Front. Eng. Manag. 2023, 10(2): 250–261
https://doi.org/10.1007/s42524-021-0180-2

RESEARCH ARTICLE

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Coupling analysis of passenger and train flows for a large-scale urban rail transit system

Abstract Coupling analysis of passenger and train flows is an important approach in evaluating and optimizing the operation efficiency of large-scale urban rail transit (URT) systems. This study proposes a passenger–train interaction simulation approach to determine the coupling relationship between passenger and train flows. On the bases of time-varying origin–destination demand, train timetable, and network topology, the proposed approach can restore passenger behaviors in URT systems. Upstream priority, queuing process with first-in-first-serve principle, and capacity constraints are considered in the proposed simulation mechanism. This approach can also obtain each passenger's complete travel chain, which can be used to analyze (including but not limited to) various indicators discussed in this research to effectively support train schedule optimization and capacity evaluation for urban rail managers. Lastly, the proposed model and its potential application are demonstrated via numerical experiments using real-world data from the Beijing URT system (i.e., rail network with the world's highest passenger ridership).

Keywords urban rail transit, coupling analysis, passenger–train interaction, large-scale simulation

Received April 16, 2021; accepted June 22, 2021

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This research was supported by the National Key R&D Program of China (Grant No. 2020YFB1600702), the National Natural Science Foundation of China (Grant Nos. 71621001, 72071015, 71701013, and 71890972/71890970), the Beijing Municipal Natural Science Foundation (Grant No. L191024), the 111 Project (Grant No. B20071), and the State Key Laboratory of Rail Traffic Control and Safety (Grant No. RCS2021ZZ001).

1 Introduction

Urban rail transit (URT) systems have been developed into a critical transportation element in metropolises worldwide as a result of large capacity, punctuality, and safety advantage (Yang, 2014; Yang et al., 2017; Gao and Yang, 2019). The Chinese URT is currently boosting its development, reaching a historically high level in terms of construction speed, scale, and investment (Ding and Guo, 2015; Ding and Xu, 2017). In recent years, the rapid development of urbanization has stimulated significant travel demand by URT systems (Yin et al., 2017; Cheng et al., 2021). The contradiction between passenger travel demand and limited train capacity has become increasingly prominent. Realistically, the arrival rate of passengers is mainly concentrated during peak hours. Such high demands result in severe operational pressure on URT systems, further leading to a reduction in service level and even bringing high risk to the operational safety of URT systems. In this case, demand-oriented train timetables should be compiled and passenger flow control measures matching with train timetables must be formulated (Shi et al., 2019).

Automated fare collection (AFC) systems have been able to gather the time-dependent passenger demand of different origin–destination (OD) pairs, thereby providing basis for URT operation optimization (Ma and Koutsopoulos, 2019). To simplify the operation design problem, a lot of studies only focus on one individual rail line or disregard some reality rules and passenger behaviors. At present, no universal method is used to jointly analyze passenger and train flows for large-scale URT networks, and the limitation of computational efficiency results in the difficulty of applying numerous methods to large-scale problems. Hence, we want to develop a collaborative simulation of passenger and train flows for large-scale URT systems, which can derive the travel trip for each passenger and approximately estimate space–time flow distribution in URT networks. The coupling analysis of passenger and train flows is executed by the average travel time of passengers, transfer waiting time, and train load factors, among others. Thereafter, the propagation process of passenger flow is deduced, and the potential bottleneck stations and sections are identified, thereby providing effective support for URT managers to optimize train timetables and evaluate train capacity.

Given the aforementioned concerns, this study used the comprehensive data of time-dependent OD demand, rail network topological structure, and train timetable as bases to propose a simulation-based approach to analyze the efficiency of URT systems by coupling passenger and train flows. The detailed contributions of this research are summarized as follows.

(1) With consideration of train capacity constraints, upstream station priority, path choice, congestion effects, and first-in-first-serve (FIFS), the proposed simulation approach is consistent with the actual passenger travel behaviors.

(2) The proposed approach can restore each passenger's complete travel chain, including entering the origin station, waiting for the train, boarding, alighting, transferring, and leaving the destination station. This technique can be used to analyze (including but not limited to) the various indicators discussed in this research.

(3) The coupling analysis of passenger and train flows is executed by the average travel time of passengers, transfer waiting time, and train load factors, among others. Thereafter, the propagation process of passenger flow is deduced, and the potential bottleneck stations and sections are identified, thereby providing effective support for URT managers to optimize train timetables and evaluate train capacity.

(4) The proposed approach can be applied to large-scale URT networks owing to its high efficiency. A case study based on real-world data from the Beijing URT system is conducted to demonstrate the effectiveness of the proposed simulation process.

The remainder of this paper is organized as follows. Section 2 provides a literature review to introduce the state-of-the-art in this field. Section 3 describes the methodology. Section 4 presents a large-scale case with the real-world operation data of the Beijing URT system. Lastly, Section 5 presents some conclusions and further studies.

2 Literature review

Previous studies have indicated that estimating and predicting the space–time distribution of passenger flows over a network can be accomplished by passenger assignment models. Passenger assignment models are divided into frequency- and schedule-based models (Fu et al., 2012; Zhu et al., 2017). Frequency-based models (Cominetti and Correa, 2001; Cepeda et al., 2006; Nökel and Wekeck, 2009; Schmöcker et al., 2011; Teng and Liu, 2015) made different assumptions on headways or frequencies to deduce variable waiting times that passengers will possibly spend at the waiting area but did not consider the capacity of each single train. Several schedule-based models are proposed to further consider specific rules for passenger traveling (Nuzzolo et al., 2012; Xie et al., 2020; Xu et al., 2021). In the optimization problems of train operation, passenger travel time (Zhang et al., 2018), passenger waiting time (Yang et al., 2019), and passenger transfer waiting time (Wang et al., 2015; Liu et al., 2018) are often used as indicators to evaluate the operation mode. However, the majority of train scheduling studies are based on an individual URT line (Barrena et al., 2014; Jamili and Pourseyed Aghaee, 2015). Unlike railways, passengers often need to transfer between transit lines to reach their final destination. Hence, without considering the network effect, the methods of dividing the network into multiple single lines are one-sided. Some studies have focused on entire networks with the objective of minimizing transfer waiting time (Wu et al., 2015). Unfortunately, the existing literature has often disregarded passenger behavior differentiation and some reality constraints, such as FIFS, platform congestion, limited train capacity, and passenger route choice (Xu et al., 2017).

Simulation is another method for solving the problem of coupling analysis of passenger and train flow. Existing studies on pedestrian movement in public transport facilities have focused on passenger characteristics and particular behaviors, such as boarding and alighting (Li et al., 2020), route choices (Li and Zhu, 2016), and evacuation (Zhang and Han, 2010). Seriani and Fernandez (2015) studied the boarding and alighting time of passengers at URT stations through simulation and experiments. Zhang and Han (2010) introduced a potential field to simulate passenger transfer behavior by the definition of tendency probability. Some studies have focused on URT system simulation. Zhao et al. (2017) proposed a method to retrieve passenger patterns and individual general travel style based on history smart card transaction data. Xu et al. (2017) developed a cell transmission model for URT networks to obtain a space–time flow distribution without the restriction of schedules. They likewise introduced the concept of continuous transmission and assumed that all passengers are allocated to their shortest path. To investigate the relationship between train and passenger delays, Jiang et al. (2012) proposed a simulation model to predict dynamic passenger distribution in a large-scale rail transit network. Ingvardson et al. (2018) investigated passenger waiting time by using a passenger arriving mixture distribution consisting of uniform and beta distributions. Poulhès (2020) presented an integrated model for the simulation of a fixed block urban rail line in interaction with passenger assignment, and verified it thereafter by applying it to Line 13 of the Paris metro. Paulsen et al. (2021) formulated an adaptive passenger path choice model based on an agent-based simulation to calculate the corresponding realized routes and passenger delays in a transport network.

When considering all common reality constraints together, the scales of networks studied in the existing literature have been extremely small, which are difficult to be applied to realistic scale networks. Moreover, tickets in URT systems do not correspond to specific train numbers, and in congestion conditions, the train number that each passenger boarded cannot be retrieved precisely. Hence, restoring passengers' travel chain (i.e., finding the train numbers that passengers have boarded) in large-scale URT networks is the core for a compiling analysis of passenger and train flows.

For comparative convenience, we list the detailed characteristics of some closely related references in Table 1 to show the innovations of this study.

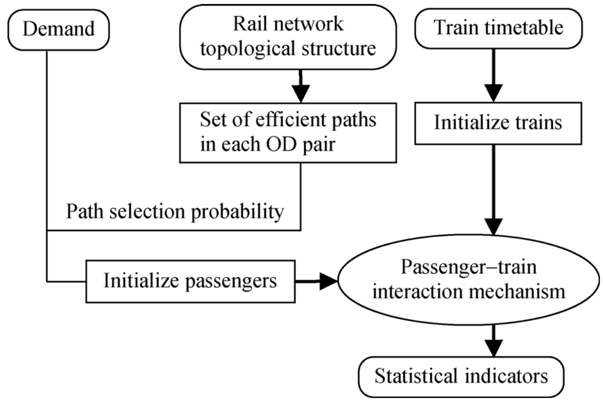


Fig. 1 Schematic indicating the passenger and train collaborative simulation.

3 Methodology: Passenger and train flow collaborative simulation

This section first obtains the accurate travel demand by analyzing the AFC system data, including the origin station, destination station, and arriving time of each passenger. We develop a collaborative simulation of passenger and train flows to restore each passenger's travel track, such that all trains that the passenger boarded can be recorded. Thereafter, the number of transferred and passed passengers from each station can be obtained accurately. On this basis, subsequent analysis of network transmission capacity, passenger service level, and potential bottleneck stations or sections can be conducted. The proposed simulation can closely imitate passengers' behavior in the URT system, and all simulation parameters are validated with practical manual survey data and huge historical data.

We consider a directed urban rail network, including a finite set of stations denoted as N, and we define an OD pair from station r to station s as (r, s), where $r, s \in N$. Let T denotes the simulation period, and the continuous time horizon is discretized into a set of time intervals. The unit of a time interval can be any value, such as 30 s, 1 min, or 5 min.

The overall simulation architecture is designed as shown in Fig. 1. Suppose that the time-dependent OD demand, rail network topological structure, and train timetable are given. We are convinced that the passenger path choice probability is fixed and can be calculated in advance. Yin et al. (2011) proposed a K-shortest path finding (KSPF) algorithm based on Floyd for path identification problems in URT systems. Accordingly, we first calculate the K-shortest path set ($K = 3$) of each OD pair by the KSPF algorithm according to the rail network topological structure and the definition of effective paths. Thereafter, combined with the passenger demand data and passenger path selection behavior, the passengers are initialized. By taking the realistic train operation information and the dynamic passenger demand as input, the travel behavior of passengers and events in each link of travel are simulated. Lastly, diversified passenger flow indicators, such as the average travel time of passengers, transfer waiting time, train full load indicator, and real-time waiting number on platforms, are analyzed to evaluate the matching degree between passenger and train flows.

3.1 Passenger path choice

The K-shortest path set of OD pair (r, s) is obtained according to the rail network topological structure. Thereafter, passengers can choose their path by roulette-wheel selection. The path of the URT network refers to the path connecting any two stations in a network. In general, the passenger travel path includes the entrance passage and

Table 1 Characteristics comparison of closely related studies

Publications	Methods	Scope	Notes
Cepeda et al. (2006)	Frequency-based passenger assignment model	URT network	Not considering each train's capacity
Wu et al. (2015)	Schedule-based passenger assignment model	URT network	Focusing only on transfer stations
Poulhès (2020)	Integrated simulation model	URT network	Not considering passenger route choices
Xu et al. (2017)	Dynamic assignment model	URT line	Considering passenger traveling rules
This paper	Collaborative simulation model of passenger and train flows	URT network	Considering passenger traveling rules

escalator from the non-paid area to the platform, train operation section, transfer connecting passage and escalator after arriving at the transfer station, and exit passage and escalator from the platform to the exit gate. The passenger travel cost (time cost, similarly hereinafter) of the path in URT network is defined as follows:

$$C_{rs}^{u} = C_{\text{node}}^{u} + C_{\text{block}}^{u} + \sigma T_{\text{transfer}}^{u}, \ u \in K_{rs}, \tag{1}$$

where C_{rs}^{u} is the passenger travel cost of path u in the K-shortest path set K_{rs} of the OD pair (r, s), and C_{block}^{u} is the section cost (i.e., train running time of the sections). Node cost, which is denoted as C_{node}^{u}, is the passenger transfer walking time if the station is a transfer node that passengers need to transfer to the other line; otherwise, it is the train stop time at this station. Parameter T_{transfer}^{u} is the transfer time, and σ is the penalty coefficient. In this situation, $\sigma = 8\,\text{min}$ is taken. That is, every time a passenger transfers, the path cost increases by 8 min.

If there are numerous transfer times of the path or the path cost is considerably different from the cost of the shortest path, then the probability of passengers choosing this path is extremely low. Therefore, the path with a cost that does not exceed 1.5 times the shortest path cost is defined as an efficient path. The set of efficient paths of the OD pair (r, s) is denoted as K_{rs}^{*}, satisfying $K_{rs}^{*} \subseteq K_{rs}$.

For convenience, path u from station r to station s is denoted as $K_{rs}^{u} = \{S_{l_1,a_1,a_2}^{f_1}, S_{l_2,a_3,a_4}^{f_2}, \ldots\}$, which is illustrated in Fig. 2. Note that the path passes through section a_1 to a_2 in the direction f_1 of line l_1, transfers to line l_2 thereafter through the transfer station n_{a_2,a_3}, and passes through section a_3 to a_4 in the direction f_2, until arrives at the destination station.

	$S_{l_1,a_1,a_2}^{f_1}$			$S_{l_2,a_3,a_4}^{f_2}$			...
Block	a_1	...	a_2	a_3	...	a_4	...
Line	l_1			l_2			...
Direction	f_1			f_2			...

Fig. 2 Illustration of the path.

If there is only one path in the K-shortest path set K_{rs}^{*}, then all passengers in the OD pair (r, s) will choose this path. If the elements in K_{rs}^{*} are not unique, then the probability of each path being selected is calculated, and passengers are allocated to these efficient paths in proportion. The higher the path cost is, the lower the probability of being selected will be. A traditional method in the assignment of passenger flow is the logit-based algorithm, which has been widely applied in URT networks (Wu et al., 2019). Moreover, the probability of path u in K_{rs}^{*} being selected for passengers in the OD pair (r, s) can be calculated as follows:

$$p_{rs}^{u} = \frac{\exp(-\theta C_{rs}^{u})}{\sum_{w \in K_{rs}^{*}} \exp(-\theta C_{rs}^{w})}, \ u \in K_{rs}^{*}, \tag{2}$$

where $\sum_{u \in K_{rs}^{*}} p_{rs}^{u} = 1$ and θ is a parameter. A large θ means that passengers have a full understanding of the network, so that the error of the perceived path cost function is small, and passengers tend to choose the optimal path with the lowest cost. By contrast, a smaller θ indicates that a limited understanding of the network will result in passengers randomly choosing numerous paths at the beginning of the travel, including some high-cost paths. Han et al. (2015) showed that $\theta \in [1, 5]$ is superior. Hence, we set $\theta = 2$.

3.2 Passenger–train interaction mechanism

On the basis of the planned train timetable, virtual trains with limited capacity are generated as containers for passenger transportation to control and propel the simulation. All trains operate precisely according to the timetable scheduled in advance. The simulation of passenger traveling in URT systems is incorporated to the simulation of train running. As the train runs, passengers from upstream to downstream stations board and alight in turn. This situation reflects upstream priority, which means that passengers from upstream stations have the priority to board the train compared with those from downstream stations. The travel process of passengers is divided into several aspects, including passenger generation, inbound, boarding and alighting, transfer, and outbound. Note that passenger queues at entrance passages, platforms, transfer passages, and exit passages according to the single-channel FIFS rule.

(1) Passenger generation

As shown in Fig. 3, a station along the train running direction of a URT line is selected first to execute the passenger generation process until all lines and stations have been operated. The station can be selected randomly or in a given order. At the current simulation, the same number of passengers as the input demand will be generated. These passengers will select their travel paths using the roulette-wheel mechanism, and they will be added thereafter to the tail of the queue of the corresponding origin station's virtual entrance passage (divided into two directions of up and down). When the passenger generation process of the station is completed, it can continue to generate passengers for other stations or execute the next process.

(2) Inbound

The process of entering the station can be defined as the process from passengers swiping their cards to walking to the platform, and "virtual entrance passage" is used to describe the passenger inbound process. After the passenger generation in the previous step, passengers are added to the tail of the queue in the virtual entrance passage

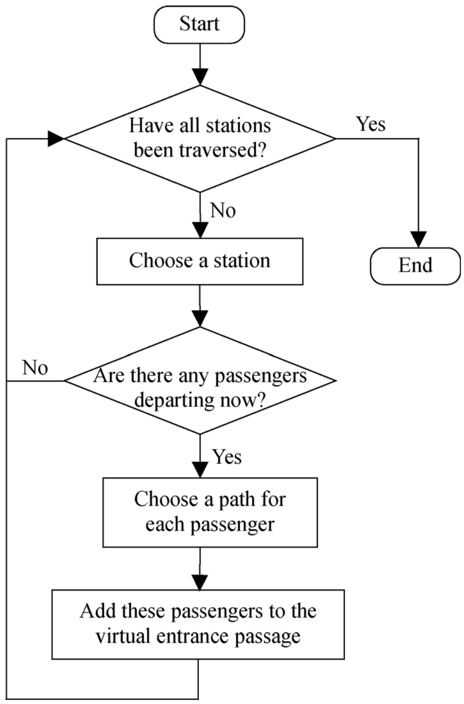


Fig. 3 Illustration of the passenger generation process at each simulation.

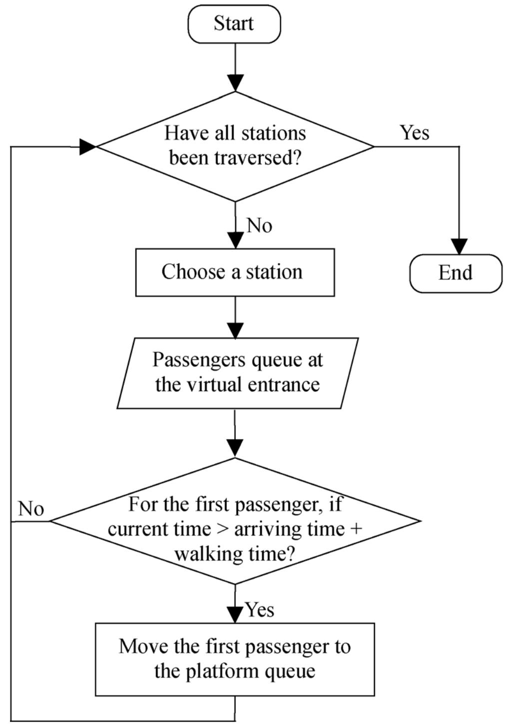


Fig. 4 Illustration of the inbound process at each simulation.

in a timed sequence. When the current time is enough for the passenger to arrive on the platform, i.e., current time > arriving time + walking time, the passenger will be moved from the head of the virtual entrance passage to the tail of the waiting queue on the platform. This process is summarized in Fig. 4.

(3) Boarding and alighting

When we model the boarding and alighting processes, considering the limitation of train capacity, passengers will board the train after all passengers who need to get off have left the train (see Fig. 5). When the train arrives at the station, the boarding and alighting processes are executed. In the alighting process, if passengers have completed their trip, they will be moved to the outbound passage; otherwise, they will be moved to the tail of the queue in the transfer passage. In the boarding process, the number of boarding passengers should be calculated according to the remaining capacity of the train. If the remaining capacity is larger than the total number of passengers waiting on the platform, then all waiting passengers will get on the train; otherwise, passengers who arrive on the platform early will get on the train first.

When train v arrives at station i at time instant t, passengers who can board the train can be determined by the following linear programming model:

$$\max \sum\nolimits_{p \in P_{i,t}} q_{i,p,t_1,v}, \tag{3}$$

$$s.t. \quad q_{i,p_1,t_1,v} \geqslant q_{i,p_2,t_2,v}, \quad \forall p_1,\, p_2 \in P_{i,t}, \quad t_1 < t_2 \leqslant t, \tag{4}$$

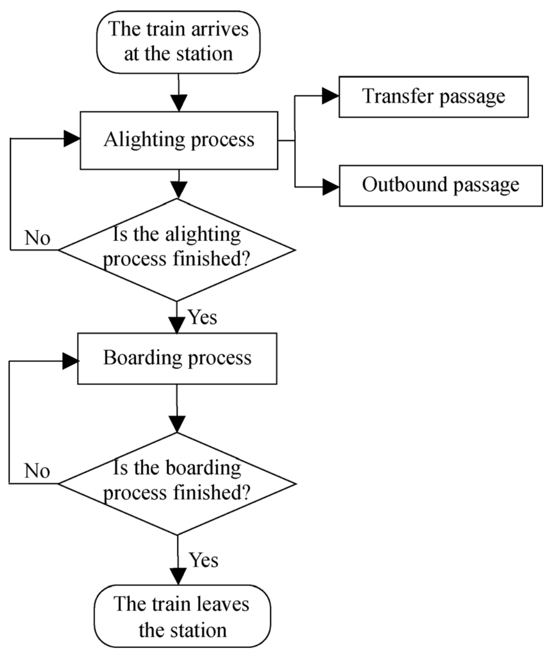


Fig. 5 Illustration of the boarding and alighting process at each simulation.

$$\sum\nolimits_{p \in P_{i,t}} q_{i,p,t_1,v} \leqslant C_{i,v}^{\text{remain}}, \tag{5}$$

where $P_{i,t}$ is the set of passengers waiting on the platform at station i at time t and $q_{i,p,t_1,v}$ is a binary variable to indicate whether passenger p who arrives on the platform at t_1 will board train v. Constraint (4) ensures that the passengers who arrive on the platform earlier will also leave the platform and board the train sooner. If the arriving time of passenger p_1 (t_1) is earlier than that of passenger p_2 (t_2), then constraint (4) restricts passenger p_1 will be served earlier. Constraint (5) ensures that the number of each train's loading passengers cannot exceed the maximum loading capacity. If the train arrives at the originating station, then its remaining capacity is the maximum loading capacity; otherwise, its remaining capacity is the difference between the maximum loading capacity and the number of loading passengers when the train departs from the last station minus the number of passengers getting off at the current station. The related formula is as follows:

$$C_{i,v}^{\text{remain}} = \begin{cases} \lambda C_v, & \text{if } i \text{ is the originating station} \\ \lambda C_v - Q_{i-1,v} + A_{i,v}, & \text{otherwise} \end{cases}, \tag{6}$$

where C_v is the train capacity; λ is an acceptable overloading coefficient, and in actual operation, $\lambda = 1.4$; and $A_{i,v}$ is the number of alighting passengers at station i. The number of loading passengers when the train departs from station i, $Q_{i,v}$, is calculated as follows:

$$Q_{i,v} = \begin{cases} B_{i,v}, & \text{if } i \text{ is the originating station} \\ Q_{i-1,v} - A_{i,v} + B_{i,v}, & \text{otherwise} \end{cases}, \tag{7}$$

where $B_{i,v}$ is the number of boarding passengers at station i.

(4) Transfer

As shown in Fig. 6, the transfer process refers to the process of passengers getting off the train, entering the transfer passage, and arriving on the platform of another line. When passengers get off a train, they will be added to the tail of the corresponding virtual transfer passage to another line. When the current time reaches the exit time of the passenger leaving the virtual transfer passage, i.e., current time > alighting time + walking time, the passenger will be moved from the head of the passage to the tail of the waiting queue on the platform.

(5) Outbound

The outbound process is relatively simple. In the boarding and alighting processes, if there is no next travel node, the passengers will enter the outbound passage queue. When passengers meet the outbound time, their trip will be ended, they will be removed from the system, and their travel information will be recorded. The mechanism of passenger–train interaction is summarized in Fig. 7.

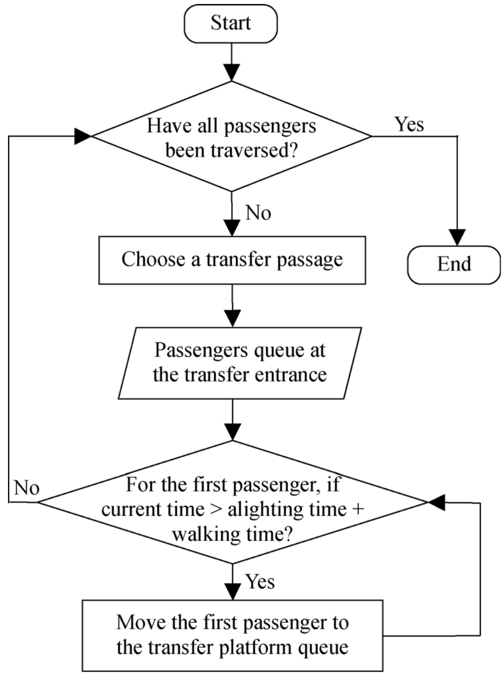


Fig. 6 Illustration of the transfer process at each simulation.

4 Case study

This section provides a real-world case study based on the Beijing URT network to demonstrate the validity and availability of the proposed analysis method. The Beijing URT network consists of 19 urban rail lines and 279 physical stations, as shown in Fig. 8. The total distance of the Beijing URT network is 574 km, and its daily average passenger flow volume is over 10 million. The dynamic passenger demands are all taken from the real-world passenger demand data at each station collected on a weekday of January 6, 2020. From 4:00 to 24:00, the total passenger demand is 4.596 million, including 3.185 million transfer passengers. Taking one minute as a time step, the simulation period is divided into 1200 time steps. A total of 281036 efficient paths were found in 115302 OD pairs. The total number of operating train services in the simulation period is 11759.

4.1 Passenger demand analysis

On the basis of network topology, train timetables, and passenger time-dependent demands, the passenger–train interaction mechanism we proposed can restore the complete travel chain of each passenger. Thus, the passenger and train flows are analyzed jointly. The distribution of passenger demand with time in the entire day is shown in Fig. 8(c) (with 15 min as the granularity). It can be seen that in peak and off-peak periods, passenger

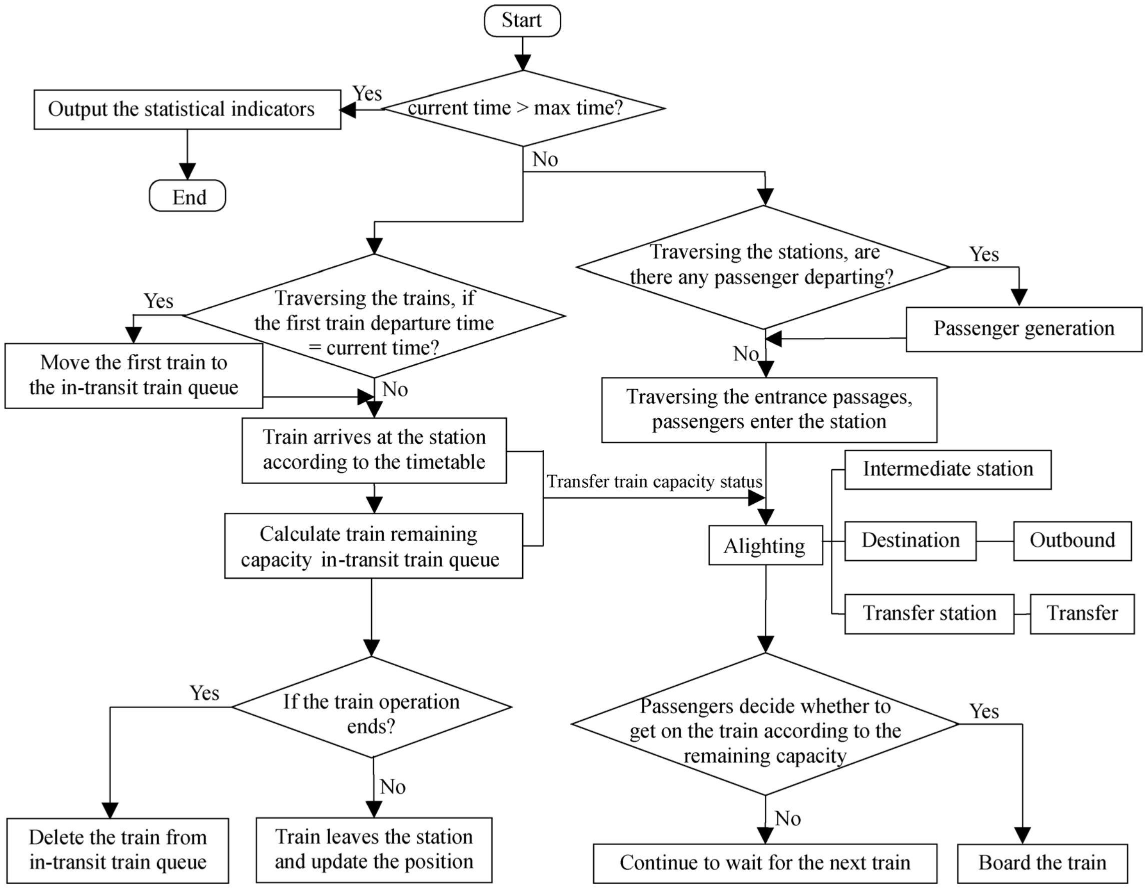
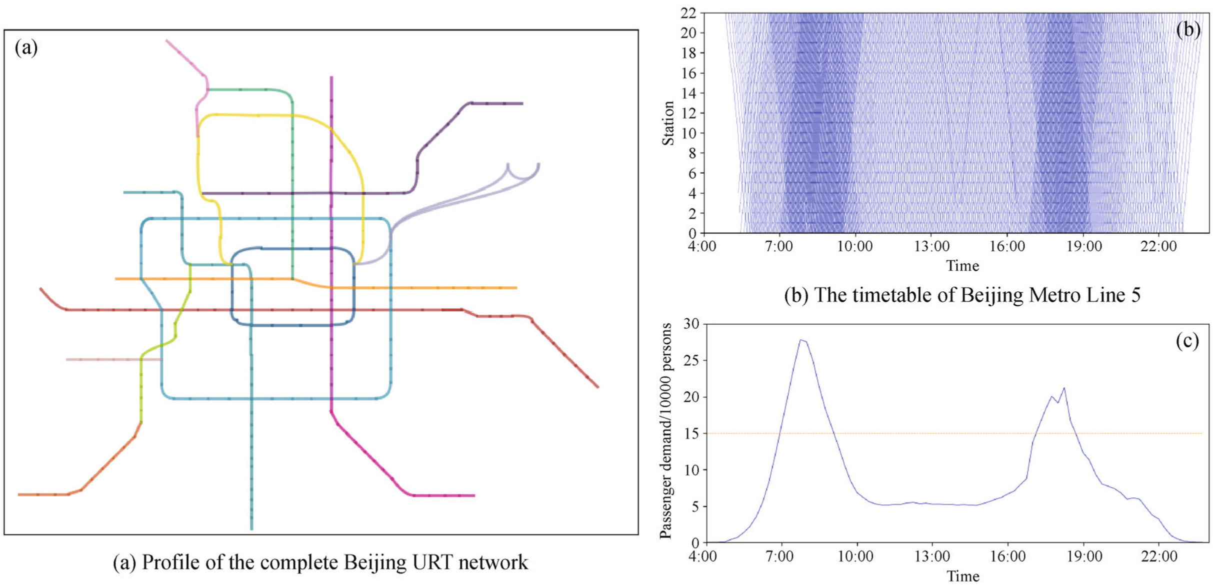


Fig. 7 Illustration of the mechanism of passenger–train interaction.



(a) Profile of the complete Beijing URT network

(b) The timetable of Beijing Metro Line 5

(c) Distribution of passenger demand with time

Fig. 8 Illustration of the Beijing URT network.

demand exhibits significant variation. Moreover, the passenger demand is evidently concentrated in the morning and evening peak hours (7:00–9:00 and 17:15–18:30, respectively) (when the demand in 15 min exceeds 150000 people). This situation shows that the URT system in the working day mainly meets the commuting demand, and the demand in peak hours increases significantly, which brings immense pressure to the URT operation. Combining Fig. 8(b) with Fig. 8(c), we can find that the timetable design is also consistent with the passenger demand with time. In peak hours, the headways are considerably smaller than those in off-peak hours.

Thereafter, we further investigate the fine-grained passenger demand distributions of different service stations at different hours of a day. As shown in Fig. 9, the size of each circle stands for the number of passengers entering the station. We found the demand patterns have significant differences between different hours of a day. For example, the passenger arrival rate during peak hours is considerably higher than that during off-peak hours. The demand in peak hours is five times more than that in off-peak hours. In off-peak hours (e.g., 12:00–14:00 and 21:00–23:00), only the demand in the core area is slightly larger but still extremely smaller than that in peak periods. Moreover, demand patterns exhibit tidal phenomena in morning- and afternoon-peak hours. Morning rush hours (7:00–9:00) bring extremely high demand in residential areas, such as Songjiazhuang, Tiantongyuan North, and Tiantongyuan. Conversely, the number of passengers originating from downtown areas peaks in the evening rush hours. For example, 29568 passengers have entered Chaoyangmen Station in 17:00–19:00.

4.2 Passenger travel time

The complete travel chain of each passenger in URT systems can be calculated by the proposed collaborative simulation of passenger and train flows, which is the basis of subsequent analysis. An illustration of a specific passenger's travel information is listed in Table 2. This passenger arrived at his origin station at 13:24 with the trip from station S1308 (Huilongguan Station) to station S1018 (Xitucheng Station). He boarded No. 141 train in the up direction of Line 13, and transferred thereafter to No. 179 train in the down direction of Line 10. The waiting times for the two trains are 255 s and 248 s, respectively, and the total travel time is 2078 s. With this information, we can restore his travel spatiotemporal trajectory in the system

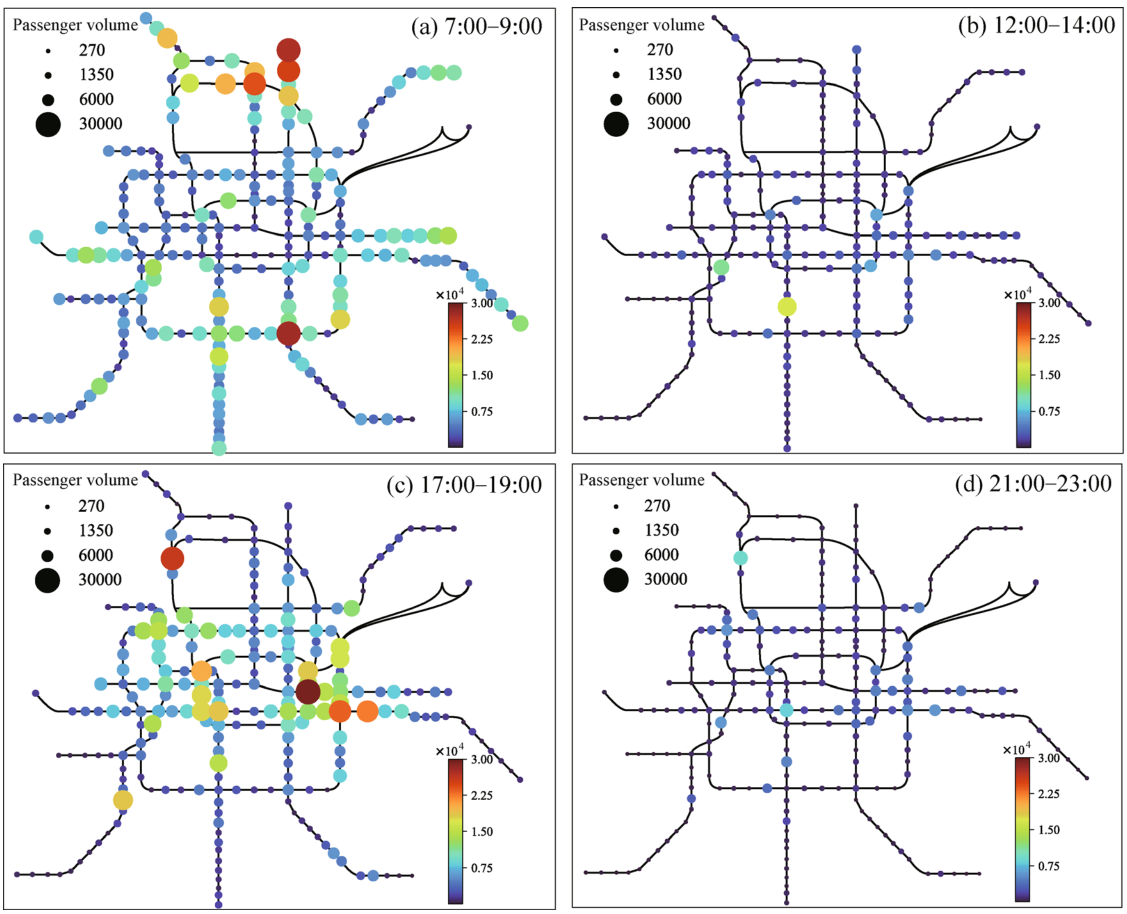


Fig. 9 Spatiotemporal unbalanced passenger demand.

Table 2 Illustration of a passenger's travel trip

OD	Arriving time	Train 1	Train 2	Waiting time (s)	Travel time (s)
S1308–S1018	13:24	Line 13; up; 141	Line 10; down; 179	255; 248	2078

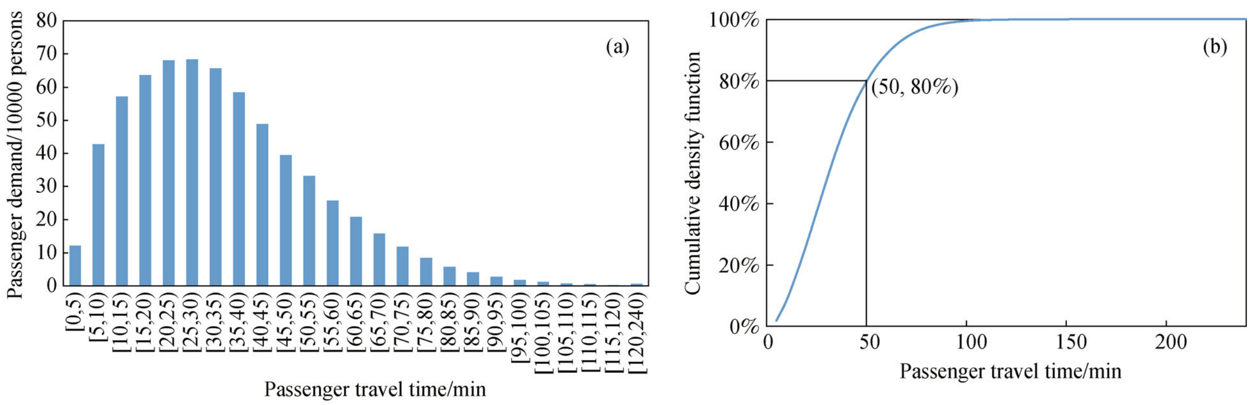
(i.e., which state he is in at any time). This information is of immense practical significance and application value.

Passenger travel time includes the waiting time of passengers on platforms (non-transfer passengers only have one platform waiting time, while transfer passengers have at least two platform waiting times), onboard time and transfer time (only for transfer passengers). The average travel time of passengers is counted, and the results are shown in Fig. 10. Note that the travel time of the majority of passengers is within 10–45 min, and 80% of passengers travel within 50 min.

The results of the passenger transfer waiting time are shown in Fig. 11. Note that the passenger transfer waiting time of the majority of passengers is under 6 min. The reason is that in the designed passenger and train collaborative simulation, among the passengers who arrive on the platform at the same time, transfer passengers are in front of passengers newly coming into the station. That is, trains give priority to meet the needs of transfer passengers, which is also consistent with the actual operation. When the demand of passenger flow is considerably large, the operator can control the entering speed of passengers outside the station to relieve the pressure of platform congestion. However, it is intractable to control the movement of the transfer passengers that have already entered the system.

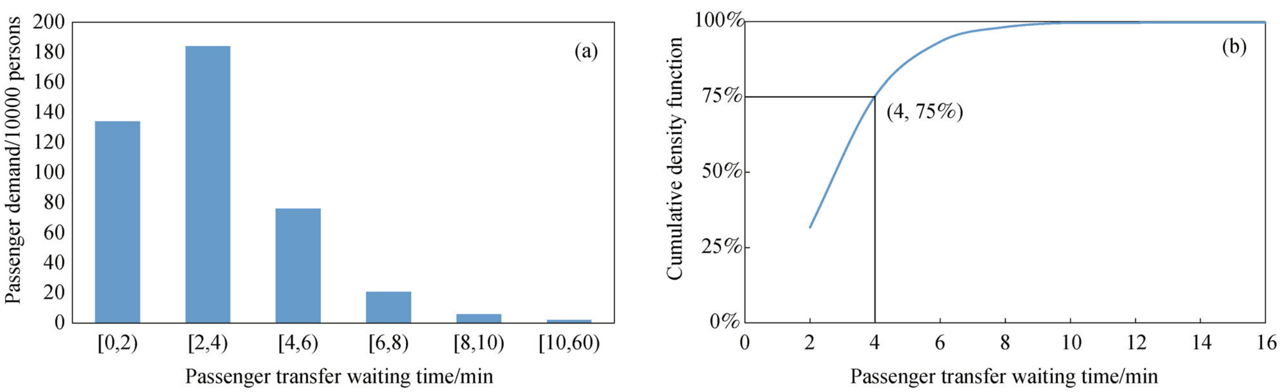
4.3 Train load factors

To illustrate the passenger loading dynamics, the train load factors with regard to each train and each station of Beijing Metro Line 5 are shown in Fig. 12. Line 5 is a



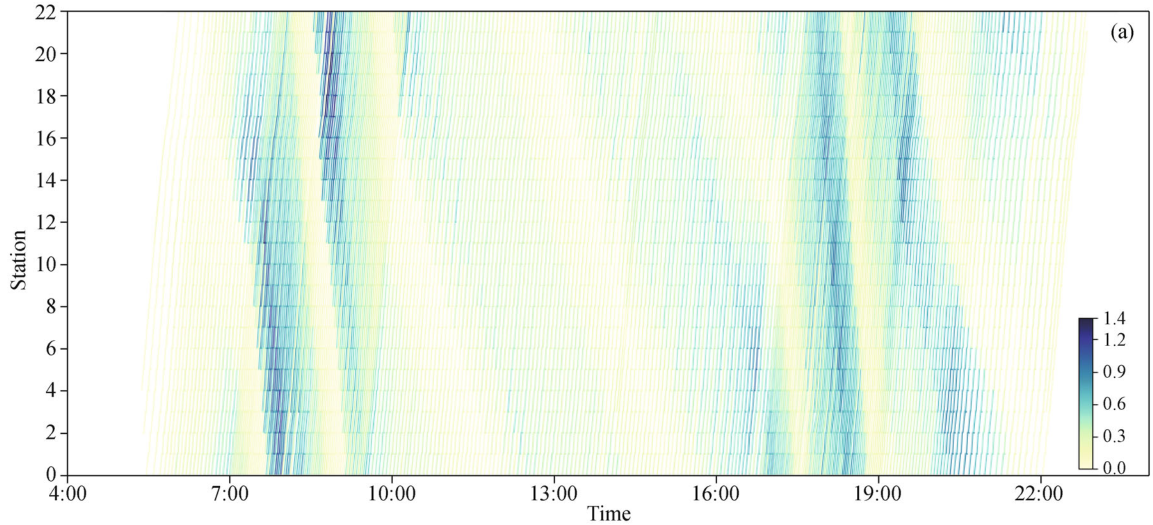
(a) Histogram of passenger travel time (b) Cumulative density function of passenger travel time

Fig. 10 Statistical results of passenger travel time.

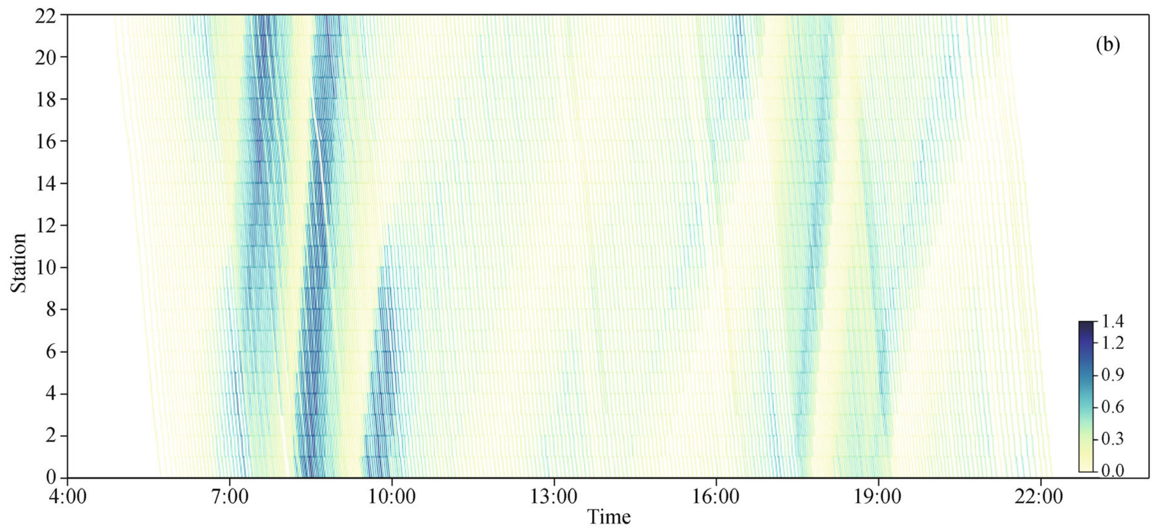


(a) Histogram of passenger transfer waiting time (b) Cumulative density function of passenger transfer waiting time

Fig. 11 Statistical results of passenger transfer waiting time.



(a) Up direction, Songjiazhuang → Tiantongyuan North



(b) Down direction, Tiantongyuan North → Songjiazhuang

Fig. 12 Train load factors of Beijing Metro Line 5.

south-to-north URT line in Beijing with 23 stations, connecting Changping District with Beijing's core areas. From Songjiazhuang in the south to Tiantongyuan North in the north, we label the stations from 0 to 22. Loading passengers in both directions exhibit significant tidal patterns. Dynamic temporal passenger demand results in long passenger waiting time on platforms and crowding in trains. Trains are substantially congested during typical commuting hours, and train load factors in the morning peak hours are significantly higher than those in the evening peak hours. In the up direction, Ciqikou Station to Chongwenmen Station (i.e., Station 4 to Station 5) and Huixinxijie North Station to Datunlu East Station (i.e., Station 15 to Station 16) are the bottleneck segments in the morning and evening peak hours, respectively. The situation in the down direction is reversed, the morning bottleneck segment is Datunlu East Station to Huixinxijie North Station, and the evening bottleneck segment is Chongwenmen Station to Ciqikou Station.

5 Conclusions

The simulation model presented in this research is effective in restoring the time–space trajectory of each passenger during the moving process in URT systems. The scenario experiments based on the passenger–train interaction mechanism provide an access to URT system performance simulation and evaluation. By taking the Beijing URT system as an example, coupling analysis is performed based on several factors, including passenger travel time, transfer waiting time, and train load factors.

A limitation of this study is the failure of our model to incorporate the non-fixed route choice on the space–time flow distribution. A promising direction of future research is to develop a tractable model and algorithm to consider dynamic passenger route choice to minimize the total passenger traveling cost. Moreover, passenger utility function with different train load factors can be estimated with some empirical method based on real data, thereby enabling the calculation of the service level.

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