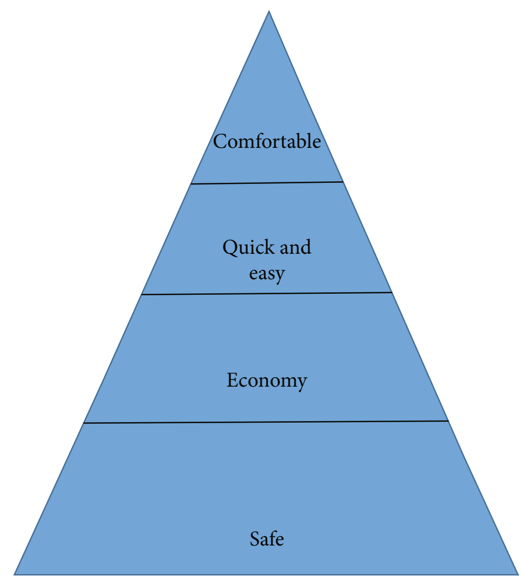

FIGURE 6: Passenger transfer psychology.

From the calculation results of the above two tables, it can be found that the passengers show similar price elasticity characteristics in the direction of gathering and easing [25]. Taking Table 3 as an example, even if the price increases (or decreases) by 100%, the impact on the selection probability of conventional bus or urban rail transit will only decrease (or increase) by about 2%. This may be related to the relatively low price system of China's public transport system. At the same time, although the direct price elasticity of taxis, private cars, and online car hailing is large, it is different from the results of taxi price elasticity >1 found in some empirical studies aimed at commuting [26]. This may be related to the occasional characteristics of passengers choosing connecting transportation mode to railway stations in this study. Travelers do not need to pay the connecting travel expenses on a daily basis, and the connecting travel expenses belong to small expenses compared with the

Table 2: Cost elasticity of gathering and connecting trips.

Cost	Bus	Subway	Taxi	Car	Car hailing
Bus	-0.0214	0.0013	0.0013	0.0011	0.0013
Subway	0.0247	-0.0111	0.0129	0.0129	0.0147
Taxi	0.0321	0.0274	-0.2314	0.0574	0.0477
Car	0.0192	0.0184	0.0341	-0.2214	0.0331
Car hailing	0.0521	0.0354	0.0769	0.0857	-0.2187

Table 3: Ease the cost elasticity of connecting trips.

Cost	Bus	Subway	Taxi	Car	Car hailing
Bus	-0.0127	0.0013	0.0011	0.0012	0.0014
Subway	0.0114	-0.0119	0.0097	0.0112	0.0107
Taxi	0.0271	0.0274	-0.1704	0.0971	0.0341
Car	0.0117	0.0124	0.0353	-0.2155	0.0171
Car hailing	0.0412	0.0344	0.0345	0.0371	-0.1746

railway train tickets for railway travel, so travelers have a higher ability to accept the connecting travel expenses. In addition, the cross price elasticity of each mode is small, indicating that the price substitution of each mode is weak; that is, the price adjustment will not cause obvious transfer of passenger connection modes [27].

4.3. In Car Time Adjustment Strategy. Combining Equations (9) and (10), we can get the time elasticity in the vehicle of various ways of gathering and easing the connecting journey, as shown in Tables 4 and 5.

It can be found that passengers show similar characteristics of in vehicle time elasticity in the direction of gathering and easing. Taking the aggregation and connection journey in Table 4 as an example, from the perspective of direct elasticity, the direct elasticity of time in conventional buses is the highest and that in urban rail transit is the lowest [28]. From the results of cross elasticity, the in vehicle time of urban rail transit has great cross elasticity to conventional public transport, but otherwise, it shows that the mutual substitution between urban rail transit and conventional public transport is asymmetric [29].

The analysis of time elasticity in the car shows that when the in car time adjustment strategy is used to optimize the connection system, the passenger selection probability of various connection modes can be increased to varying degrees by shortening the in car time. The corresponding specific measures may include reconstruction of bus lanes, optimization of bus lines (reducing stops), BRT, and cross station rail transit [30]. As the in vehicle time elasticity of conventional bus is greater than that of urban rail transit, it shows that the effect of increasing the selection probability of conventional bus through BRT and bus signal priority is more effective than that of improving the selection probability of urban rail transit by organizing inter station stop express trains.

4.4. Waiting Time Adjustment Strategy. According to formulas (9) and (10) and the above model calibration results, the influence of the waiting time change of each connection mode on the selection results of passenger connection modes in the aggregation and relief connection journey is obtained, as shown in Tables 6 and 7 [31].

Table 4: In vehicle time elasticity of aggregation and connection journey.

Cost	Bus	Subway	Taxi	Car	Car hailing
Bus	-0.5572	0.0371	0.0240	0.0219	0.0271
Subway	0.2401	-0.1055	0.1128	0.1145	0.1098
Taxi	0.0348	0.0274	-0.2419	0.0510	0.0441
Car	0.0271	0.0219	0.0371	-0.2721	0.0394
Car hailing	0.0641	0.0410	0.0597	0.0781	-0.2264

Taking the waiting time elasticity of aggregation connection trip as an example, the elasticity value of waiting time to selection mode generally meets $0 < E < 1$, showing the result of lack of elasticity. The direct elasticity of waiting time of urban rail transit and network car hailing is small. Since the model does not consider the waiting time of private cars, there is no direct elastic calculation result of waiting time of private cars in the table.

4.5. Calculation of Waiting Time Value. In the utility function, the willingness to pay for waiting time is the marginal substitution ratio between waiting time and cost attributes. In the utility function modeling, it is considered that the time value of individual passengers is certain, and different passengers choose connecting transportation modes with different time service levels because of different time value. According to the different expression of utility function of individual passenger and sample population, the time value of individual passenger and sample population can be obtained, respectively [32, 33]. Let x_k represent the waiting time attribute in the selection branch, the corresponding parameter calibration result is β_k, x_m is the cost attribute in the selection branch, and the corresponding parameter calibration result is β_m. V_{nsj} is the observable utility of the selected branch j to the respondent n under the test scenario s. The waiting time and willingness to pay of the attribute k of the respondent n in the selected branch j under the selected scenario s are shown in

$$\mathrm{WTP}_{\mathrm{msjk}} = \frac{\Delta x_k}{\Delta x_m} = \frac{\partial V_{\mathrm{nsj}}/\partial_{x_k}}{\partial V_{\mathrm{nsj}}/\partial_{x_m}} = \frac{\beta_k}{\beta_m}. \tag{11}$$

From the perspective of sample population, the willingness to pay of attribute K in branch J is the expectation of individuals in different scenarios. The same selection probability weighting method (pwt) as the elastic analysis part is adopted, as shown in

$$\mathrm{WTP}_{\mathrm{jk}} = \frac{1}{N}\sum_{n=1}^{N}\sum_{s=1}^{S_n}\frac{P_{\mathrm{ins}}}{\sum_{s=1}^{S_n} P_{\mathrm{ins}}} \cdot \mathrm{WTP}_{\mathrm{nsjk}}. \tag{12}$$

In the hybrid model, the parameter estimation vector of

Table 5: Time elasticity in the vehicle for relieving the connection journey.

Cost	Bus	Subway	Taxi	Car	Car hailing
Bus	-0.6914	0.0748	0.0591	0.0541	0.0857
Subway	0.2648	-0.2481	0.1798	0.2087	0.2817
Taxi	0.0614	0.0491	-0.3815	0.1941	0.0911
Car	0.0271	0.0314	0.0778	-0.5109	0.0341
Car hailing	0.1065	0.0914	0.0775	0.0704	-0.4269

Table 6: Waiting time elasticity of gathering and connecting journey.

Cost	Bus	Subway	Taxi	Car	Car hailing
Bus	-0.1522	0.0087	0.0094	0.0077	0.0124
Subway	0.0562	-0.0341	0.0544	0.0519	0.0412
Taxi	0.0144	0.0107	-0.1087	0.0257	0.0219
Car hailing	0.0123	0.0071	0.0187	0.0244	-0.0514

Table 7: Elasticity of waiting time for easing connection travel.

Cost	Bus	Subway	Taxi	Car	Car hailing
Bus	-0.1084	0.0111	0.0102	0.0109	0.0140
Subway	0.0377	-0.0371	0.0354	0.0374	0.0351
Taxi	0.0144	0.0114	-0.0745	0.0465	0.0151
Car hailing	0.0089	0.0071	0.01098	0.0074	-0.0401

the interviewed individual n is shown in

$$\widehat{\beta}_n = \sum_{c=1}^{C} \widehat{H}_{c|n} \widehat{\beta}_c, \quad (13)$$

where $\widehat{\beta}_c$ is the parameter calibration result of the respondent in category c. $\widehat{H}_{c|n}$ is the posterior probability that respondent n belongs to category c.

Bring formula (13) into formula (12) to obtain the expression of willingness to pay for the selected branch j attribute k in the sample population, as shown in

$$\mathrm{WTP}_{\mathrm{jk}} = \frac{1}{N} \sum_{n=1}^{N} \sum_{s=1}^{S_n} \frac{P_{\mathrm{ins}}}{\sum_{s=1}^{S_n} P_{\mathrm{ins}}} \cdot \frac{\sum_{c=1}^{C} \widehat{H}_{c|n} \beta_k}{\sum_{c=1}^{C} \widehat{H}_{c|n} \beta_m}. \quad (14)$$

Calculate the individual waiting time value of the interviewed passengers in the convergence direction of gathering and easing according to Equation (11), and draw the cumulative distribution curve of waiting time value. It can be found that the individual waiting time of the interviewed passengers who ease the connection direction presents a uniform distribution due to the homogenization preference assumption of the model. The cumulative distribution curve of passenger waiting time in the convergence direction shows obvious segmentation characteristics, as shown in Figure 7.

Calculate the overall waiting time value of the sample of the interviewed passengers in the convergence direction of gathering and easing according to Equation (14), and different types of passengers in the convergence direction of gathering have different waiting time values. Easing the connection direction has the same waiting time value for passengers, as shown in Table 8.

Each group of solutions in the Leto solution set contains the completion of different subobjectives. It is necessary to further select the most representative scheme as the recommended scheme for decision-making. Considering the fuzzy characteristics in the decision-making problem, the fuzzy membership method is used to calculate the best compromise solution. The membership degree is usually calculated in combination with the maximum and minimum values of the subobjective function in the Pareto solution set, and the optimization degree of the subobjective corresponding to each nondominated solution is quantified by the fuzzy membership degree value bounded by [0,1]: The larger the membership function value is, the higher the optimization degree of the corresponding subobjective is. Because the multiobjective model in this paper aims at minimizing the value, assuming that the membership function is a strictly monotonically decreasing continuous function, the following functions are selected to calculate the membership value. After obtaining the membership values of the subgoals in each group of Pareto solutions, the sum of the membership values of each subgoal can be calculated and normalized to express the degree of completion of each group of nondominated solutions to the overall goal in the Pareto solution set, and then the optimal compromise solution can be selected. Let μk represent the membership function value of the group k Pareto optimal solution to the total objective, as shown in

$$\mu_k = \frac{\sum_{i=1}^{2} \omega_i \cdot \mu_{\mathrm{ik}}}{\sum_{k=1}^{q} \sum_{i=1}^{2} \omega_i \cdot \mu_{\mathrm{ik}}}, \quad (15)$$

where ω_i is the membership weight of subobjectives given to decision-makers, as shown in

$$\sum_{i=1}^{2} \omega_i = 1. \quad (16)$$

Then, the screening decision rule of the optimal compromise solution is shown in

$$\max\left(\mu_k : k = 1, 2, \cdots, q\right). \quad (17)$$

That is, when the total objective membership function value is the largest, the corresponding nondominated solution is the best compromise solution. It can be observed that the decision-maker's weighting of operator cost and passenger waiting time cost may affect the choice of the best compromise solution.

This paper mainly studies the coordination optimization model of connection system under the heterogeneous demand elasticity of passenger connection mode selection. Firstly, based on the calibration results of passenger transfer

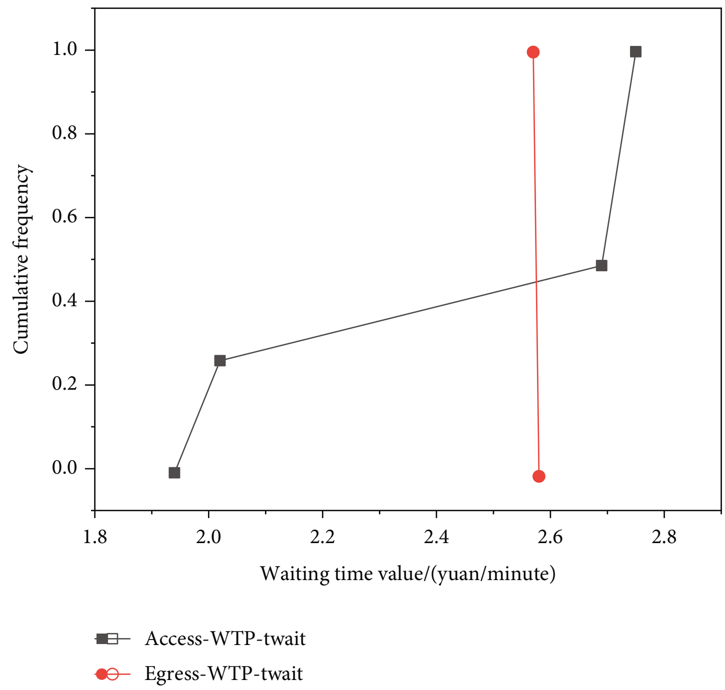

Figure 7: Line chart of cumulative frequency of willingness to pay for waiting time.

Table 8: Calculation results of overall waiting time value of interviewed passengers.

	Convergence direction (yuan/minute)		Ease the connection direction (yuan/minute)	
Passenger classification	Proportion	wtp-wait	Proportion	wtp-wait
FAA	15.53%	2.743	14.10%	2.570
ANA	47.51%	2.743	31.30%	2.570
ACMA	15.29%	1.942	10.20%	2.570
ACMA-ANA	21.67%	1.942	44.40%	2.570

behavior analysis model in Chapter 5, the elasticity analysis method is used to analyze the elasticity value of three coordination strategies of price adjustment, in vehicle time adjustment and waiting time adjustment and their feasibility in the existing traffic policy environment, and the waiting time adjustment strategy is selected for subsequent coordination modeling analysis. This paper uses the willingness to pay method to calculate the important parameter "passenger connection waiting time value" in the coordination of the connection system. Then, under the two coordination and management mechanisms of centralized command and self-organization, the ability coordination and time coordination of the connection system are jointly modeled. Among them, the coordination modeling of the connection system under the centralized command mechanism fully combines the heterogeneous demand elasticity of passenger connection mode selection behavior, takes the average waiting time of passengers in each connection mode as the variable, takes the minimum operation cost of the connection system and the minimum waiting time cost of passengers as the double objectives, and considers the transportation capacity constraints and departure interval constraints of the connection mode to construct a multiobjective optimization model. According to the characteristics of Pareto solution set in the solution of multiobjective optimization problem, the solution algorithm based on Nsgaii and the best compromise solution selection method based on fuzzy membership are designed. The coordination modeling of cohesion system under self-organization mechanism takes each cohesion mode as the player. Considering the heterogeneous demand elasticity of passenger connection mode selection behavior, taking the average waiting time of connection mode as the strategy set, the self-income of each connection mode as the payment function, and the transportation capacity and departure interval of connection mode as the constraints, the generalized Nash equilibrium game model of operators of each connection mode is constructed to describe the competitive behavior between connection modes. The existence of generalized Nash equilibrium solution is proved, which is transformed into a nonlinear programming problem with nonlinear constraints, and a genetic algorithm is designed to solve it [34].

Taking Chengdu East Railway Station as the background, the multiobjective optimization model of centralized command mechanism and the generalized Nash equilibrium game model of self-organization mechanism are analyzed. The results show that:

① Both coordination mechanisms can fully consider the interaction between the change of waiting time service level of connection mode and the selection behavior of passengers' connection mode, and make strategy selection from their respective perspectives, so as to obtain less system operation cost, passenger waiting time cost, total cost of participants in connection system and more benefits of connection system operators

② The centralized command mechanism can better balance the total cost of the three main participants: operators, passengers, and government management departments, and is more conducive to the overall cost savings of the system. However, we need to pay attention to the possible negative benefits of conventional bus operators caused by the goal of minimizing passenger waiting time. In the process of implementation, corresponding institutions are needed to carry out service level formulation and coordinate the relationship between operators

③ The self-organization mechanism evolves the game with the maximum benefits of the operators in the connection mode. In the equilibrium state, the total income of the connection system is better than the current value and the coordination state value of the centralized command mechanism, but the self-organization mechanism can not only guarantee to improve the income limit of each connection subsystem, but also will bring higher passenger waiting cost and total system cost than the centralized command mechanism

Based on the above analysis, policy suggestions are given: ① The interactive relationship between service level and passenger behavior should be considered in the coordination and management of railway passenger transport hub connection system. ② Pay attention to the time difference in the coordination and management of the connection system of railway passenger transport hub. ③ It is suggested to adopt the coordination and optimization method of centralized command mechanism in management.

5. Conclusion

This paper studies the investigation and experimental design strategy of connecting and transferring behavior of railway gathering and relieving passengers, the analysis and modeling of connecting and transferring behavior considering composite heterogeneity, the value of waiting time of connecting and transferring passengers, and the coordination modeling technology of connecting system considering heterogeneous demand elasticity. A compound heterogeneity model of transfer behavior analysis is proposed, which can simultaneously express the double heterogeneity of attribute preference and attribute processing of the interviewed passengers, which improves the interpretation ability of the transfer behavior analysis model, expands the all attribute processing hypothesis in the traditional discrete selection model, and makes up for the defect that only the heterogeneity of attribute preference can be described. The model deals with the heterogeneity of the attributes of the interviewed passengers found in the process of data investigation, introduces the indicator variable and combined weighting parameter variable into the utility function, and realizes the composite expression of composite heterogeneity in the discrete selection model combined with the discrete preference distribution description of passenger preference heterogeneity. It proves the feasibility of modeling the Mobility as a Service(MaaS) collaborative dispatching system of railway passenger transport hub based on neural network algorithm, which can effectively solve the problem of people's travel, meet people's demand for convenient travel, make up for the shortage of high traffic travel pressure, and improve people's living standards.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this article.

Acknowledgments

This work was supported by the Sichuan Science and Technology Plan Project Research on the Theory and Methodology of Mobility as a Service (MaaS) System Planning for Integrated Passenger Transport Hub (project no. 2021YJ0076).

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