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Research Article

Hybrid Random Regret Minimization and Random Utility Maximization in the Context of Schedule-Based Urban Rail Transit Assignment

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Route choice is one of the most critical passenger behaviors in public transit research. The utility maximization theory is generally used to model passengers' route choice behavior in a public transit network in previous research. However, researchers have found that passenger behavior is far more complicated than a single utility maximization assumption. Some passengers tend to maximize their utility while others would minimize their regrets. In this paper, a schedule-based transit assignment model based on the hybrid of utility maximization and regret minimization is proposed to study the passenger route choice behavior in an urban rail transit network. Firstly, based on the smart card data, the space-time expanded network in an urban rail transit was constructed. Then, it adapts the utility maximization (RUM) and the regret minimization theory (RRM) to analyze and model the passenger route choice behavior independently. The utility values and the regret values are calculated with the utility and the regret functions. A transit assignment model is established based on a hybrid of the random utility maximization and the random regret minimization (RURM) with two kinds of hybrid rules, namely, attribute level hybrid and decision level hybrid. The models are solved by the method of successive algorithm. Finally, the hybrid assignment models are applied to Beijing urban rail transit network for validation. The result shows that RRM and RUM make no significant difference for OD pairs with only two alternative routes. For those with more than two alternative routes, the performance of RRM and RUM is different. RRM is slightly better than RUM in some of the OD pairs, while for the other OD pairs, the results are opposite. Moreover, it shows that the crowd would only influence the regret value of OD pair with more commuters. We conclude that compared with RUM and RRM, the hybrid model RURM is more general.

1. Introduction

Analysis of travelers' route choice behavior is very important for daily urban rail transit operation. However, for a complex urban rail transit network, passengers' route cannot usually be obtained directly, because only the departure and destination station are recorded in smart card data records in most urban rail transit networks. In this situation, passengers travel route choice can be estimated through a transit assignment model given OD demand data and train timetable. The accuracy of the estimation is highly dependent on the extent to which the model can reflect the realized passenger behaviors.

The majority of existing studies of traveler's route choice behavior are based on the random utility maximization (RUM) [1]. These RUM models assume that when faced with a number of travel choice options, a traveler is rational enough and he or she will choose the one that has the highest utility value according to the information which was obtained by the traveler. However, it is difficult to fully get the accurate traffic information for the travelers. Moreover, the travelers' route choices are affected by their preferences and attitudes, and the practical behavior of travelers' route choice does not fully respect the axiomatic system of expected utility theory. So many scholars try to find a more realistic theory than RUM theory to explain and describe travelers' route choice behavior. Among them, Loomes and Sudgen in 1982 and Bell in [2] independently proposed a regret theory, and they pointed out that the single factor's utility function cannot explain the behavior of nonrational decision well. People would compare the actual situation and possible situations according to their decision-making factors. If they find the chosen one can get better results than other options, they tend to rejoice. Otherwise, they would feel regret. Based on the regret theory, Casper proposed a random regret minimization (RRM) model. RRM supposed that the satisfaction degree of a travel route depends not only on the utility of selected travel route, but also on the regret of other options [3].

Sociologists found that human behavior is far more complicated than a single standard [4]. Some people tend to maximize their utility while others would minimize their regret. This is also obvious from the travelers' behavior in route choice. Passengers may not choose a faster but unfamiliar route, because they try to avoid regret from choosing the route. Moreover, for different user class, the degree of maximizing utility and minimizing the regret may be also different. Any single standard behavior assumption may not fully explain the complex route choice behavior of passengers. Based on this, this study tries to answer the research questions as follows: What is the outcome of hybrid of utility maximization and regret minimization? Which behavior assumption reflects the route choice behavior more accurately in urban rail transit?

In this study, the hybrid route choice behaviors of random utility maximization and random regret minimization are proposed and formulated to analyze the travelers' route choice for an urban rail transit network. Although the regret theory has been applied to many fields, including road traffic assignment [5, 6], to the best of the author's knowledge, this is the first research which applies the hybrid of utility theory and regret theory in the context of an urban rail transit. Different from cars on a road network where many routes can be selected, passengers in an urban rail transit network have less choices. Besides, the behaviors of drivers and passengers are different. Therefore, it is worth testing whether the hybrid of two kinds of behavioral assumptions is effective on an urban rail transit. The hybrid route choice was applied to a space-time expanded network. Till now, most transit assignment models considering the regret are based on the frequency and a physical network, which belongs to the frequency-based assignment. This research applies the regret to a schedule-based transit assignment by constructing a space-time expanded network from smart card data. Moreover, passengers' heterogeneous choice behavior (e.g., regret, disappointment) is neglected in most previous studies. This paper incorporates regret minimization and utility maximization into a transit assignment model to characterize travelers' route choice behavior. Two types of hybrid rules are considered, namely, attributes level hybrid rule and decision level hybrid rule. The effects of both of the hybrid rules are discussed. The model is applied to a real world case study in Beijing urban rail transit network. The effectiveness of the model is validated by the travel time estimated from smart card data. Compared with existing validation data relying on empirical investigation, using smart card data is more objective.

The remainder of the paper is organized as follows. Section 2 is the literature review. Section 3 proposes some basic assumptions and terminologies; Section 4 proposes the methodology. After that, Section 5 explains the MSA algorithm for solving the model. Furthermore, Section 6 applies the method to Beijing metro network, showing the effect of attributes level hybrid rule and decision level hybrid rule. Finally, Section 7 draws the conclusion.

2. Literature Review

The existing transit assignment models can be classified into frequency-based assignment models [7] which are known as "line-oriented" and schedule-based model [8] which are known as "run or vehicle-oriented" [9]. The former assigns the traffic to a service transit lines, while the latter assigns the traffic to service runs. Due to strong capability of assignment of the dynamic assignment model, we are in particular interested in the latter one.

On frequency-based transit network, each train on transit lines is supposed to run with a constant headway, and the network is represented in a static manner. Generally the procedures of the assignments include 3 steps: path searching, path choice probability estimation, and traffic assignment. The first step searches effect and possible path between all O-D pairs of the network. In the second step, we compare each path in the effect and possible path set by the generalized cost function or utility function individually. With the cost distribution function, the path choice probability can be estimated. Finally, we assign the demand to paths with the path probability by O-D demand matrixes. Frequency-based transit assignment models always consider a constant demand and minimize the path cost [10] or optimize the strategy choice [11] of individual passengers, which is similar to user equilibrium assignment on network. Schmöcker et al. [12] proposed an assignment model based on frequency of departure. The model considered the probability of passengers finding seats in their perception of route cost. They introduced the probability of "fail-to-sit" at boarding points to calculate the travel cost and distribute the passenger flow. Zhang et al. proposed an assignment model based on frequency considering day-to-day evolution under oversaturated conditions and studied the impact of passenger comfort on the overload conditions and frequency of departure on passenger route selection [13]. Leurent et al. considered the capacity and provided a static and macroscopic traffic assignment model from the line submodel and the network [14]. As the frequency-based assignment model usually assigns the passenger based on a physical topology network, another important concept on frequency-based transit model is based on hyperpaths approaches. Hyperpaths form a directed acyclic graph with a flow distribution rule in network representation. Wu et al. [15] firstly proposed the hyperpath concept with strategy-based transit link cost function. Kurauchi et al. [16] also introduced traffic split in hyperpaths of transit network. For the majority of these models, schedule of transit system is assumed to be sufficiently reliable. Therefore the headway is calculated by the average frequencies of transit line in frequency-based network. And the waiting time and transfer time are implicitly estimated based on headway. Since the time dimension is not considered in frequency-based transit model, the assignment results in frequency-based models are the average value in the specified time period (e.g., the rush hour).

Unlike frequency-based type model, schedule-based models generally take into account explicitly timetable or schedule of the transit system, which means that the detailed departure or arrival times of vehicles in each transit lines are used in assignment procedures. On the other hand, schedule-based assignment model considers the temporal and spatial structure of travel demand on the network; therefore the assignment results would estimate explicitly the accurate number of passengers to each vehicle of the schedule. At present, this approach becomes hot spot to researchers. For an overview, readers are referred to [17, 18]. In a schedule-based network, passengers choose not only the optimal hyperpaths for their trip, but also the departure/arrival time and vehicles of different crowded levels by minimizing their generalized travel costs. In order to combine the time-dependent choice, a time-dependent transit network should be presented according to different schedule-based transit assignment model, which can be classified into these types: (1) diachronic graph consisting of service subgraph, demand subgraph, and access/egress subgraph proposed by Nuzolo et al. [19]; (2) dual graph proposed by Moller-Pedersen [20]; (3) time-dependent graph formulation with line schedule information by Tong and Wong [8]; (4) discrete space-time graph formulation with space-time nodes and space-time arcs proposed by Nguyen et al. [21], which is improved by Hamdouch et al. [22] to time-expanded network representation.

Modeling formulations of transit assignment constitute one of the schedule-based problems. Poon et al. [23] put forward a dynamic user equilibrium model considering the crowded environment in boarding stations at time-dependent demand distribution and taking passengers' microbehavior on boarding link into account. With the numerical example in the study, dynamic user equilibrium mechanism is reasonably expressed with the factors of queueing at station due to congestion. Nieson [24] proposed a stochastic transit assignment model considering differences properties in passengers' utility function as optimized problem. Tian et al. [25] improved the model proposed by Alfa and Chen [26]. The model considers the in-vehicle crowding and schedule delay in generalized cost function with departure time decisions of passengers and presents the theoretical properties of equilibrium status.

With considering the capacity in the transit assignment model, some factors related to the capacity are concerned with the RUM model in recent years. Hamdouch et al. considered the uncertainty of vehicle capacity. Passengers used a strategy to travel under the uncertainty of capacity. Using specific examples to analyze the impact of uncertainty on passengers' travel strategies and departure time [22], Sumalee et al. considered one of the critical factors of capacity: sitting and standing capacities, and the treatment of seat allocation is considered as a random probability to get a seat or not [27]. Nuzzolo et al. presented a joint choice model by formulating departure/arrival time and train of different crowded level for maximizing the utility function. To solve the assignment model, a simulation procedure was put forward, taking congestion into account through explicit vehicle capacity. [28]. Han B et al. [29] proposed a stochastic user equilibrium model to solve transit assignment problem. This model was based on rail transit network schedule considering the travelers' behavior assumption of train's overload delay. The model was transformed into a dynamic schedule-based assignment model with splitting the origin-destination demands into the schedule-based network with time-space routes, using the Beijing urban rail transit (BURT) network as a case to verify the rationality of the model [29].

In terms of different behavior assumptions, the transit assignment model can be classified into the random utility maximization model and random regret minimization model.

The majority of the transit assignment models have used the random utility maximization (RUM) rooted in discrete choice analysis [1, 30]. The RUM model assumes that when a traveler is faced with a number of travel choices, he or she will choose the one with the highest utility. Poon et al. [23] assumed that a traveler can get all travel information including travel time and transfer time and constructed a generalized travel cost function. This function included in-vehicle travel cost, waiting cost, transfer cost, and transfer penalty and in-vehicle crowds. The transit assignment model was constructed based on the train schedule, and computer simulation is used to solve the model. Nuzzolo et al. [19] expressed the traffic network using diachronic graph and proposed a schedule-based assignment model considering the vehicle capacity limit. Considering the dynamics of passenger demand, Tong and Wong [8] established a stochastic transit assignment model, in which waiting time and walking time are defined as a density function, and employed Monte Carlo approach to solve the model. Nieson [24] proposes a stochastic transit assignment model considering differences preferences in passengers' utility functions as optimized problem, which presents a framework for transit assignment based on a basic probit model.

Regret theory was presented decades ago [31], and, similar to prospect theory (PT), it originally assumed a decision-making process under uncertainty. RRM constitutes an alternative to both utility theory (UT) and PT. When an individual's awareness perceives the product of the nonchosen alternative to be better than the result of the chosen alternative, it will build an emotion called regret [32]. The concept of regret as a determinant of decisions is often employed in areas such as psychology [33, 34], marketing [35], and finance [36]. The RRM model develops from the angle of bounded rationality and captures the scheme between multiple attribute trades-offs to the traveler's choice of psychological and traffic behavior based on minimization of the perceived regret decision criteria [3]. Recently, regret-based choice models have gained in popularity in travel behavior research, as an alternative approach to modeling choice behavior, under conditions of both certainty and uncertainty [32, 37, 38]. The RRM model has been used to analyze and predict a wide variety of choices, such as departure time choices, route choices, mode-destination choices, activity choices, on-line dating choices,

Table 1: Typical researches on transit assignment problem.

Literature	Research subject	RRM/RUM/Hybrid	Schedule based	Capacity constraint	Smart card data
Schmöcker et al. [12]	underground network	RUM	×	√	√
Leurent et al. [14]	bus transit network	RUM	×	√	×
Zhang S et al. [13]	feeder bus service	RUM	×	√	×
Tong et al. (1998)	urban rail transit	RUM	√	×	√
Poon et al. [23]	bus transit network	RUM	√	√	×
Hamdouch et al. [22]	bus transit system	RUM	√	√	×
Nuzzolo et al. [28]	bus transit system	RUM	√	√	×
Han B et al. [29]	urban rail transit	RUM	√	√	√
Chorus et al. [32, 37]	bus transit system	RRM	×	×	×
Chorus et al. [38]	bus transit system	Attributes level hybrid	×	×	×
this paper	urban rail transit	Attributes level and decision level hybrid	√	√	√

Note. RUM: random utility maximization; RRM: random regret minimization.

health-related choices, and policy choices [39, 40]. Chorus shows that RRM can be extended to the case of risky travel choice [32, 37]. Recently, he compared RUM with RRM in terms of theories and equations and showed their respective benefits of the scope of application [38]. Traditionally, the RUM model has dominated the travel choice behavior since it was accepted [3]. Studies to date suggest that the RRM is just as parsimonious as the standard RUM model, and it is unlike other models of contextual effects, which typically require the estimation of additional parameters [3].

Compared with the RUM, the RRM has two advantages:

(1) The RRM features logit choice probabilities and is easily estimated by using conventional discrete choice software packages in the research field [41, 42].

(2) The RRM model does not exhibit the property of independence from irrelevant alternatives (IIA), even with the assumption of independent and identically distributed (IID) error terms (Hensher et al. 2016). Therefore, RRM can be applied more widely.

Table 1 lists the typical literature of the transit assignment model, and a number of characteristics of this literature are shown, including the research subject, the assumption of choice behavior, whether it is scheduled based, whether it considers the capacity, and whether it uses the smart card data.

Table 1 shows that most of the models are based on the random utility maximization behavioral assumption. Although some assignment models have introduced the RRM, there is no adequate research on the RRM in an urban rail transit assignment. With regard to the hybrid model, attribute level hybrid and decision level hybrid are independently adopted in different literature. Moreover, there is no study on the effect of the two types of hybrid behavior rules in the rail transit assignment. This paper extends the previous literature to bridge the above-mentioned gaps.

3. Problem Statement

3.1. Assumptions. In the process of analyzing and modeling the passengers' route choice behavior in urban rail transit network, the following assumptions are made:

(1) Trains run strictly according to timetable. The unexpected incidents are not considered.

(2) The arrival time of a passenger refers to the moment when a passenger arrives at the platform and is ready to board. If the arrival time of a passenger is earlier than the arrival time of the train, the passenger can get on the train; otherwise they cannot board the train.

3.2. Representation of Transit Supply and Demand. This study is based on schedule-based approach [19]. It requires the representation of supply and demand in a detailed level. On the supply side, a space-time expanded network is developed based on the train timetable; on the demand side, the time independent OD matrix is used.

3.2.1. Space-Time Expanded Network Representation. A space-time expanded network is represented by a directed graph $G_E(N_E, A_E \mid o, d, S, L, T)$ where N_E represents the nodes and A_E represents the arcs. The nodes include a series of events associated with trains and passengers, e.g., passenger arrival node, train arrival node, passenger boarding node, passenger alighting node, and train departure node. The arcs include train running links, train stop arcs, passenger access arc, passenger egress arc, and passenger transfer arcs. o and d represent the starting and destination stations of the physical route. S represents the set of stations, L represents the sets of trains on all lines in the network, l_i represents the i-th line in the network, $L_i \subset L$ represents the set of train numbers on the i-th line, and $l_{i,j}$ expresses the j-th train on the route of the i-th line. T indicates the train timetables, which mainly include the train arrival and departure times at all stations, $T = \{at_s^{l_{i,j}}, dt_s^{l_{i,j}} \mid \forall s \in S,\ l_{i,j} \in L_j \subset L\}$. The components of urban rail transit time-expanded network are as follows.

(1) Space-Time Expanded Node. The space-time expanded node set N_E includes the train arrival and departure node set $n_t \subset N_E$, the passenger alighting and boarding node set $n_a \subset N_E$, and the passenger arrival and left node set $n_w \subset N_E$.

(i) Train Arrival and Departure Node. The train arrival and departure nodes are based on the train timetable, by expanding the station nodes of a physical topology in the time dimension. If there are n trains to the station corresponding to the physical node in the route forward direction, the node can be expanded to $2 \times n$ trains event node according to the arrival time of each train at the node. This kind of time extension node is expressed as $n_t^{s,l_{i,j}} \in n_t \subset N_E$, in which $s \in S, l_{i,j} \in L_j \subset L, t \in T$, the j train on the line l_i on the station s at the time t to the time extension node; it can be seen that this kind of node has three properties of location $Station(n_t^{s,l_{i,j}}) = s$, time $Time(n_t^{s,l_{i,j}}) = t$, and train number $Train(n_t^{s,l_{i,j}}) = l_{i,j}$. The arrival time is expressed as at and dt, respectively, and the node can be further represented as $n_{at}^{s,l_{i,j}}, n_{dt}^{s,l_{i,j}}$.

(ii) Passenger Alighting and Boarding Node. The passenger boarding node set s_1 includes the node of trip starting and the node before transfer; passenger alighting node set s_2 includes the node of trip ending and the node after transfer. This kind of node is expressed as $n_a^{s,l_{i,j}} \in n_a \subset N_E$, which represents the events of passenger boarding or alighting the j train at station s of the line l_i at the time a. It also has three attributes: location $Station(n_a^{s,l_{i,j}})$, time $Time(n_a^{s,l_{i,j}})$, and train $Train(n_a^{s,l_{i,j}})$. Among them, the boarding node satisfies the following condition.

$$\begin{aligned} & s \in s_1 \\ & l_{i,j} \in L_j \subset L \\ & a \in \left\{Time\left(n_{dt}^{s,l_{i,j}}\right) \mid n_{dt}^{s,l_{i,j}} \in n_t\right\} \end{aligned} \tag{1}$$

The alighting node satisfies the following condition.

$$\begin{aligned} & s \in s_2 \\ & l_{i,j} \in L_j \subset L \\ & a \in \left\{Time\left(n_{at}^{s,l_{i,j}}\right) \mid n_{at}^{s,l_{i,j}} \in n_t\right\} \end{aligned} \tag{2}$$

(iii) Passenger Arrival and Left Node. A passenger arrival time extension node is expanded by the gate entry time recorded by the automatic fare collection systems when a passenger swipes his or her card. $n_w^s \in n_w \subset N_E$ is used to represent this kind of node. In which s represents the station corresponding to the starting and destination points, w represents the time when a passenger swipes his card. For passenger arrival node, it satisfies

$$\begin{aligned} s &= o \\ w &= t_{entry}^{i} \end{aligned} \tag{3}$$

where o is the enter station which is recorded by the smart card. t_{entry}^{i} indicates the entry time and the card number is i. This kind of node has two attributes of location: $Station(n_w^s) = s$ and time $Time(n_w^s) = w$.

(2) Time Extension Arc. The time-expanded arc set A_E includes passenger access and egress arcs $a_{walkin} \subset A_E$ and $a_{walkout} \subset A_E$, train running arc $a_{operation} \subset A_E$, train stop arc $a_{stop} \subset A_E$, and passenger transfer arc $a_{transfer} \subset A_E$.

(i) Passenger Access and Egress Arcs. The passenger access arc connects the passenger arrival node and boarding node in space-time expanded network. $a_{walkin}(n_{t_o}^{s_o}, n_{t_b}^{s_o,l_{i,j}})$ is used to represent the access arc between the extension nodes from the passenger arrival time t_o at the physical node s_o to the node of the passenger boarding time t_b of the j train on the line l_i. The weight $w_{walkin}(n_{t_o}^{s_o}, n_{t_b}^{s_o,l_{i,j}})$ of the access arc is represented by the sum of passenger walking time and passenger waiting time.

$$w_{walkin}\left(n_{t_o}^{s_o}, n_{t_b}^{s_o,l_{i,j}}\right) = t_{walkin}^{s_o} + t_{wait}^{s_o} = t_b - t_o \tag{4}$$

$t_{walkin}^{s_o}$ indicates passenger walking time in station s_o from ticket gate to platform. $t_{wait}^{s_o}$ indicates passenger waiting time on s_o platform, $s_o \in S, l_{i,j} \in L_i \subset L, t_b \in T$.

The egress arc is the connection between the passenger alighting node and the left node. $a_{walkout}(n_{t_a}^{s_d,l_{i,j}}, n_{t_d}^{s_d})$ is used to represent the egress arc between the extension nodes from the alighting time t_a of the j train at physical node s_d on line l_i to the passenger left time t_d. The weight $w_{walkout}(n_{t_a}^{s_d,l_{i,j}}, n_{t_d}^{s_d})$ of egress arc is represented by passenger departure time as

$$w_{walkout}\left(n_{t_a}^{s_d,l_{i,j}}, n_{t_d}^{s_d}\right) = t_{walkout}^{s_d} = t_d - t_a \tag{5}$$

where $t_{walkout}^{s_d}$ indicates the passenger's walking time from platform to ticket gate, $s_d \in S, l_{i,j} \in L_i \subset L, t_a \in T$.

(ii) Train Running Arc. The train running arc connects the adjacent departure node and arrival node of the same train. $a_{operation}(n_{dt}^{s_k,l_{i,j}}, n_{at}^{s_{k+1},l_{i,j}})$ represents the train running arc from the departure time dt of the j train of the line l_i to the arrival time at at the next station. The $w_{opertation}(n_{dt}^{s_k,l_{i,j}}, n_{at}^{s_{k+1},l_{i,j}})$ of train running arc is expressed by the running time of the train in the section:

$$w_{opertation}\left(n_{dt}^{s_k,l_{i,j}}, n_{at}^{s_{k+1},l_{i,j}}\right) = at - dt \tag{6}$$

where $s_k, s_{k+1} \in S, l_{i,j} \in L_i \subset L, at, dt \in T$.

(iii) Passenger Transfer Arc. The passenger transfer arc connects the expanded node of passenger alighting node and boarding node between different lines. $a_{transfer}(n_{at_1}^{s_m,l_{i,j}}, n_{dt_2}^{s_n,l_{p,k}})$ represents the passenger transfer arc which is from the passenger alighting time from the j-th train at station s_m on line l_i, to the boarding time to the kth train at station s_n on line l_p. The weight of passenger transfer arcs $w_{transfer}(n_{at_1}^{s_m,l_{i,j}}, n_{dt_2}^{s_n,l_{p,k}})$ is the sum of passenger walking time and waiting time:

$$w_{transfer}\left(n_{at_1}^{s_m,l_{i,j}}, n_{dt_2}^{s_n,l_{p,k}}\right) = t_{transfer}^{s_m,s_n} + t_{wait}^{s_n} = dt_2 - at_1 \tag{7}$$

where $t_{transfer}^{s_m,s_n}$ indicates the passenger's walking time from s_m to s_n. $t_{wait}^{s_n}$ indicates the waiting time on the s_n platform,

$s_m, s_n \in S$, $l_{i,j} \in L_i \subset L$, $l_{p,k} \in L_p \subset L$, $at_1, dt_2 \in T$. The feasible transfer arc should satisfy the weight of not less than the minimum transfer time:

$$w_{transfer}\left(n_{at_1}^{s_m,l_{i,j}}, n_{dt_2}^{s_n,l_{p,k}}\right) \geq t_{transfer\_\min}^{s_m,s_n} \quad (8)$$

where $t_{transfer\_\min}^{s_m,s_n}$ represents the minimum walking time required to transfer from s_m to s_n.

3.2.2. Approaches to Construct Expanded Network Based on Timetable and Smartcard Data. In the time-expanded network of urban rail transit, a passenger travel route between an OD pair can be defined as a sequential node and a set of arcs in the space-time expanded network. Feasible routes should satisfy the temporal and spatial constraints of AFC data recording and the connectivity between nodes.

Given the timetable and smart card data, the process of constructing a space-time expanded network of urban rail transit is as follows:

Step 1. A subtopology network $G_s(N_s, A_s)$, $N_s \in N$, $A_s \in A$, based on the physical network, is built. Only stations on the route are kept, including the origin station, the destination station, the passing station, and the transfer station. Then the interval arcs are built between the station nodes on the same line, and the transfer arcs are built between the nodes of the transfer stations as shown in Figure 1(a).

Step 2. According to the arrival and departure time of the trains at the corresponding stations in the physical route of the train timetable, all the physical nodes N_s in G_s are expanded to train arrival and departure nodes in the time dimension. In addition, the arrival time and the departure time of all the trains in all directions in the stations corresponding to the physical nodes are expressed as the corresponding expanded nodes. A time label was added to the nodes to indicate the arrival and departure of the train at the station. Each time-expanded node can be expressed as line, train number, station, and arrival time/departure time, as shown in Figure 1(b).

Step 3. According to the direction of the train running, the train running arc is formed by connecting the same train number of the extension node to the adjacent physical node to the time corresponding to the time. The arc tail is the extension node corresponding to the train departure time, the arc head is the extension node corresponding to the train arrival time, and the same physical node is the same vehicle. The expanded nodes corresponding to the station and departure time are connected to form a train stop arc, and the arrival time of the two physical nodes connected to the transfer arc in the same station and the extension node corresponding to the departure time are connected to form a transfer arc. The arrival time and the departure time should meet the transfer time constraint (8), among which the arc tail is the expanded node corresponding to the arrival time of the train before transfer, and the arc head is the expanded node corresponding to the departure time of the train after transfer, as shown in Figure 1(c).

Step 4. According to the passenger arrival and left time from the AFC data, the expanded physical nodes of the origin station n_O and the destination n_D are further expanded in the time dimension, and the time label is added to form the expanded node to express the time of the passengers' arrival and departure, as shown in Figure 1(d).

Step 5. The train arrival expansion node n_O corresponding to the origin station time is connected to the passenger arrival expansion node. The arrival time should meet the access time constraint (4) and egress time constraint (5) at the station, as shown in Figure 1(e).

Taking the Beijing subway as an example, a passenger's AFC record shows that the passenger arrived at 7:10:28 from the CHEGONGZHUANG station and 7:28:18 from the TIAN'ANMEN West. The passenger's physical route is only "CHEGONGZHUANG-FUCHENGMEN-FUXINGMEN (transfer station)-XIDAN-TIAN'ANMEN West", but in the time-expanded network, there are three time-expanded routes satisfying the condition of passenger arrival time and passenger departure time, which are shown in Figure 2. This could happen when the trains are too crowded during peak hours so that passengers have to choose the next train.

3.2.3. Demand Representation. On the demand side, the proposed assignment model is specified considering a reference period (e.g., a day) divided into n elementary time intervals of width h (e.g., $h = 2$ min), for which the generic time slice covers time interval $[t, t+h]$.

We consider an urban rail transit network, in which the AFC system is a tap in and tap out system, where both passengers' swipe card information is accurately recorded. Thus, based on the AFC system records, any passenger origin station, destination station, tap in time, and tap out time can be obtained directly.

In the AFC system, there are two records for one trip. One is created when the passenger taps in, and the other is created when the passenger taps out. Trips with only one record are considered as incomplete trips and are neglected in this study.

3.3. Generalized Travel Cost of Passengers. A passenger would choose his or her travel route based on the generalized travel cost of the corresponding route on a space-time expansion network. In this study, the passengers' generalized travel cost is represented by a weighted sum of a number of independent variables, such as access time, egress time, in-vehicle time, in-vehicle crowd, and transfer time.

(1) Access Time. The access time of passenger is the cost on the access arc. In Section 3.2.1 , the access time includes the walking time and waiting time. This time can be obtained from the space-time expanded network. Passengers' arrival time is different and the train is different, so the arrival time is different. The access time is represented by ET. Based on the space-time expanded network, the formula of aces' time is

$$ET = t_{walkin}^{s_o} + t_{wait}^{s_o} = t_b - t_o \quad (9)$$

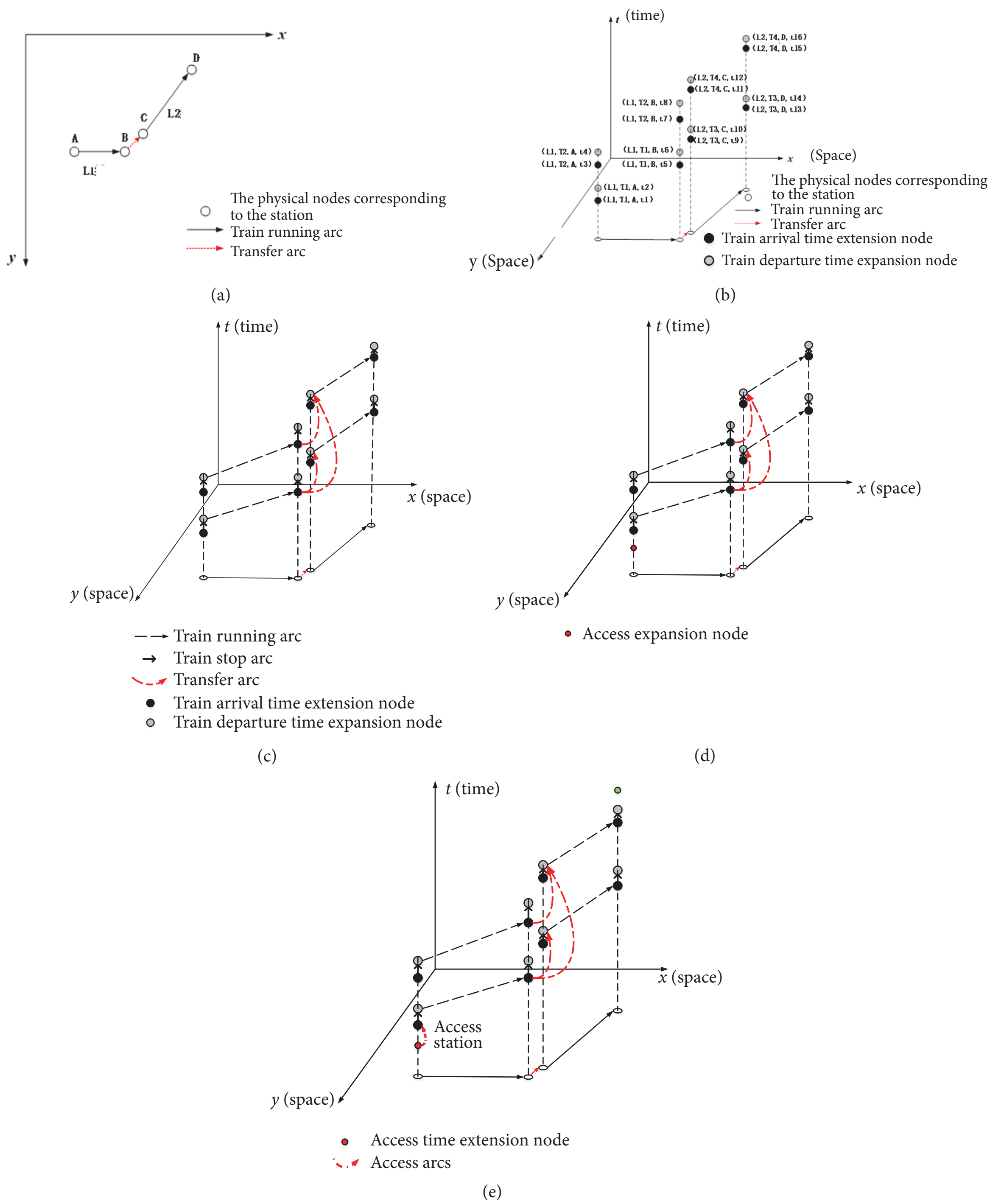

Figure 1: The construction process of urban rail transit time-expanded network.

where $t_{walkin}^{s_o}$ indicates passengers' walking time from the tap in gate to the platform at station s_o and $t_{wait}^{s_o}$ indicates passenger waiting time on the platform at station s_o.

(2) Train Running Time. Train running time is the cost of the train running arc. In the space-time expanded network, the train running time includes train dwell time and train stop time. In the urban rail transit system, the train operation strictly follows the train timetable, so the cost of the train running arc e_l is known and fixed, in other words, the running time of the train between two stations. When VT is used to indicate the running time of trains, the formula of train running time is as follows.

$$VT = w_{opertation}\left(n_{dt}^{s_k,l_{i,j}}, n_{at}^{s_{k+1},l_{i,j}}\right) = at - dt \qquad (10)$$

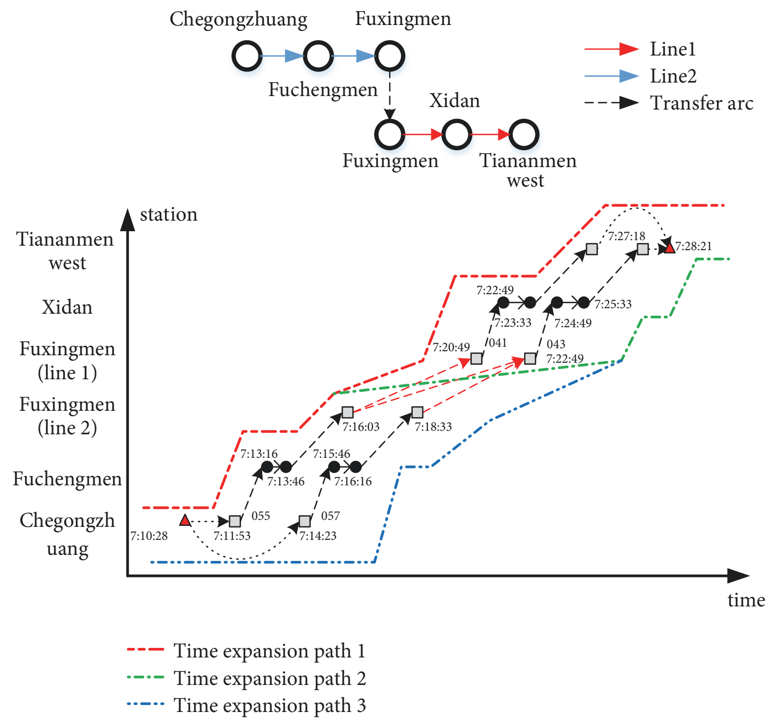

Figure 2: The schematic diagram of time-expanded route.

(3) Crowd Cost. In the train operation, the more passengers on the train, the more uncomfortableness perceived by the passengers. When the number of passengers in the train is large, the capacity limit of the train will cause the crowding between passengers. If the number of passengers in the train does not reach the number of train seats, there will be no congestion. The degree of crowding caused by the number of passengers on trains is expressed by the crowd coefficient ρ, which is estimated by

$$\rho(t) = \begin{cases} 0 & x_e(t) < Z_l \\ \dfrac{\alpha(x_e(t) - Z_l)}{Z_l} & Z_l < x_e(t) < N_l \\ \dfrac{\alpha(x_e(t) - Z_l)}{Z_l} + \dfrac{\beta(x_e(t) - N_l)}{N_l} & x_e(t) > N_l \end{cases} \quad (11)$$

where $\rho(t)$ is the crowd coefficient based on passengers number on train running arcs during t interval, $x_e(t)$ is the number of passengers on the running arc e during t interval, Z_l is the number of seats on the train running arc e on the line l, N_l is the maximum capacity of train running arc e on line l, and α, β are corresponding coefficients, which are derived from specific statistical data.

When considering the impact of crowd, the train running time on the running arcs is magnified, which is represented by CT. It is calculated as follows:

$$CT = VT \cdot \rho_{e_l}(t) \quad (12)$$

where c_ρ is the passenger congestion cost on train running arcs e_l and t_{e_l} is the train running time on operation arcs e_l in space-time expanded network.

(4) Transfer Time. Transfer time includes transfer walking time and transfer waiting time. In the space-time expanded network, the transfer time is the cost on the transfer arc. The cost is composed of two parts, which are the transfer time and the number of transfers, respectively. The transfer time on the transfer arc can be expressed as

$$t_{i,t_1,t_2}^{l_1,l_2} = t_{transfer}^{s_m,s_n} + t_{wait}^{s_n} = dt_2 - at_1 \quad (13)$$

where t_2 and t_1 represent the starting and ending times of transfer arcs, respectively.

The perceived cost of transfer time will be greater than in-vehicle time and waiting time. This is because the passengers need to walk during transfer and pay much physical effort. Therefore, the transfer time perception cost on the transfer arc is magnified and expressed as ((4)-(6))

$$\tilde{t}_{i,t_1,t_2}^{l_1,l_2} = \theta t_{i,t_1,t_2}^{l_1,l_2} \quad (14)$$

where $\theta > 0$ and θ can be estimated by fitting the survey data.

When the number of transfers is more than two times, the passenger will increase the extra psychological cost for each additional transfer. The additional cost is expressed as κ. The comprehensive cost on the transfer arc is expressed by TT, which can be expressed as follows.

$$TT = \tilde{t}_{i,t_1,t_2}^{l_1,l_2} + \kappa = \theta(t_2 - t_1) + \kappa \quad (15)$$

In summary, the generalized travel cost of passengers is represented as the sum of the four parts. It is formulated as follows.

$$C = \beta_{ET}ET + \beta_{VT}VT + \beta_{CT}CT + \beta_{TT}TT \tag{16}$$

Substituting the formulation of variables to (16), the generalized cost can be represented as follows.

$$\begin{aligned} C = {} & \beta_{ET}\left(t_b - t_o\right) + \beta_{VT}\left(t_2^l - t_1^l\right) + \beta_{CT}\left(t_{e_l} \cdot \rho_{e_l}(t)\right) \\ & + \beta_{TT}\left(\theta\left(t_2 - t_1\right) + \kappa\right) \end{aligned} \tag{17}$$

4. Methodology

4.1. Passenger Route Choice Behavior. At present, there are two basic types of the choice behavior assumptions: one is that the choice behavior of passengers is fully rational, which is mainly based on the theory of utility maximization, and the other is that the choice behavior of passengers is finite rational, which is mainly based on the theory of regret minimization.

We would argue that neither RUM nor RRM could reflect the complexity of the travelers' route choice behavior. Therefore, this paper uses the hybrid of utility maximization rule and the regret minimization rule to model the passenger route choice behavior. Based on the different route choice rules, the random utility maximization (RUM) route choice model, the random regret minimization (RRM) route choice model, and the hybrid utility-regret (RURM) route choice model are established, respectively.

4.1.1. Random Utility Maximization (RUM) Formulation. The random utility maximization (RUM) is aiming to choose the least generalized travel cost in the process of the passenger route choice and choose the route with the maximum utility value.

Under the rule of utility maximization, it is assumed that the passengers' choice is completely rational; that is, the passengers always compare the utility of different routes and choose a route with the maximum travel utility. The travel utility of a route consists of two parts: one is determined cost, which can be calculated through the generalized travel cost of passengers. The other part is random cost, which is caused by some uncertain factors such as the different passengers' attributes or the estimated deviation of passengers. Determined cost and random cost together constitute the travel cost of passengers, and the reverse number of travel costs is the utility function.

Assuming that there are J routes between a certain OD pair, the random utility function is composed of two parts: a deterministic trip cost which reflects the impact of observed variables and a random error term which represents unobserved factors. The two parts of the cost reflect the average perception of the passenger's route utility and the perception error, respectively. The random utility function of the route i can be expressed as follows.

$$\begin{aligned} RU_i &= C_i + \varepsilon_i \\ &= \left(\beta_{ET}ET_i + \beta_{VT}VT_i + \beta_{CT}CT_i + \beta_{TT}TT_i\right) + \varepsilon_i \\ & \qquad i \in J \end{aligned} \tag{18}$$

Here, RU_i is the random utility value of the route i and C_i is the determined utility value of the route i, which can be determined by the analyst. ε_i is the random error.

If the distribution of random error ε_i is known, it is possible to calculate the probability of different routes being selected. If the route i is selected, it needs to satisfy the following equation.

$$\begin{aligned} P_U(i) &= prob\left(RU_i > RU_j,\ \forall i \neq j\right) \\ &= prob\left(C_i + \varepsilon_i > C_j + \varepsilon_j,\ \forall i \neq j\right) \end{aligned} \tag{19}$$

When the random error obeys the independent identical distribution with Generalized Extreme Value Distribution type I (also known as Gumbel distribution), the probability of passenger choosing route i can be formulated as follows.

$$P_U(i) = prob\left(C_i > C_j,\ \forall j \neq i\right) = \frac{\exp\left(C_i\right)}{\sum_{j=1,\ldots J} \exp\left(C_j\right)} \tag{20}$$

4.1.2. Random Regret Minimization (RRM) Formulation. The random regret minimization rule assumes that when there are multiple routes corresponding to one travel OD pair, passengers can compare the attributes of different routes. After choosing a route, if passengers find that other unselected routes' travel costs of a certain attribute are less than their chosen routes, regret will arise. Under the regret minimization rule, passengers will choose a route with the least regret.

The regret value of choosing a route can be quantified by a regret function. The regret function is a function of the properties x_i and x_j of the two or more alternatives. Taking two alternatives as an example, the regret function is $R_{ij}(s) = \varphi(x_i(s), x_j(s))$. It is assumed that $R_{ij}(s) = -R_{ij}(s)$. Consider a traveler n who faces a route choice among alternatives i, j, and k, and the alternatives are fully defined in terms of the attributes x, y, and z; the regret associated with alternative i can be defined as follows.

$$R_{ij} = \varphi_x\left(x_i, x_j\right) + \varphi_y\left(y_i, y_j\right) + \varphi_z\left(z_i, z_j\right) \tag{21}$$

In this study, the regret function of route choice is defined as a logarithm function as in the following equation.

$$\varphi_x\left(x_i, x_j\right) = \ln\left(1 + \exp\left[\gamma_x \cdot \frac{\left(x_j - x_i\right)}{x_i}\right]\right) \tag{22}$$

Similar to the composition of random utility functions, the random regret function is also composed of two parts of the deterministic regret term and the random regret term. The deterministic term indicates the perception of the travelers' average regrets between different routes, and the random regret term represents the perception of the passengers' regrets caused by random errors.

For route i, the regret value generated by passengers choosing this route can be calculated by the random regret function of

$$\begin{aligned} RR_i = {} & \sum_{j \neq i} \ln\left(1 + \exp\left[\gamma_{ET} \cdot \frac{\left(ET_j - ET_i\right)}{ET_i}\right]\right) \\ & + \sum_{j \neq i} \ln\left(1 + \exp\left[\gamma_{VT} \cdot \frac{\left(VT_j - VT_i\right)}{VT_i}\right]\right) \\ & + \sum_{j \neq i} \ln\left(1 + \exp\left[\gamma_{CT} \cdot \frac{\left(CT_j - CT_i\right)}{CT_i}\right]\right) \\ & + \sum_{j \neq i} \ln\left(1 + \exp\left[\gamma_{TT} \cdot \frac{\left(TT_j - TT_i\right)}{TT_i}\right]\right) + \varepsilon_i \end{aligned} \tag{23}$$

where RR_i is the random regret value of the route i, R_i is the determined regret value of the route i, γ_{ET} is the coefficient of the entry time, γ_{VT} is the coefficient of the train running time, γ_{CT} is the coefficient of the crowd cost, and γ_{TT} is the coefficient of the transfer time, which is between 0 and 1.

The probability of passengers choosing route i is shown in the following formula.

$$\begin{aligned} P_R(i) &= prob\left(RR_i < RR_j,\ \forall j \neq i\right) \\ &= \frac{\exp\left(-RR_i\right)}{\sum_{j=1,\ldots,J} \exp\left(-RR_j\right)} \end{aligned} \tag{24}$$

4.1.3. Hybrid of Utility Maximization and Regret Minimization (RURM). In the above, the corresponding choice models of the random utility maximization and the random regret minimization are established, respectively. However, passengers' behavior can be a hybrid of both. In this study two types of hybrid rules are applied, namely, attribute hybrid rule and decision level hybrid rule.

Attribute level hybrid rule reflects the different behavioral tendencies (utility or regret) for different decision attributes. In the actual travel process, passengers may have different behaviors when facing different route attributes such as time and crowd. For some attributes, passengers tend to maximize the utility, while for others, passengers tend to minimize the regret. Chorus [5, 6] introduced regret-weights to model such kind of hybrid. As a result, the hybrid utility and regret function can be formulated as

$$\begin{aligned} HUR_i & \\ = {} & \left(\begin{aligned} & \sum_{j \neq i} \ln\left(\varpi_{ET} + \exp\left[\gamma_{ET} \cdot \frac{\left(ET_j - ET_i\right)}{ET_i}\right]\right) \\ & + \sum_{j \neq i} \ln\left(\varpi_{VT} + \exp\left[\gamma_{VT} \cdot \frac{\left(VT_j - VT_i\right)}{VT_i}\right]\right) \\ & + \sum_{j \neq i} \ln\left(\varpi_{CT} + \exp\left[\gamma_{CT} \cdot \frac{\left(CT_j - CT_i\right)}{CT_i}\right]\right) \\ & + \sum_{j \neq i} \ln\left(\varpi_{TT} + \exp\left[\gamma_{TT} \cdot \frac{\left(TT_j - TT_i\right)}{TT_i}\right]\right) \end{aligned} \right) \\ & + \varepsilon_i \end{aligned} \tag{25}$$

where ϖ_{ET}, ϖ_{VT}, ϖ_{CT}, and ϖ_{TT} are attributes level hybrid parameters (since this parameter is only one kind of hybrid rule in terms of attributes, we use the term "attributes level hybrid parameter" instead of regret-weight) for access time, in-vehicle time, crowd cost, and transfer time, respectively. These parameters represent the behavioral tendencies of utility maximization or regret minimization. When the value of the attributes level hybrid parameter is zero for observed variables, the decision tends to be close to RUM.

Decision level hybrid rule refers to the coincident traits of passengers when making decisions. For instance, some individuals are more risk averse than others considering the heterogeneity of passengers. These traits are unobservable and related to some observable characteristics such as age or gender (Hess 2013). Without loss of generality, the possibility of a passenger choosing RUM or RRM can be considered as a latent variable. As a result, the method of developing a hybrid of utility and regret can be represented by a latent class model with the variable. In this case, the hybrid function of random utility-regret of the passenger selection route i is formulated in the following equation.

$$\begin{aligned} HUR_i &= \rho \cdot RU_i - (1 - \rho) \cdot RR_i \\ &= \rho \cdot \left(\beta_{ET} ET_i + \beta_{VT} VT_i + \beta_{CT} CT_i + \beta_{TT} TT_i\right) \\ &\quad - (1 - \rho) \\ &\quad \cdot \left(\begin{aligned} & \sum_{j \neq i} \ln\left(1 + \exp\left[\gamma_{ET} \cdot \frac{\left(ET_j - ET_i\right)}{ET_i}\right]\right) \\ & + \sum_{j \neq i} \ln\left(1 + \exp\left[\gamma_{VT} \cdot \frac{\left(VT_j - VT_i\right)}{VT_i}\right]\right) \\ & + \sum_{j \neq i} \ln\left(1 + \exp\left[\gamma_{CT} \cdot \frac{\left(CT_j - CT_i\right)}{CT_i}\right]\right) \\ & + \sum_{j \neq i} \ln\left(1 + \exp\left[\gamma_{TT} \cdot \frac{\left(TT_j - TT_i\right)}{TT_i}\right]\right) \end{aligned} \right) \\ &\quad + \varepsilon_i \end{aligned} \tag{26}$$

Here, ρ is a decision level hybrid rule parameter, which represents the proportion of utility maximization rule in route choice decision.

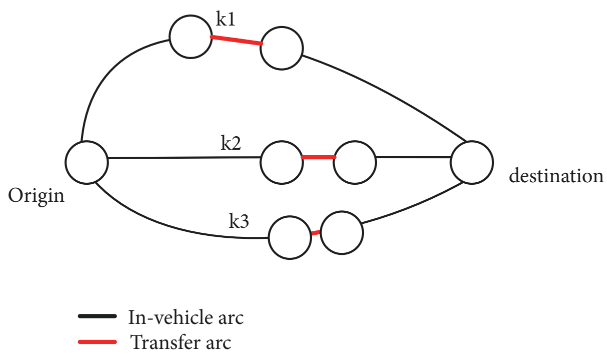

FIGURE 3: An illustrative example.

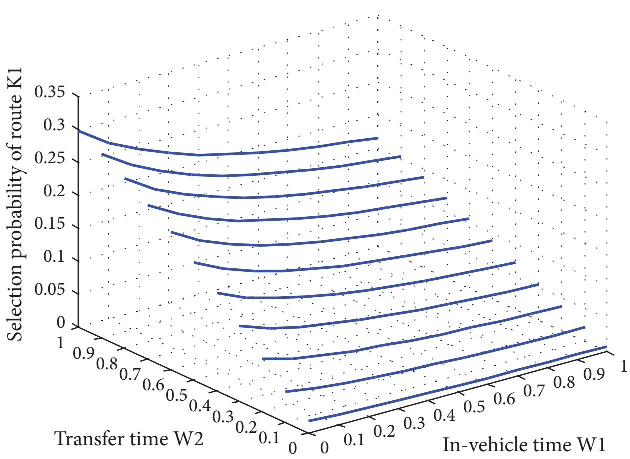

FIGURE 4: The influence of the value of attribute level hybrid parameters on the route probability for K1.

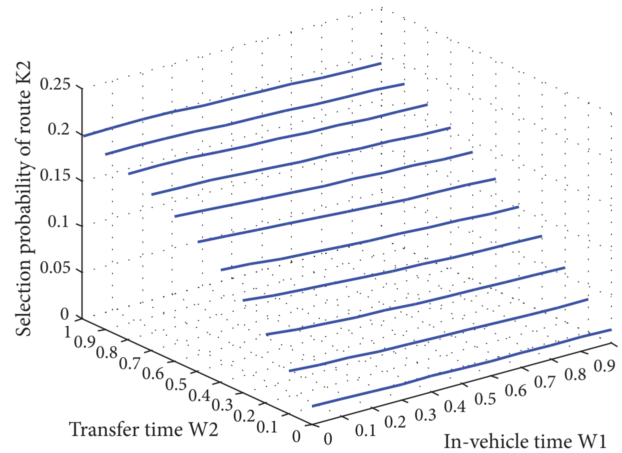

FIGURE 5: The influence of the value of attribute level hybrid parameters on the route probability for K2.

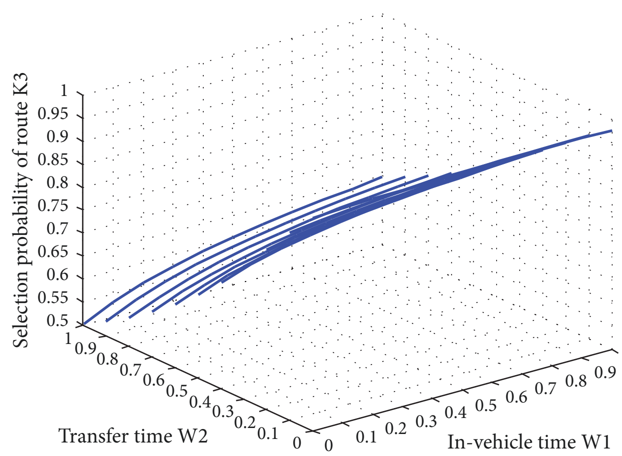

FIGURE 6: The influence of the value of attribute level hybrid parameters on the route probability for K3.

4.1.4. Illustrative Example. In order to compare and analyze the effect of hybrid of RUM and RRM on route choice behavior, a small numerical experiment is selected, which is shown in Figure 3. There are three routes: k_1, k_2, and k_3; the in-vehicle times of them are 15min, 20min, and 25min, and the transfer times are 5min, 4min, and 2min, respectively. To simplify the case, other attributes are neglected. The parameters of the in-vehicle time β_{VT} and γ_{VT} are -1/min, and the parameters of the transfer time β_{TT} and γ_{TT} are -2/min. Both attribute level hybrid rule and decision level hybrid rule are applied.

(1) Effects of Attribute Level Hybrid on Passengers' Route Choice Behavior. Assuming ϖ_1 and ϖ_2 are attributes level hybrid parameters for in-vehicle time and transfer time, respectively, in order to study the effect of the attributes level hybrid parameters on the route selection probability, ϖ_1 and ϖ_2 are chosen from values range [0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1], respectively. The closer the attributes level hybrid parameters to 1, the greater the possibility of using the regret minimization model for the route; otherwise, the utility maximization model will be used. The selection probabilities of the three routes of the above cases are illustrated in Figures 4–6.

As can be seen from Figures 4, 5, and 6 , when attributes level hybrid parameters ϖ_1 for in-vehicle time keep a constant, with the increase of the attributes level hybrid parameters ϖ_2 for transfer time, the selection probability of route 1 and route 2 increases and the selection probability of route 3 decreases rapidly. This implies that the route selection is very sensitive to the regret of transfer time. The transfer time of route 1 and route 2 is longer than that of the route 3. Passengers prefer to choose route 3 under RUM condition. Increasing the value of decision regret parameter ϖ_2 leads to more regret of this decision, and thus the probability of selecting route 3 decreased. Then ϖ_2 keeps a constant, and with the increase of ϖ_1, the selection probability of route 3 increases and the selection probability of route 1 and route 2 decreases gradually. This is because the in-vehicle times of the route 1 and the route 2 are less than the in-vehicle time of the route 3. Increasing the value of attribute level parameter ϖ_1 would generate regret of choosing route 1 and route 2, and thus the probability of selecting route 1 and route 2 decreases.

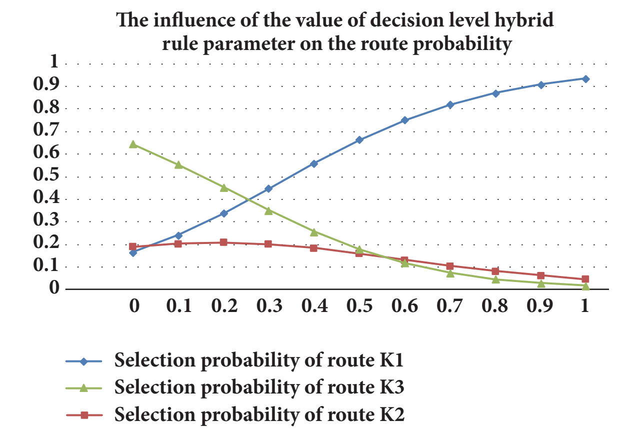

FIGURE 7: The influence of the value of decision level hybrid rule parameter on the route probability.

(2) Effects of Decision Level Hybrid on Passengers' Route Choice Behavior. In order to study the effect of the decision level hybrid rule parameter on the route selection probability, the decision level hybrid rule parameter ρ is chosen from values range [0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1]. The closer the decision level hybrid rule parameter ρ to one, the greater the possibility of using the utility maximization model for the route; otherwise, the regret minimization model will be used. The route selection probabilities of the above cases are listed in Figure 7.

As can be seen from Figure 7 , under regret minimization decision rule (ρ=0), most passengers would choose the route 3 to reduce their regret. With the increase of the decision level hybrid rule parameter ρ (meaning passengers tend to make decision by utility maximization), the selection probability of route 1 increases and the selection probability of route 3 decreases. In this particular case, the selection results of RUM and RRM are significantly different.

4.2. Transit Assignment Model. It is assumed that the passenger flow of the urban rail transit network meets the user equilibrium distribution, which means passengers can obtain accurate travel information. Based on the user equilibrium theory, the dynamic transit assignment model of urban rail transit can be developed based on RURM. The dynamic transit assignment model based on the space-time expanded network is

$$\min \quad Z = \sum_{k} \left[(1-\rho) \cdot RR_k - \rho \cdot RU_k \right] \tag{27}$$

$$\text{s.t.} \quad q_{rs} = \sum_{k} f_k^{rs}, \quad \forall r, s \tag{28}$$

$$f_k^{rs} > 0 \tag{29}$$

$$x_{mn} = \sum_{rs} \sum_{k} f_k^{rs} \cdot \delta_{mn,k}^{rs} \tag{30}$$

where x_{mn} represents the traffic on the space-time arc $m \longrightarrow n$; f_k^{rs} represents the flow of OD pair rs on route k; $\delta_{mn,k}^{rs}$ represents the relationship between route k and arc $m \longrightarrow n$; q_{rs} represents passenger demand of OD pair rs.

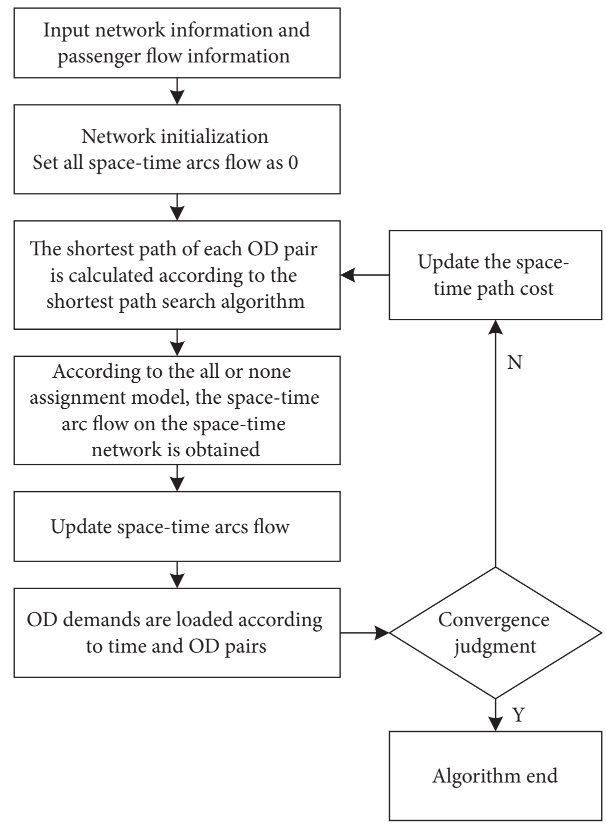

FIGURE 8: Assignment algorithm of MSA.

Formula (29) represents the conservation of OD demand and route traffic flow. Formula (30) indicates the conservation of route traffic flow and space-time arc's traffic flow.

When the network reaches an equilibrium, it satisfies

$$v_{rs} - f_{rs} = \begin{cases} 0 & f_k^{rs} > 0, \\ \leq 0 & f_k^{rs} = 0, \end{cases} \tag{31}$$

where v_{rs} is the traffic flow on the minimum hybrid RURM route.

5. Algorithm

The method of successive algorithm (MSA) is applied to solve the transit assignment model. The steps of the algorithm are shown in Figure 8.

Step 1 (initialization). Firstly, set the number of iterations $n = 0$. At this time, all space-time arc flows in the space-time expanded network are set to 0, and each space-time arc has an initial cost. According to the shortest route search algorithm, the route corresponding to the minimum hybrid RUM and RRM value (RURM) of each OD pair in the space-time network can be obtained. Then, all the OD demands that meet the train departure time are assigned to the shortest

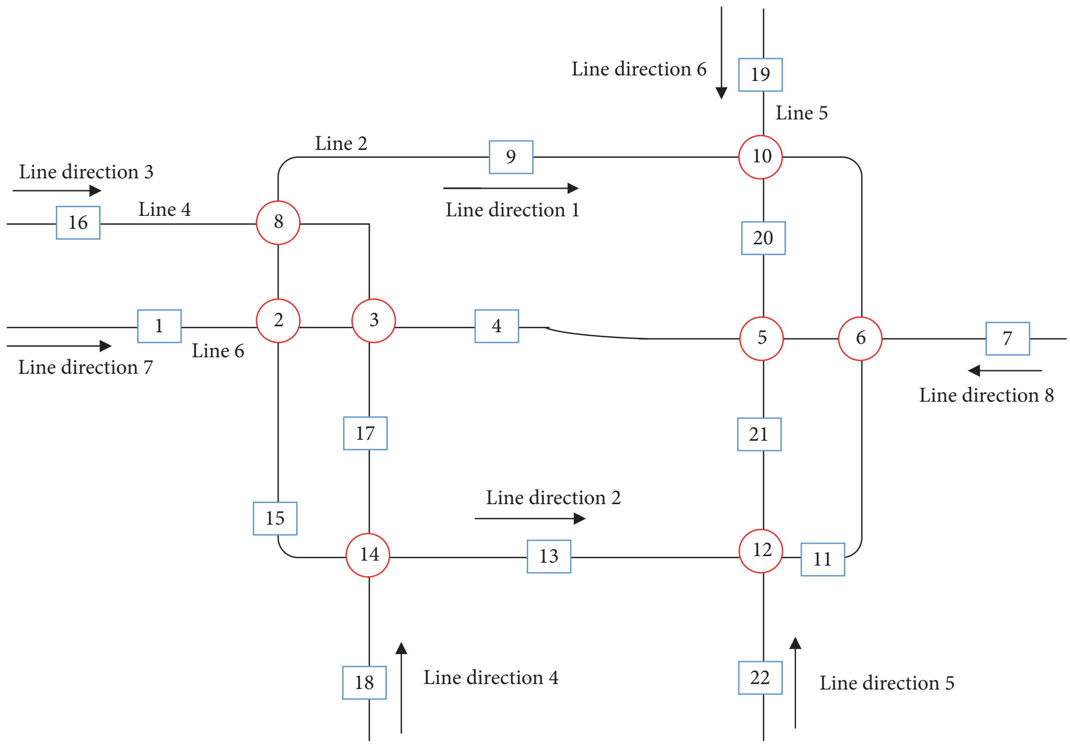

Figure 9: Subway network physical topology.

space-time route, and the space-time route flow is $f_k^{rs(0)}$. According to the corresponding relationship between the space-time route and the space-time arc, the flow of space-time arc for the space-time route is $x_{mn}^{(0)}$. At this point, the number of iterations is $i = 1$.

Step 2 (update the hybrid RUM and RRM value of the space-time arc). According to flow of the space-time arcs which is obtained in Step 1, the space-time arcs' costs under the utility maximization rules and the regret minimization rule are calculated.

Step 3 (calculate the additional flow of space-time arc). After calculating the cost of each space-time arc by Step 2, the cost of space-time route is calculated under the utility maximization rule for formula (17), and the cost of space-time route is calculated under the regret minimization rule for formula (20).

According to the shortest route algorithm, the new route of the minimum travel cost or minimum regret value between each OD pair in the space-time network is obtained. Then, all the OD demands that meet the train departure time are assigned to the new space-time route. At this time, according to the relationship between space-time arc and space-time route and the all-or-none assignment model, the space-time arc flow $y_{mn}^{(i)}$ on the space-time network is obtained, and the additional space-time arc flow is $y_{mn}^{(i)}$.

Step 4 (update the time and space arc flow). The updated space-time arcs flows are determined by the following formula.

$$x_{mn}^{(i+1)} = x_{mn}^{(i)} + \frac{1}{n}\left(y_{mn}^{(i)} - x_{mn}^{(i)}\right) \tag{32}$$

Step 5 (convergence judgment). If there is no significant difference between the flows of space-time arcs obtained in two successive times, that is to say, the following formula can be satisfied, then the flow assignment ends; otherwise, it will return to Step 2. Here, ε is a very small number, which will be taken as 0.5.

$$\max\left\{x_{mn}^{(i+1)} - x_{mn}^{(i)}\right\} \leq \varepsilon \tag{33}$$

6. Case Study

6.1. Case Information

6.1.1. Case Description. In this study, part of the Beijing subway network is selected to test the models. Beijing subway is the second largest metro network in China, with 22 operation lines and 370 stations in the network. The scale of the Beijing subway network is 608 kilometers. This paper selects four busiest lines in the Beijing subway network in 2017. The four lines are line 2, line 4, line 5, and line 6, respectively. All transfer stations are retained. For convenience, some intermediate stations are neglected, which does not affect the estimation result. The physical topology of the test network is shown in Figure 9.

In the physical topology in Figure 9 , the stations marked by the boxes represent intermediate stations, and the stations marked by the circle represent the transfer stations. The physical topology network is a directed graph, so the two running directions of the same line should be represented

Table 2: Line direction and number.

Line direction	Real line direction
Line direction 1	The clockwise direction of inner ring of line 2
Line direction 2	The counter clockwise direction of the outer ring of line 2
Line direction 3	The direction of the TIANTONGYUAN on line 4
Line direction 4	The direction of the ANHEQIAO North on line 4
Line direction 5	The direction of the TIANTONGYUAN North on line 5
Line direction 6	The direction of the SONGJIAZHUANG on line 5
Line direction 7	The direction of the LUCHENG on line 6
Line direction 8	The direction of the HAIDIAN WULUJU on line 6

Table 3: Station number.

Station number	Real station	Station number	Real station
1	CHEGONGZHUANG West	12	CHONGWENMEN
2	CHEGONGZHUANG	13	HEPINGMEN
3	PINGANLI	14	XUANWUMEN
4	NANLUOGUXIANG	15	CHANGCHUNJIE
5	DONGSI	16	National Library
6	CHAOYANGMEN	17	LINGJING Hutong
7	HUJIALOU	18	Beijing South Railway Station
8	XIZHIMEN	19	HEPINGXIQIAO
9	GULOUDAJIE	20	BEIXINQIAO
10	YONGHEGONG	21	DONGDAN
11	Beijing Railway Station	22	TIANTANDONGMEN

Table 4: Passenger demand.

Time	OD pair										
	7-16	16-7	16-13	1-20	16-22	1-22	18-19	1-7	19-1	22-1	7-18
9:02	65	50	32	69	65	43	45	44	52	55	53
9:04	50	79	68	47	84	59	51	60	56	54	54
9:06	48	52	42	52	30	48	49	47	39	47	55
9:08	37	52	49	49	69	50	45	49	49	41	44
9:10	73	47	69	30	58	57	56	53	57	50	48
9:12	62	40	78	79	39	62	50	60	62	45	54
9:14	56	55	40	58	49	58	50	57	42	45	51
9:16	68	61	82	49	63	65	57	64	59	54	61
9:18	45	80	69	74	52	68	50	67	69	48	64
9:20	58	54	59	40	68	52	61	50	58	58	48
9:22	61	45	60	60	50	55	53	54	54	50	51
9:24	59	82	54	59	72	53	61	52	65	58	49
9:26	60	75	52	62	58	68	63	62	60	60	59
9:28	49	62	62	59	60	65	52	65	56	49	62
9:30	59	42	59	52	51	46	49	44	46	47	42

separately. For the convenience of the following research, the different directions of each line are numbered separately, as shown in Table 2. In addition, the stations' numbers are shown in Table 3.

Taking 9:00 to 9:30 as the study period, each 2 min is a time step, so there are 15 periods in total. 4 OD pairs (10 routes) in Figure 9 are selected and the passenger demand data are obtained from smart card records at each period in Table 4. The train timetables of all lines are shown in the appendix.

6.1.2. Route Selection Survey and Parameter Estimation. In order to verify the applicability of the improved generalized random regret model in the route selection, the parameter estimation in the model was carried out based on

Table 5: Estimation results.

parameter	values	parameters	values
θ	1.3	Z_l	256
κ	2	N_l	1428
γ_{ET}	-1	γ_{TT}	-3
γ_{VT}	-1	ϖ_{ET}	0.5
γ_{CT}	-2.5	ϖ_{VT}	0.5
α	0.5	ϖ_{CT}	0.9
β	0.8	ϖ_{TT}	0.8

Note. The number of seats Z_l and the capacity of train N_l are directly obtained from rolling stock profile.

the data derived from a survey on passenger route choice behavior.

Route choice data were collected based on a face to face SP survey [43]. The survey was conducted between 8:00 and 17:00 on Sept. 12 and Sept. 19 in trains and at stations. A questionnaire is designed to obtain the route choice result of passengers who use Beijing urban rail transit. Responders are asked to make a choice among a number of possible routes given the associated values of attributes on the subnetwork. A total number of 1030 effective samples are collected in the survey. The parameters of utility maximization model and regret minimization model are estimated by Biogeme software [44]. The results are shown in Table 5.

Three experiments are designed: (1) random utility maximization; (2) hybrid of random utility maximization and random regret minimization with attributes level; (3) hybrid of random utility maximization and random regret minimization with decision level.

6.2. Result with Attributes Level Hybrid Rule. According to the physical topology network, train timetable, and the smart card data, the space-time extended network is constructed, passenger demand and the parameter value are put into the algorithm, and the results can be obtained by using the random utility maximization and the random regret minimization model with different attributes level hybrid parameters, which are shown in Table 6.

6.2.1. Route Choice. Under the utility maximum rule, for the OD pair from Beijing South Railway Station to HEPINGXIQIAO at 9:06, there are two effective routes. The number of transfers of the two routes is two, and the transfer time at the two transfer stations is close, so the difference of the number of passengers choosing the two routes is only 4. For OD pair at 9:14 from CHEGONGZHUANG West to TIANTANDONGMEN, there are also two effective routes between the OD pair. The route 1 needs two transfers, and the route 2 needs one transfer. The number of passengers who choose route 1 is much greater than the number of those who choose route 2. The reason is that the train connection time is long (7 minutes) at DONGSI station on route 2, which increases the passenger transfer waiting time. For O-D at 9:04 from the National Library to TIANTANDONGMEN, there are four routes to choose. In Table 8, the number of passengers on each path is different. In general, the number of passengers with large travel costs is relatively few, and the number of passengers with less travel costs is large. This shows that passengers follow the utility maximization rule when choosing a route.

With regard to RRM with attributes level hybrid parameter, the route choice result is quite different from RUM according to the different number of alternatives. For OD pairs, such as National Library-HEPINGMEN, CHEGONGZHUANG West-TIANTANDONGMEN, Beijing South Railway Station-HEPINGXIQIAO, there are only two alternative routes, and the optimal route with RRM is close to RUM. In contrast, for those with more than two alternative routes, the route choice with RRM and RUM is different. Taking OD pair National Library-TIANTANDONGMEN as an example, it has four alternative routes; the optimal route is the same with RRM and RUM. However, the suboptimal route with RRM and RUM is different. This means that the route associated with the second largest utility is not the same as the route associated with the second smallest regret. This is because, based on the utility maximization rule, the utility value of route 1 (transfer at XUANWUMEN and CHONGWENMEN) is larger. But based on regret minimization rules, the attribute hybrid parameter of the crowd is larger than other observed variables. Therefore, the degree of crowd regret has a greater impact on the route choice. The crowd cost of route 3 (transfer at PINGANLI and DONGSI) is 0; that is, more passengers tend to choose a more comfortable environment to avoid crowding regret.

6.2.2. Flow Assignment. The transit assignment results of RUM and RRM with attributes level hybrid parameters are shown in Figures 10 and 11. In the figures, the number represents the passenger flow on each section, and the time for each train stopping at the station is indicated beside the station.

It can be observed from Figures 10-11 that the flows assigned to the links are different with different rules. The results show that most of the passengers would choose the fastest route under RUM conditions, while under RRM with different attributes level hybrid parameters, more passengers choose a moderate route.

Between the same OD, the route traffic under RUM is different from the route traffic under RRM. For example, there are two routes of National Library-HEPINGMEN; the first route is National Library- XUANWUMEN -HEPINGMEN, and the second route is National Library-XIZHIMEN-HEPINGMEN. They have the same departure time and number of transfer times, but the transfer station is different, so the transfer time is different. Under the RUM, the flow of the first route is less than the flow of second route, but under the RRM, the flow of the first route decreases and the flow of the second route increases. The reason is that the transfer time of the first route in XUANWUMEN is longer than the transfer time of the second route in XIZHIMEN. In addition, the attribute hybrid parameter of the transfer time is larger under the regret rule, which indicates that the passenger's

Table 6: Route choice result under utility maximization and regret minimization.

O-D	Station sequence/Time sequence on the route	Line direction	Transfer station	Utility value	Assignment	Regret value	Assignment
National Library-HEPINGMEN (16-13)	National Library9:08-XIZHIMEN9:13-PINGANLI9:18-LINGJING Hutong9:21-XUANWUMEN9:25(9:30)-HEPINGMEN9:32	3-2	XUANWUMEN	34.4	38	3.26	33
	National Library9:08-XIZHIMEN9:13(9:16)-CHEGONGZHUANG9:18-CHANGCHUNJIE9:25-XUANWUMEN9:27-HEPINGMEN9:29	3-2	XIZHIMEN	**28.8**	72	**0.81**	77
CHEGONGZHUANG West-TIANTANDONGMEN (1-22)	CHEGONGZHUANG West9:14-CHEGONGZHUANG9:16(9:18)-CHANGCHUNJIE9:25-XUANWUMEN9:27-HEPINGMEN9:29-CHONGWENMEN9:34(9:36)-TIANTANDONGMEN9:38	7-2-6	CHEGONGZHUANG CHONGWENMEN	**29.9**	115	**2.64**	108
	CHEGONGZHUANG West9:14-CHEGONGZHUANG9:16-PINGANLI9:19-NANLUOGUXIANG9:24-DONGSI9:27(9:34)-DONGDAN9:38-CHONGWENMEN9:40-TIANTANDONGMEN9:44	7-6	DONGSI	36.1	62	2.74	69
Beijing South Railway Station-HEPINGXIQIAO (18-19)	Beijing South Railway Station9:06-XUANWUMEN9:14(9:18)-HEPINGMEN9:20-CHONGWENMEN9:25(9:28)-DONGDAN9:30-DONGSI9:34-BEIXINQIAO9:38-YONGHEGONG9:40-HEPINGXIQIAO9:45	4-2-5	XUANWUMEN CHONGWENMEN	**48.3**	50	**1.06**	57
	Beijing South Railway Station9:06-XUANWUMEN9:14-LINGJING Hutong9:18-PINGANLI9:22(9:29)-NANLUOGUXIANG9:34–DONGSI9:37(9:42)-BEIXINQIAO9:46–YONGHEGONG9:48-HEPINGXIQIAO9:53	4-7-5	PINGANLI DONGSI	54.7	46	1.56	39
National Library-TIANTANDONGMEN (16-22)	National Library9:04-XIZHIMEN9:09-PINGANLI9:14-LINGJING Hutong9:17-XUANWUMEN9:21(9:24)-HEPINGMEN9:26-CHONGWENMEN9:31(9:36)-TIANTANDONGMEN9:40	3-2-6	XUANWUMEN CHONGWENMEN	44.2	15	5.86	15
	National Library9:04-XIZHIMEN9:09(9:13)-CHEGONGZHUANG9:15-CHANGCHUNJIE9:22-XUANWUMEN9:24-HEPINGMEN9:26-CHONGWENMEN9:31(9:36)-TIANTANDONGMEN9:40	3-2-6	XIZHIMEN CHONGWENMEN	44.5	14	7.69	5
	National Library9:04-XIZHIMEN9:09-PINGANLI9:14(9:19)-NANLUOGUXIANG9:24-DONGSI9:27(9:34)-DONGDAN9:38-CHONGWENMEN9:40-TIANTANDONGMEN9:44	3-7-6	PINGANLI DONGSI	45.6	8	5.79	16
	National Library9:04-XIZHIMEN9:09(9:12)-GULOUDAJIE9:18-YONGHEGONG9:22(9:24)-BEIXINQIAO9:26-DONGSI9:30-DONGDAN-9:34-CHONGWENMEN9:36-TIANTANDONGMEN9:40	3-1-6	XIZHIMEN YONGHEGONG	**43.3**	28	**5.23**	29

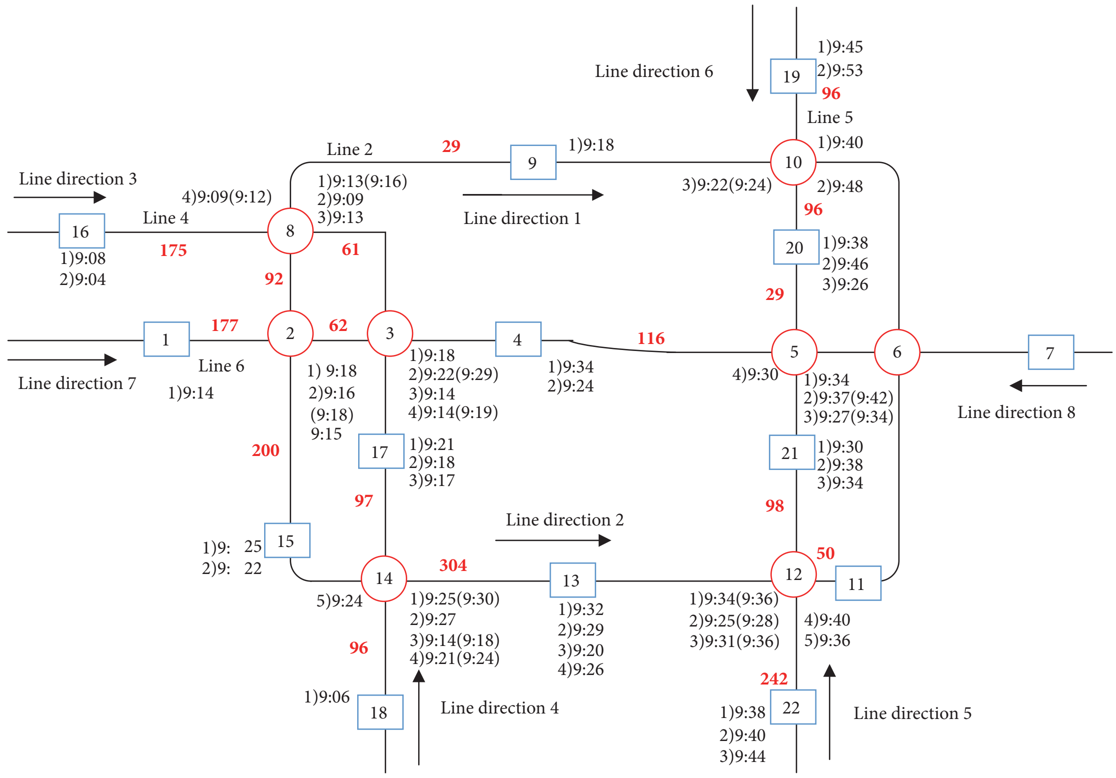

FIGURE 10: The assignment results based on RUM.

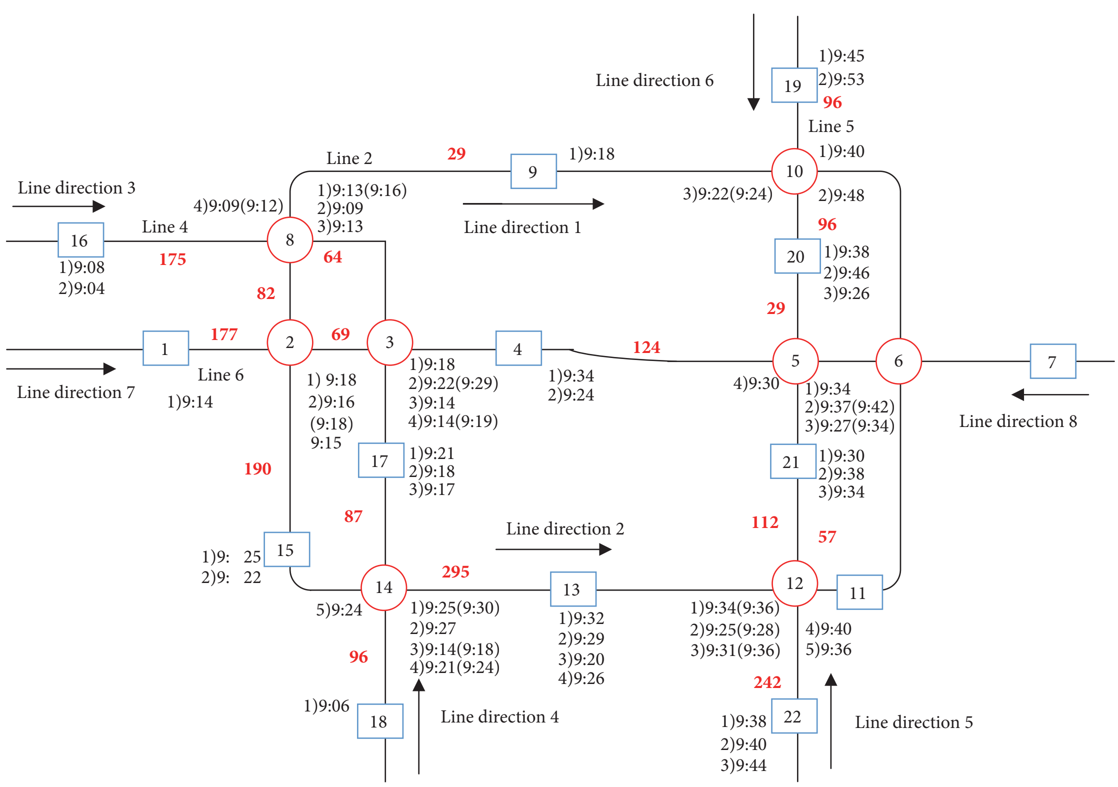

FIGURE 11: The assignment results based on RRM.

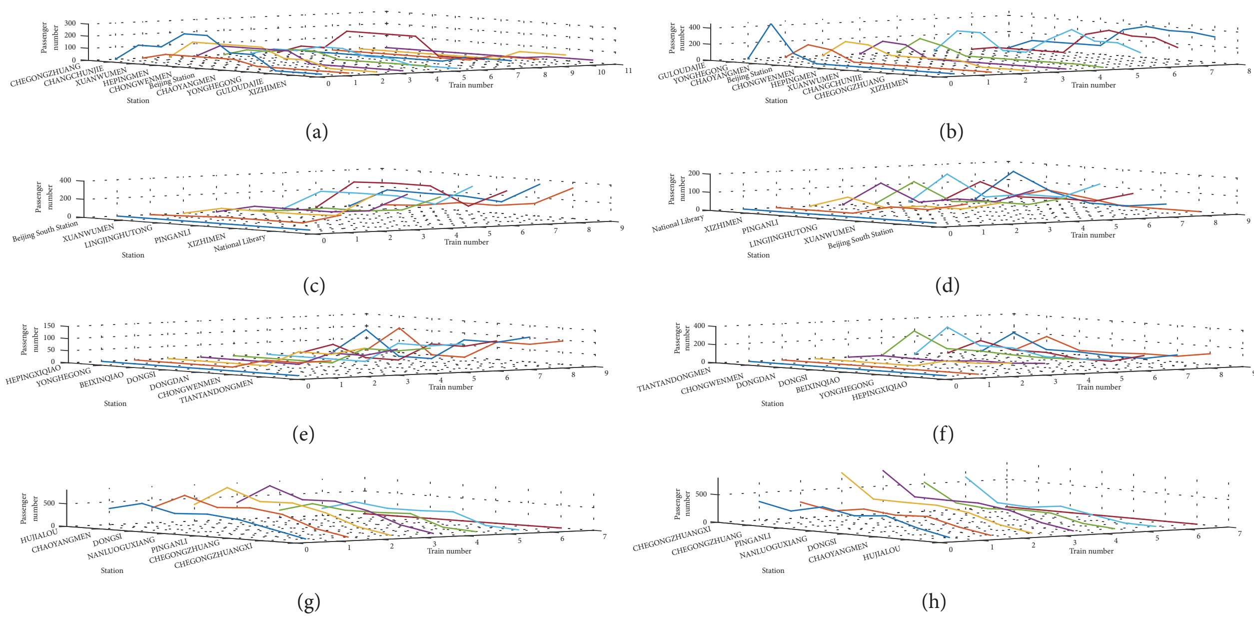

Figure 12: The number of people in the train. The train departs at each station based on RUM.

avoidance of the transfer time is higher, so the flow rate of the second route will increase.

6.2.3. Train Occupancies. Based on the route choice result on the space-time expanded network, the number of passengers is assigned to different trains. So the train occupancies can be obtained under different behavioral assumptions.

(1) Based on Utility Maximization. The number of passengers in each train at each section of each line based on the utility maximization model is shown in Figure 12.

In the above assignment results, the number of people in the train departing at each station is different depending on trains. That is, the number of people in the train changes dynamically with time. In the results of the above assignment, the number of people on the train in the station at the time of departure is 0, or the number of people in a train on a certain line is all 0, because in this case, only the OD demand within 30 minutes is selected. Moreover, due to limited data acquisition, the OD passenger flow demand is not between the two OD, so that some stations or trains appear with 0 people in the train. If we study the assignment results of a longer period of time and can get the passenger flow demand between all ODs, we can get more detailed assignment results. It can be seen from the above assignment results that each train shows the change of passenger flow only when passengers get on the train at the starting point of the OD and transfer stations, which is consistent with the actual urban rail transit operation.

(2) Based on Regret Minimization. The number of passengers in each train at each section of each line based on regret minimization model is shown in Figure 13.

In the assignment results under the regret minimization rule, the number of people in the train at the time of departure at each station is different from the utility maximization rule. Because under the regret rule, the regrets of passengers are different for various times in the train, transfer times, etc., the number of people in the train is different from the number under the utility rule.

6.2.4. Validation. The result is validated by the travel times of passengers derived from smart card data. At first, the travel time of each route is calculated, and then the OD travel time is aggregated according to the passenger flow distribution in Section 6.2 . After that, the accuracy of the result is verified by comparing it with the actual travel time obtained from the AFC. The results are shown in Table 7.

The estimation errors are calculated by formula (34), and the errors with different models are listed in Table 8.

$$\begin{aligned}&\mathit{OD\ travel\ time\ error}\\&\quad=\left|\frac{(\mathit{Calculated\ time}-\mathit{actual\ time})}{\mathit{actual\ time}}\right|\times 100\%\end{aligned}\tag{34}$$

The validation result shows that, from the aspect of travel time, RRM is slightly better than RUM for some of the OD pairs. For some OD pairs, the RRM performs worse than RUM. This is different from previous research findings in road traffic. This can be explained by the fact that passengers' behavior in urban rail transit is different from that of road travelers. For different types of OD pairs, passenger behaviors can be different. In urban rail transit, some people tend to maximize their utility while others would minimize their regret. Some passengers may choose a faster route to maximize their utility and ignore the risk of crowd regret, but some passengers also may not choose a faster but crowd route, because they try to avoid crowd regret from choosing the route. Any single standard behavior assumption may not fully explain the complex route choice behavior of humans.

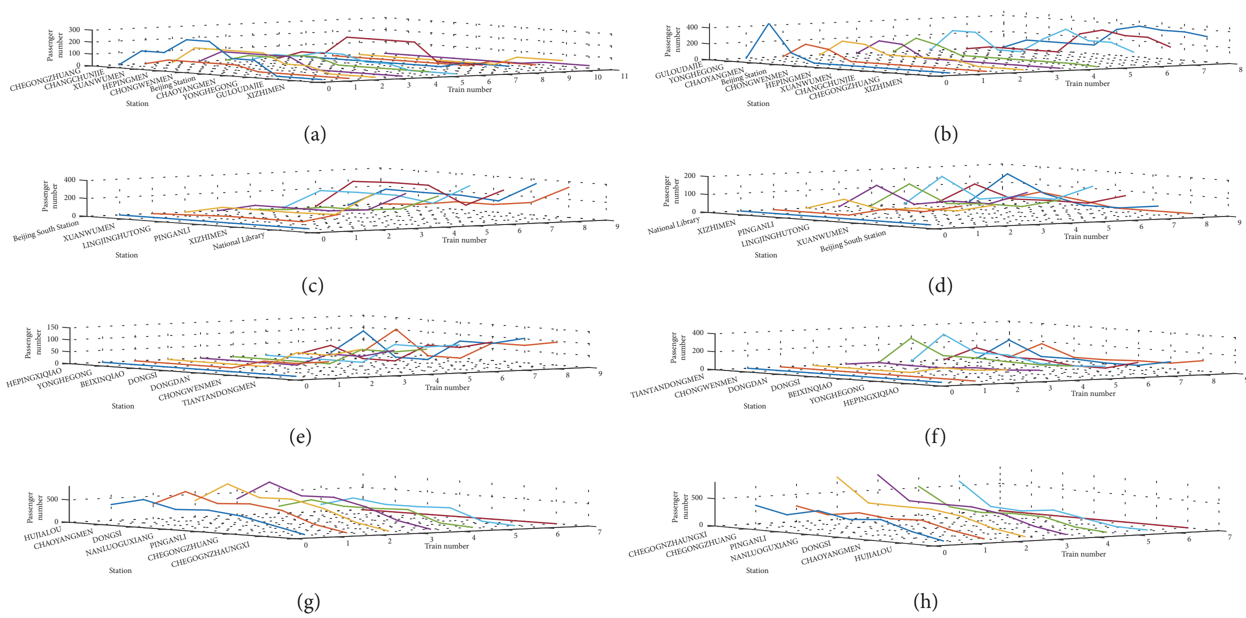

Figure 13: The number of people in the train. The train departs at each station based on RRM.

Table 7: Calculation results of travel time.

OD pair	Line direction	Transfer station	Route travel time(s)	OD travel time (s)		
				RUM	RRM	Actual
National Library-HEPINGMEN (16-13)	3-2	XUANWUMEN	2852	2358	2324	2260
	3-2	XIZHIMEN	2098			
CHEGONGZHUANG West-TIANTANDONGMEN (1-22)	7-2-6	CHEGONGZHUANG CHONGWENMEN	4239	3708	3648	2854
	7-6	DONGSI	2724			
Beijing South Railway Station-HEPINGXIQIAO (18-19)	4-2-5	XUANWUMEN, CHONGWENMEN	2520	2779	2739	2874
	4-7-5	PINGANLI, DONGSI	3060			
National Library - TIANTANDONGMEN (16-22)	3-2-6	XUANWUMEN, CHONGWENMEN	3604	3327	3392	3043
	3-2-6	XIZHIMEN, CHONGWENMEN	3004			
	3-7-6	PINGANLI, DONGSI	3496			
	3-1-6	XIZHIMEN, YONGHEGONG	3292			

From this point of view, we only assign transit flow based on the different rules and compare the differences. Moreover, considering the land use of the station in different OD pairs, it is observed that the crowd would influence the regret value of the OD pairs with more commuters, e.g., 16-13 and 1-22. The crowd does not influence the route choice of the OD pairs with more tourists, e.g., 18-19 and 16-22.

6.3. Result with Decision Level Hybrid Rule. In order to study the different effects of utility and regret on passenger route choice, the different values of decision level hybrid parameter are also tested. The value of the decision level hybrid parameter ρ is taken from 0 to 1, and the route choice and flow assignment results are obtained.

6.3.1. Flow Assignment. The results are shown in Figures 14–22.

Based on the hybrid utility and regret rule, the route flow of the same OD is different in different decision level hybrid parameters. With the increase of ρ, the route flow gradually tends to the flow based on the utility maximization rule, which means the proportion of passengers choosing utility maximization rule increases.

From Figures 14–22, we can find that, with the increase of ρ, there are eight sections whose flows remain unchanged,

Table 8: Travel time error of each OD.

OD pair	OD travel time error	
	RUM	RRM
National Library-HEPINGMEN (16-13)	4.36%	**2.84%**
CHEGONGZHUANG West-TIANTANDONGMEN (1-22)	29.93%	**27.83%**
Beijing South Railway Station-HEPINGXIQIAO (18-19)	**0.70%**	4.02%
National Library – TIANTANDONGMEN (16-22)	**16.58%**	18.85%

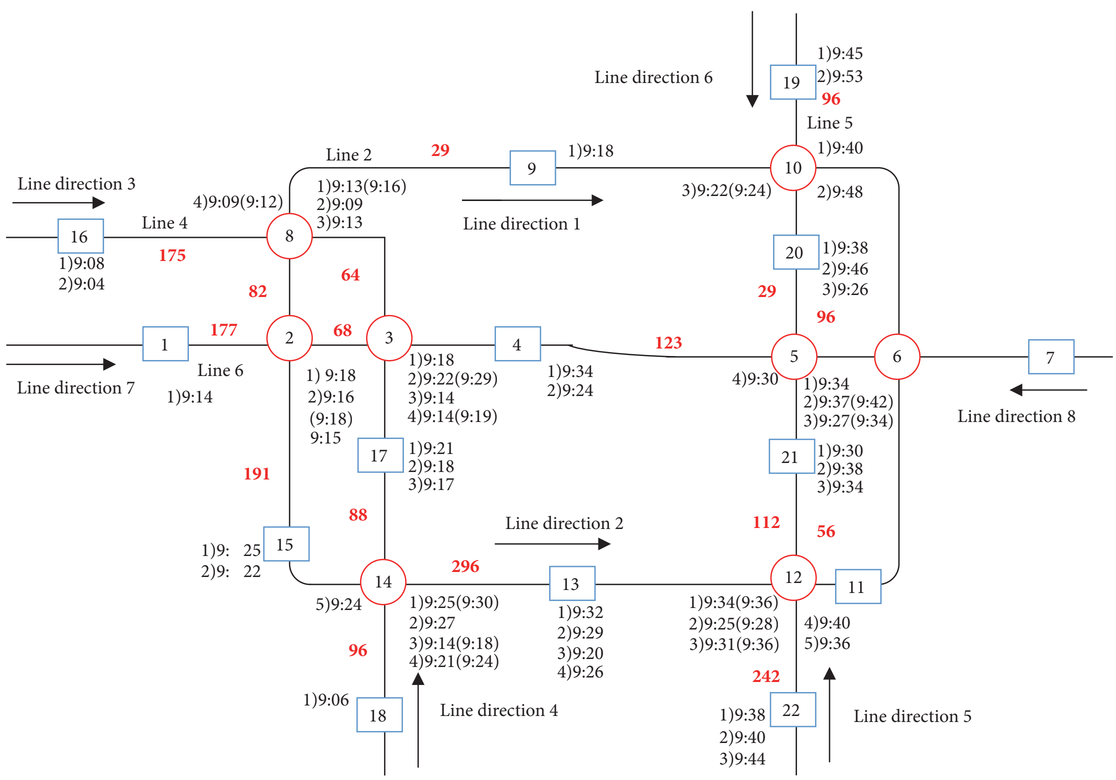

Figure 14: Flow distribution based on hybrid of RUM and RRM (ρ=0.1).

and nine sections whose flows have changed. The distribution of passenger flow in four sections has increased, which are LINGJING Hutong-XUANWUMEN, XIZHIMEN-CHEGONGZHUANG, CHEGONGZHUANG-CHANGCHUNJIE, and XUANWUMEN-HEPINGMEN. The passenger flow in five sections has decreased, which are XIZHIMEN-PINGANLI, CHEGONGZHUANG-PINGANLI, NANLUOGUXIANG-DONGSI, CHONGWENMEN-Beijing Railway Station, and DONGDAN-CHONGWENMEN.

The distribution of passenger flow in the vicinity of transfer station changed greatly. In addition, when ρ is reduced, the distribution of passenger flow is more uniform, especially in the vicinity of XIZHIMEN.

6.3.2. Validation. Figure 23 shows that, from the aspect of travel time, with the increase of ρ, some OD travel time errors with different hybrid parameter perform slightly better than RRM and some OD perform slightly worse. For National Library-HEPINGMEN and CHEGONGZHUANG West-TIANTANDONGMEN, RRM is slightly better than RUM. For Beijing South Railway Station-HEPINGXIQIAO and National Library-TIANTANDONGMEN, RUM is slightly better than RRM.

Taking CHEGONGZHUANG West-TIANTANDONGMEN as an example, RRM is slightly better than RUM. The study time is after 9 a.m., and the route travel cost is smaller for route 1 (transfer at XUANWUMEN and CHONGWENMEN), but during this period, more people will be less busy, and these people will choose a more comfortable route, which means more people tend to choose the less crowded and less transfer time route. The crowd cost of route 2 (transfer at DONGSI) is 0 and transfer time is one. Therefore, more passengers tend to choose route 2, so RRM is slightly better than RUM.

In this case, we do not think that the transit assignment model based on the random utility maximization or the random regret minimization rule is more advantageous. Compared to attribute hybrid parameter, the decision level hybrid parameter does not have much greater impact on route choice.

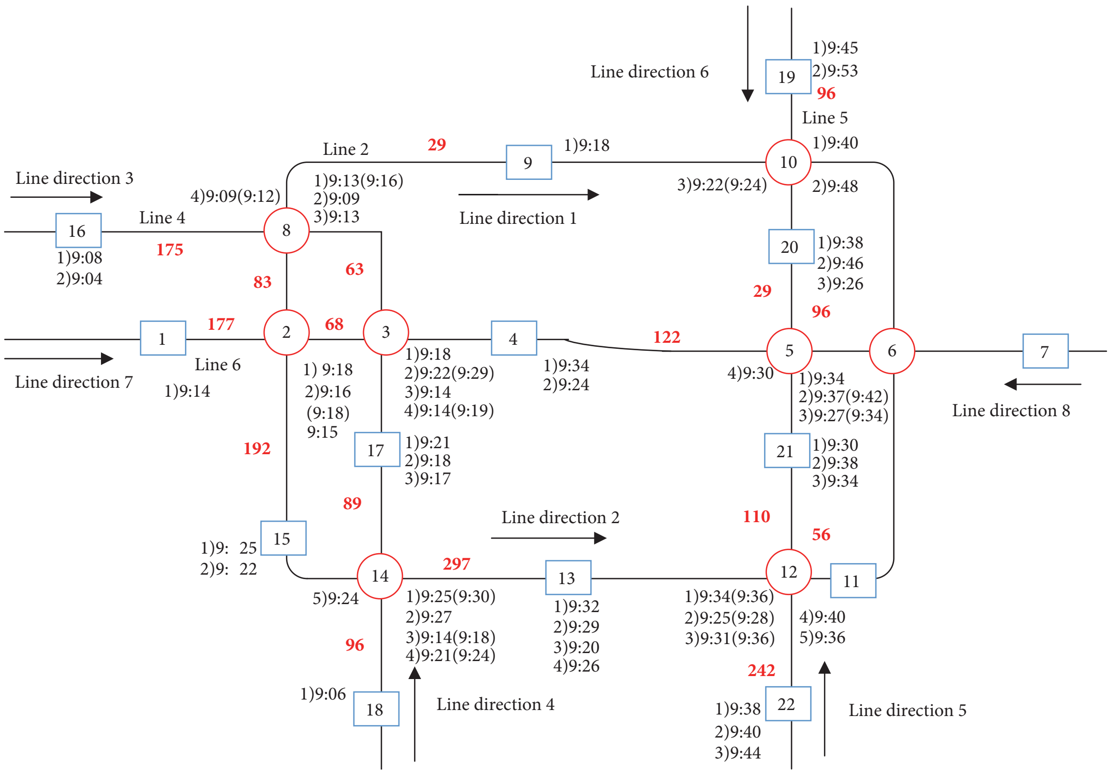

Figure 15: Flow distribution based on hybrid of RUM and RRM (ρ=0.2).

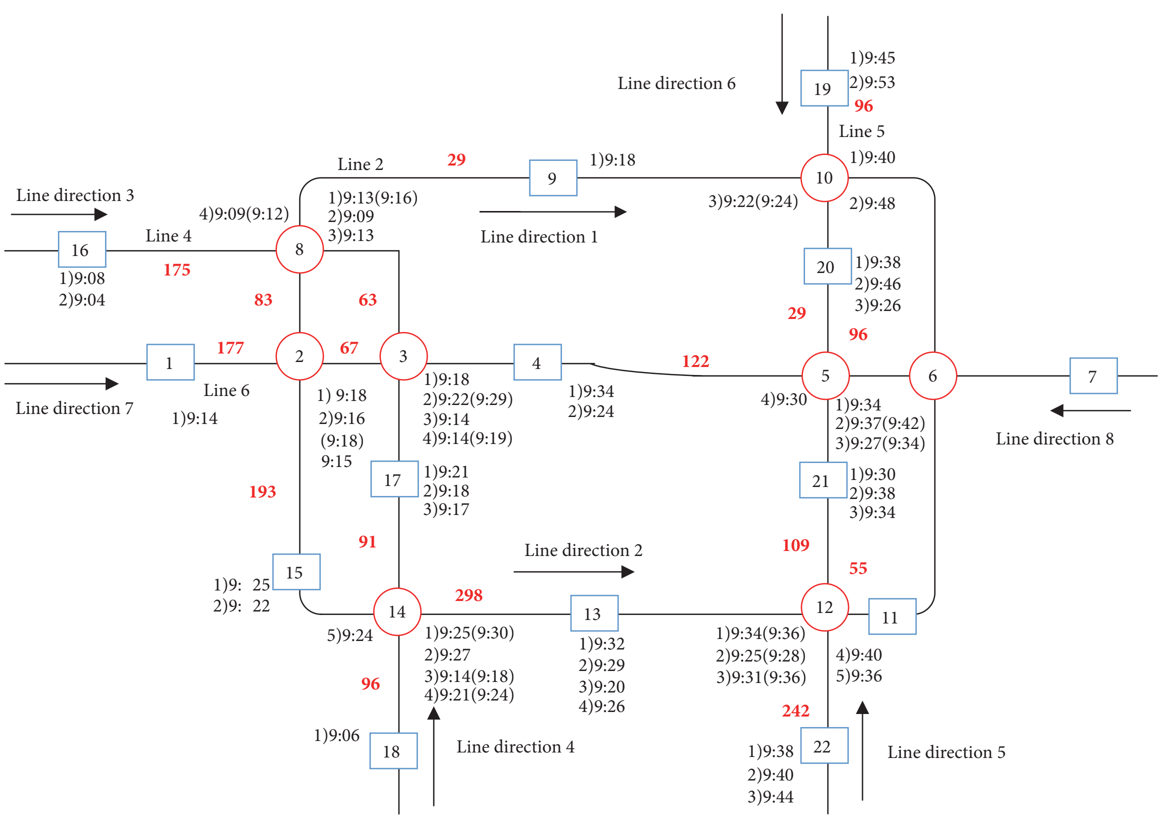

Figure 16: Flow distribution based on hybrid of RUM and RRM (ρ=0.3).

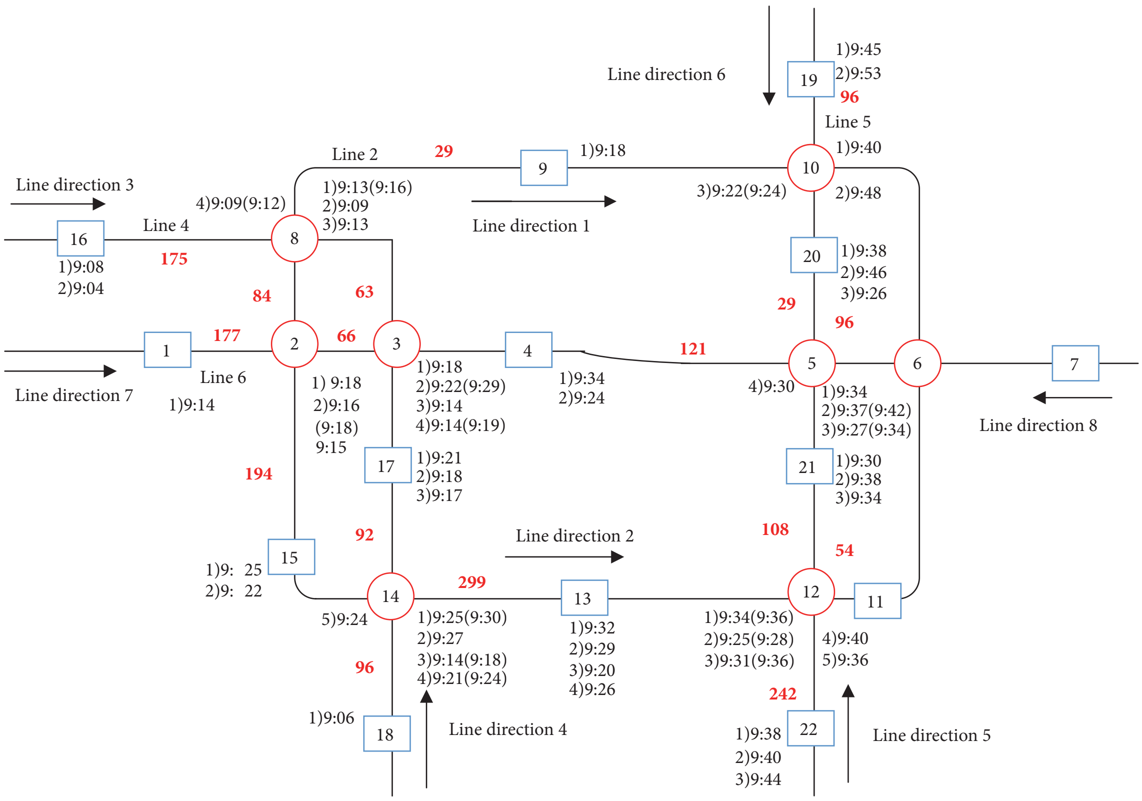

Figure 17: Flow distribution based on hybrid of RUM and RRM (ρ=0.4).

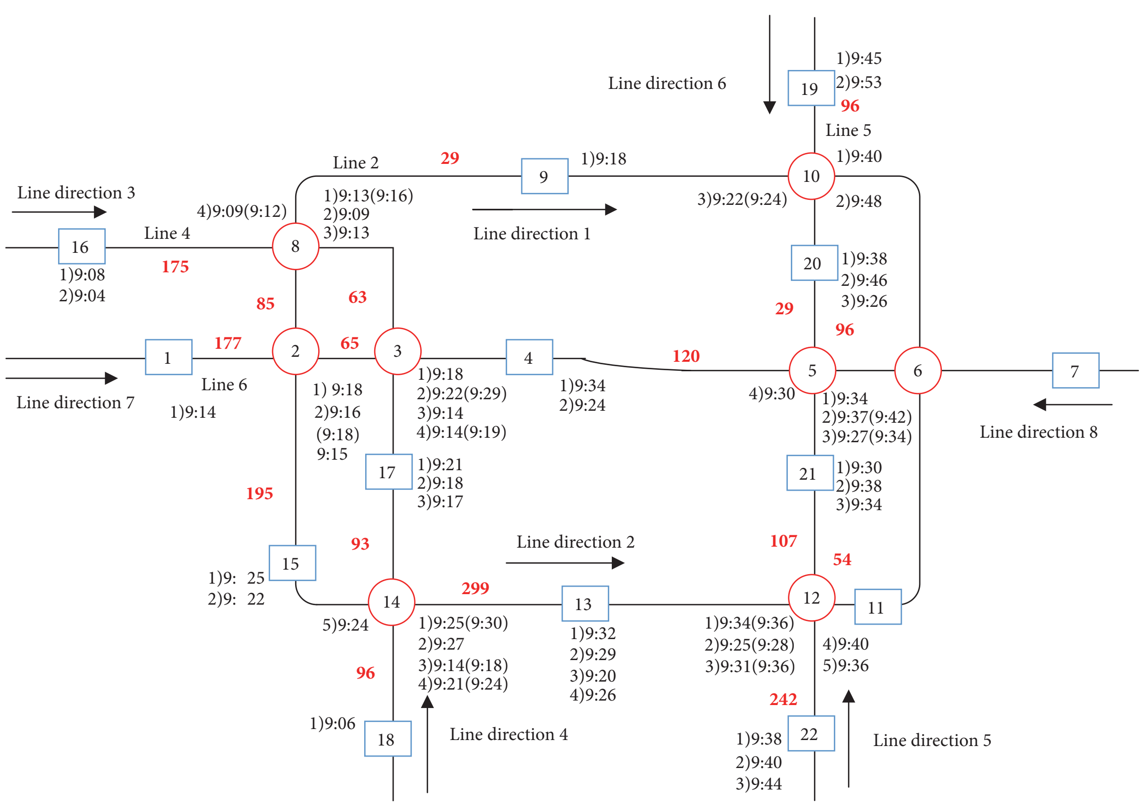

Figure 18: Flow distribution based on hybrid of RUM and RRM (ρ=0.5).

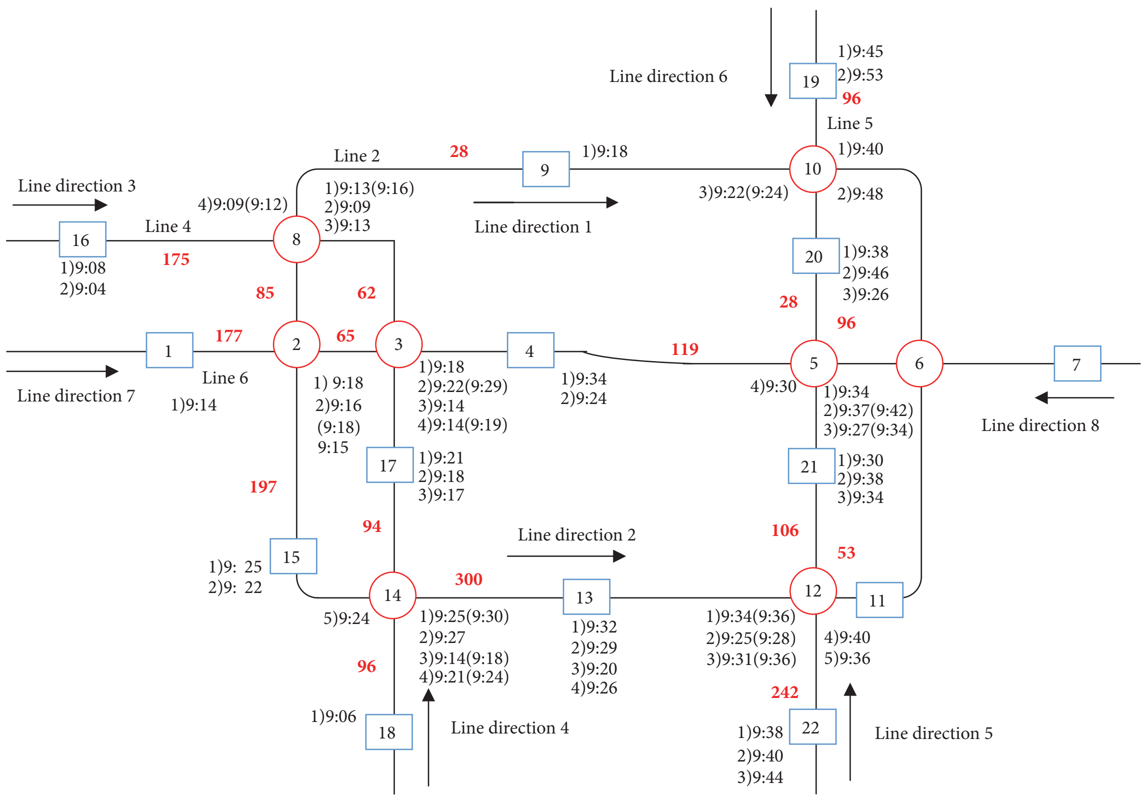

Figure 19: Flow distribution based on hybrid of RUM and RRM (ρ=0.6).

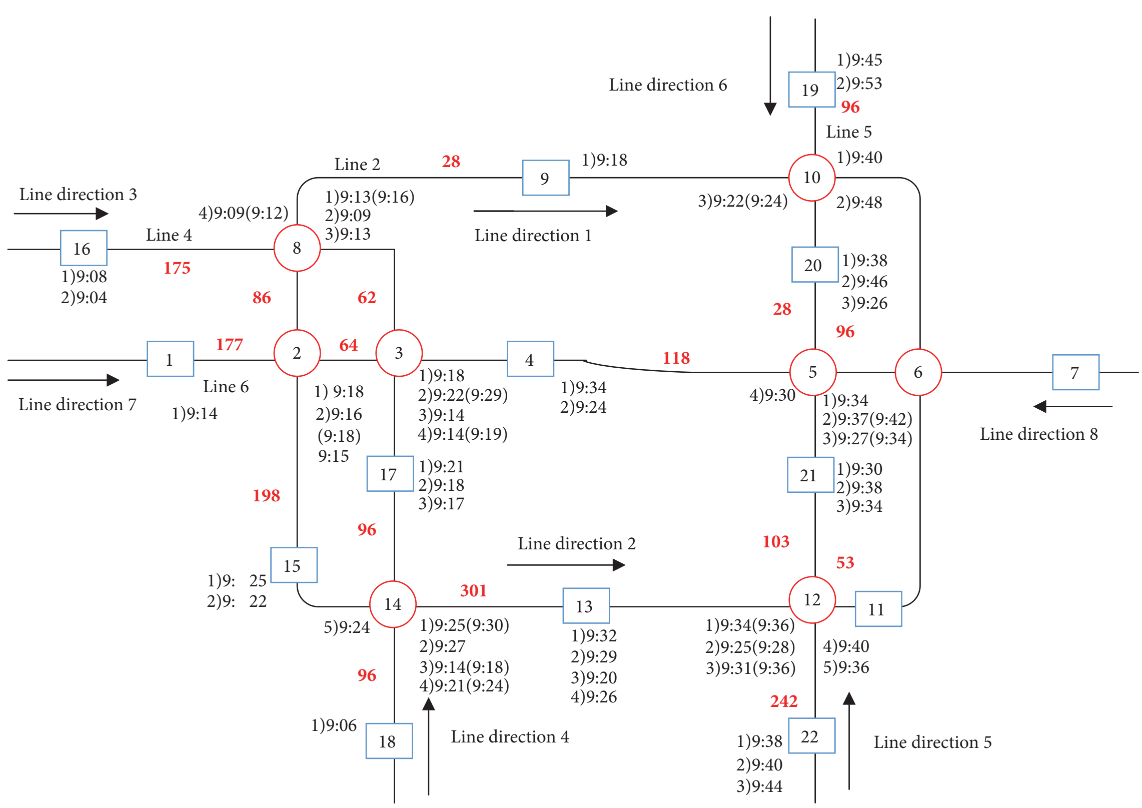

Figure 20: Flow distribution based on hybrid of RUM and RRM (ρ=0.7).

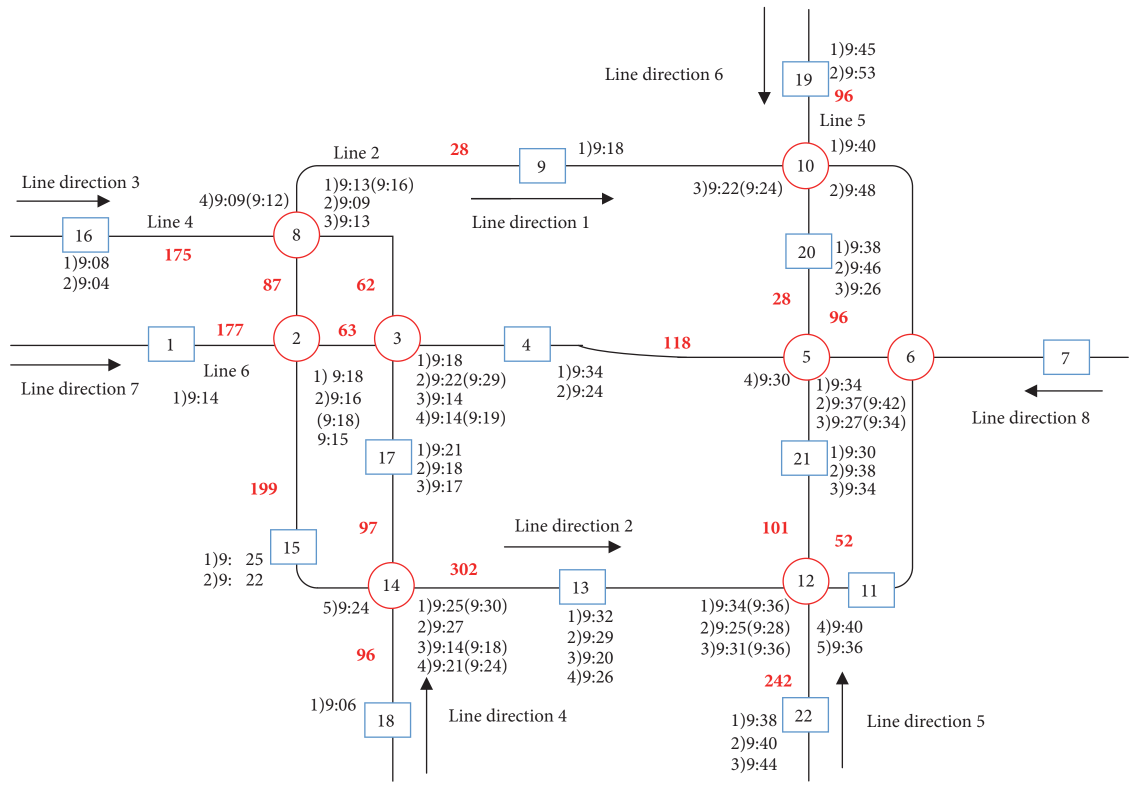

Figure 21: Flow distribution based on hybrid of RUM and RRM (ρ=0.8).

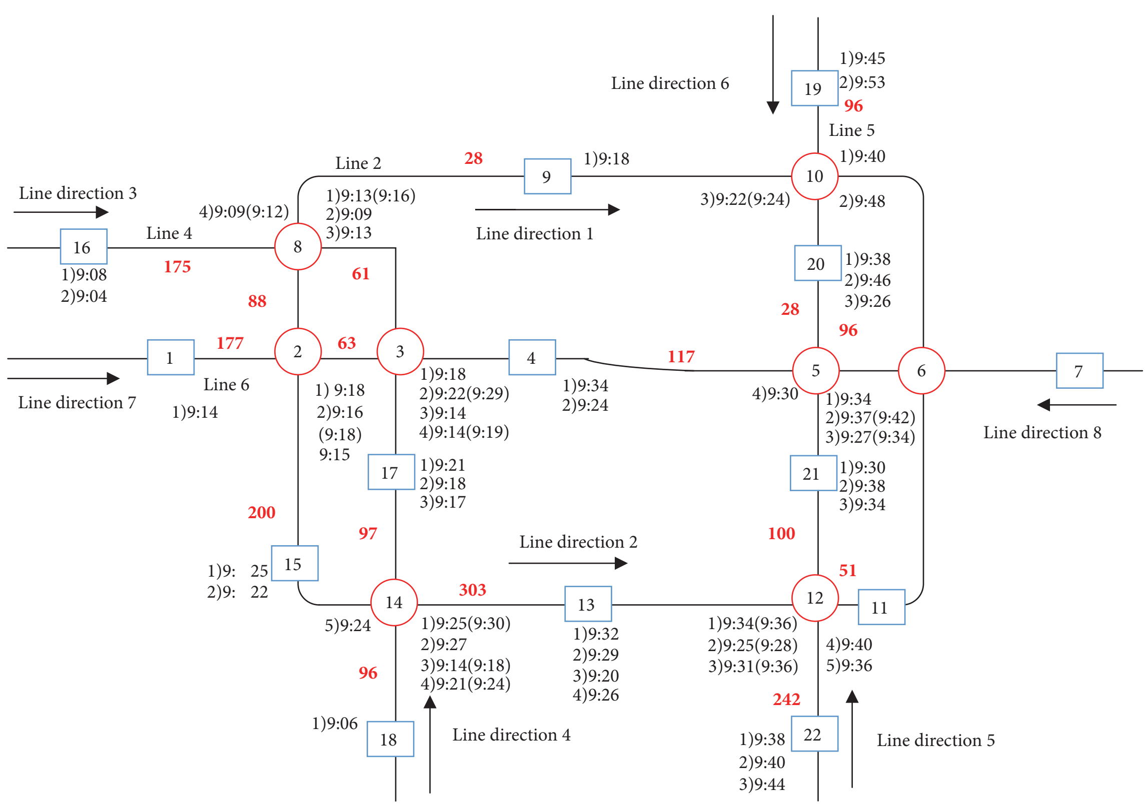

Figure 22: Flow distribution based on hybrid of RUM and RRM (ρ=0.9).

Table 9: Timetable of line 1.

Station	Train 1	2	3	4	5	6	7	8	9	10	11
XIZHIMEN	9:00	9:03	9:06	9:09	9:12	9:15	9:18	9:21	9:24	9:27	9:30
GULOUDAJIE	9:06	9:09	9:12	9:15	9:18	9:21	9:24	9:27	9:30	9:33	9:36
YONGHEGONG	9:10	9:13	9:16	9:19	9:22	9:25	9:28	9:31	9:34	9:37	9:40
CHAOYANGMEN	9:19	9:22	9:25	9:28	9:31	9:34	9:37	9:40	9:43	9:46	9:49
Beijing Railway Station	9:23	9:26	9:29	9:32	9:35	9:38	9:41	9:44	9:47	9:50	9:53
CHONGWENMEN	9:26	9:29	9:32	9:35	9:38	9:41	9:44	9:47	9:50	9:53	9:56
HEPINGMEN	9:31	9:34	9:37	9:40	9:43	9:46	9:49	9:52	9:55	9:58	10:01
XUANWUMEN	9:33	9:36	9:39	9:42	9:45	9:48	9:51	9:54	9:57	10:00	10:03
CHANGCHUNJIE	9:35	9:38	9:41	9:44	9:47	9:50	9:53	9:56	9:59	10:02	10:05
CHEGONGZHUANG	9:42	9:45	9:48	9:51	9:54	9:57	10:00	10:03	10:06	10:09	10:12

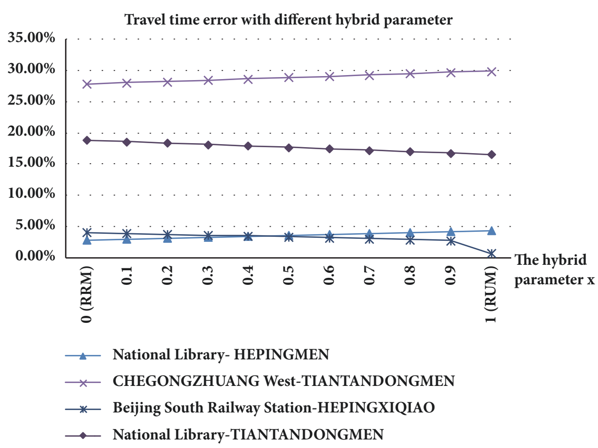

Figure 23: Travel time errors with different hybrid parameter.

7. Conclusions

This paper proposed a hybrid model of passenger route choice in urban rail transit network. The utility maximization rule and regret minimization rule are combined to analyze the passengers' route choice behavior. Two types of hybrid rules are introduced, namely, attributes level hybrid rule and decision level hybrid rule. Based on the train timetable, the space-time extension network is constructed based on the smart card data. The utility function and regret function are formulated by calculating the utility value and the regret value of different space-time arcs, respectively. After that, the MSA algorithm is used to solve the model. Finally, it took some OD pairs in Beijing urban rail transit network as an example to validate the hybrid model.

Three conclusions can be drawn from this study:

(1) Passengers' route choice behavior in urban rail transit does not obey a single criteria, e.g., utility maximization or regret minimization. For some OD pairs, regret minimization model performs slightly better than utility maximization, while for others, the results are opposite. For those in which RRM performs better, this implies that the utility of the chosen route is not only related to its own utility, but also related to the utility value of other unselected routes, which provide the multiangle method for transit assignment of urban rail transit.

(2) For OD pairs with only two alternative routes, the optimal route with RRM is close to RUM. In contrast, for those with more than two alternative routes, the route choice with RRM and RUM is different.

(3) Case studies show that crowd would only influence the regret value of the OD pair with more commuters. The crowd does not influence the route choice of OD pairs with more tourists. So it is necessary to use different attributes level hybrid parameters for different observable variables considering the types of passengers traveling between two stations.

So far, it is not clear for what kind of OD pairs, RRM is better. So an alternative choice is to use a hybrid transit assignment model which can reduce the risk of average estimation error.

This research is only a pilot study of hybrid route choice model in an urban rail transit network. The future research would focus on the key problem of which is the main influencing factor on RUM or RRM in an urban rail transit network. It is also necessary to validate the result in a more practical manner for a larger network scale. The advantages and disadvantages of passenger route choice behavior based on the utility maximization and regret minimization would be verified from the actual situation.

Appendix

See Tables 9, 10, 11, 12, 13, 14, 15, and 16.

Data Availability

The data are available from Beijiao SRAIL Technology (Beijing) Co., Ltd, for researchers who meet the criteria for access to confidential data. Access to data used in this paper is granted through a formal application process that requires

Table 10: Timetable of line 2.

Station	Train										
	1	2	3	4	5	6	7	8	9	10	11
XIZHIMEN	9:01	9:04	9:07	9:10	9:13	9:16	9:19	9:22	9:25	9:28	9:31
CHEGONGZHUANG	9:03	9:06	9:09	9:12	9:15	9:18	9:21	9:24	9:27	9:30	9:33
CHANGCHUNJIE	9:10	9:13	9:16	9:19	9:22	9:25	9:28	9:31	9:34	9:37	9:40
XUANWUMEN	9:12	9:15	9:18	9:21	9:24	9:27	9:30	9:33	9:36	9:39	9:42
HEPINGMEN	9:14	9:17	9:20	9:23	9:26	9:29	9:32	9:35	9:38	9:41	9:44
CHONGWENMEN	9:19	9:22	9:25	9:28	9:31	9:34	9:37	9:40	9:43	9:46	9:49
Beijing Railway Station	9:22	9:25	9:28	9:31	9:34	9:37	9:40	9:43	9:46	9:49	9:52
CHAOYANGMEN	9:26	9:29	9:32	9:35	9:38	9:41	9:44	9:47	9:50	9:53	9:56
YONGHEGONG	9:35	9:38	9:41	9:44	9:47	9:50	9:53	9:56	9:59	10:02	10:05
GULOUDAJIE	9:39	9:42	9:45	9:48	9:51	9:54	9:57	10:00	10:03	10:06	10:09
XIZHIMEN	9:45	9:48	9:51	9:54	9:57	10:00	10:03	10:06	10:09	10:12	10:15

Table 11: Timetable of line 3.

Station	Train								
	1	2	3	4	5	6	7	8	9
National Library	9:00	9:04	9:08	9:12	9:16	9:20	9:24	9:28	9:32
XIZHIMEN	9:05	9:09	9:13	9:17	9:21	9:25	9:29	9:33	9:37
PINGANLI	9:10	9:14	9:18	9:22	9:26	9:30	9:34	9:38	9:42
LINGJING Hutong	9:13	9:17	9:21	9:25	9:29	9:33	9:37	9:41	9:45
XUANWUMEN	9:17	9:21	9:25	9:29	9:33	9:37	9:41	9:45	9:49
Beijing South Railway Station	9:25	9:29	9:33	9:37	9:41	9:45	9:49	9:53	9:57

Table 12: Timetable of line 4.

Station	Train								
	1	2	3	4	5	6	7	8	9
Beijing South Railway Station	9:01	9:06	9:11	9:16	9:21	9:26	9:31	9:36	9:41
XUANWUMEN	9:09	9:14	9:19	9:24	9:29	9:34	9:39	9:44	9:49
LINGJING Hutong	9:13	9:18	9:23	9:28	9:33	9:38	9:43	9:48	9:53
PINGANLI	9:17	9:22	9:27	9:32	9:37	9:42	9:47	9:52	9:57
XIZHIMEN	9:22	9:27	9:32	9:37	9:42	9:47	9:52	9:57	10:02
National Library	9:27	9:32	9:37	9:42	9:47	9:52	9:57	10:02	10:07

Table 13: Timetable of line 5.

Station	Train								
	1	2	3	4	5	6	7	8	9
TIANTANDONGMEN	9:00	9:04	9:08	9:12	9:16	9:20	9:24	9:28	9:32
CHONGWENMEN	9:04	9:08	9:12	9:16	9:20	9:24	9:28	9:32	9:36
DONGDAN	9:06	9:10	9:14	9:18	9:22	9:26	9:30	9:34	9:38
DONGSI	9:10	9:14	9:18	9:22	9:26	9:30	9:34	9:38	9:42
BEIXINQIAO	9:14	9:18	9:22	9:26	9:30	9:34	9:38	9:42	9:46
YONGHEGONG	9:16	9:20	9:24	9:28	9:32	9:36	9:40	9:44	9:48
HEPINGXIQIAO	9:21	9:25	9:29	9:33	9:37	9:41	9:45	9:49	9:53

peer review. Further information can be obtained by readers from the company manager Dr. Lu (srail_beijing@163.com).

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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Table 14: Timetable of line 6.

Station	Train								
	1	2	3	4	5	6	7	8	9
HEPINGXIQIAO	8:59	9:03	9:07	9:11	9:15	9:19	9:23	9:27	9:31
YONGHEGONG	9:04	9:08	9:12	9:16	9:20	9:24	9:28	9:32	9:36
BEIXINQIAO	9:06	9:10	9:14	9:18	9:22	9:26	9:30	9:34	9:38
DONGSI	9:10	9:14	9:18	9:22	9:26	9:30	9:34	9:38	9:42
DONGDAN	9:14	9:18	9:22	9:26	9:30	9:34	9:38	9:42	9:46
CHONGWENMEN	9:16	9:20	9:24	9:28	9:32	9:36	9:40	9:44	9:48
TIANTANDONGMEN	9:20	9:24	9:28	9:32	9:36	9:40	9:44	9:48	9:52

Table 15: Timetable of line 7.

Station	Train						
	1	2	3	4	5	6	7
CHEGONGZHUANG West	8:59	9:04	9:09	9:14	9:19	9:24	9:29
CHEGONGZHUANG	9:01	9:06	9:11	9:16	9:21	9:26	9:31
PINGANLI	9:04	9:09	9:14	9:19	9:24	9:29	9:34
NANLUOGUXIANG	9:09	9:14	9:19	9:24	9:29	9:34	9:39
DONGSI	9:12	9:17	9:22	9:27	9:32	9:37	9:42
CHAOYANGMEN	9:14	9:19	9:24	9:29	9:34	9:39	9:44
HUJIALOU	9:19	9:24	9:29	9:34	9:39	9:44	9:49

Table 16: Timetable of line 8.

Station	Train						
	1	2	3	4	5	6	7
HUJIALOU	9:00	9:05	9:10	9:15	9:20	9:25	9:30
CHAOYANGMEN	9:05	9:10	9:15	9:20	9:25	9:30	9:35
DONGSI	9:07	9:12	9:17	9:22	9:27	9:32	9:37
NANLUOGUXIANG	9:10	9:15	9:20	9:25	9:30	9:35	9:40
PINGANLI	9:15	9:20	9:25	9:30	9:35	9:40	9:45
CHEGONGZHUANG	9:18	9:23	9:28	9:33	9:38	9:43	9:48
CHEGONGZHUANG West	9:20	9:25	9:30	9:35	9:40	9:45	9:50

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