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A Discrete-Event Simulation System for Estimating Passenger Flow in Urban Rail Transit

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ABSTRACT

Establishing simulation models is a widely used and effective approach for analysing passenger flow distribution in urban rail transit systems. Recently, multi-agent and discrete event-based simulation models have shown exceptional performance in studying passenger flow information within urban rail transit systems. While simulations of passengers and trains often yield satisfactory results, few models capture the overall operational status of urban rail transit systems. The complex interactions among stations, trains and passengers make it challenging to integrate these elements into a unified system framework. In this paper, we introduce a triple simulation framework that integrates stations, trains and passengers as foundational elements to comprehensively simulate the entire urban rail transit system and observe overall passenger flow distribution. Experimental results demonstrate that our system surpasses existing advanced simulation models, achieving an accuracy rate of 88.44% with a tolerance for a 30% deviation. To further illustrate the effectiveness of our framework in analysing passenger flows, we conducted experiments using the Nanjing Metro AFC dataset, analysing passenger flow distributions at stations and on trains.

KEYWORDS

urban rail transit; event-driven simulation; travel time; passenger flow.

1. INTRODUCTION

Urban rail transit systems form the backbone of public transport in modern medium to large cities, alleviating traffic congestion and offering a dependable mode of daily commute [1]. In the operation of urban rail transit systems, advertising emerges as a major revenue stream within this complex system [2]. However, advertising revenues display uneven characteristics due to significant variations in passenger flows across stations, routes and time periods. Accurately capturing the distribution of passenger flows at each station is crucial for effectively managing and optimising advertising resources. As technology advances, simulation models have become central to urban rail transit research, enabling researchers to predict and evaluate the impacts of various operational strategies without making actual changes to the system [3, 4]. Currently, the simulation methods for studying urban rail transit are broadly categorised into micro and macro simulations. Micro simulations concentrate on passengers' actions, often requiring significant resources to accurately simulate activities like walking, boarding and alighting. Macro simulations are focused on the arrangement of train timetables and the overall design of the rail network.

Macro simulation approaches emphasise collective behaviours in rail transit, focusing on large-scale traffic flows rather than individual behaviours. Zhang et al. used cellular automata to simulate trains and manage passenger flows during disruptions [5]. Shakibayifar et al. and Altazin et al. developed models for optimising train traffic in disrupted conditions, applied to the Iranian railway and the Paris system respectively [6, 7]. Hassannayebi et al. focused on dynamically adjusting train timetables to reduce passenger waiting times [8]. These studies primarily consider changes in passenger flows from train operations, often neglecting individual travel experiences.

Utilising AFC systems, Su et al. modelled travel times to assess disruption impacts on the Chongqing Metro [9]. Hänseler et al. analysed pedestrian facility use at the Lausanne train station using data on pedestrian movements [10]. Yili Tang et al. proposed a model to adjust fare schemes during peak and off-peak times to manage congestion [11]. Microsimulation models, as used by Zhang et al. for Beijing Metro's passenger behaviours [12], Qu et al. with their cellular automata for floor field models [13] and Zheng et al.'s social force model for pedestrian movements in subway stations [14], focus on detailed aspects of passenger interactions and train operations. Zhang et al. combined microsimulation and machine learning to optimise pedestrian facilities at railway stations, using random forests to dynamically predict performance metrics [15]. Xu et al. designed a discrete-event simulation for energy-efficient train operations on single-track railways [16].

Both macro and micro simulations target specific elements of urban rail systems, often overlooking the operational state as a whole. Conversely, mesoscopic models, like those developed by Chen et al. and Lei et al., use multi-agent technology to simulate both trains and passengers, facilitating comprehensive analyses of interactions and operational strategies within subway platforms and urban rail networks [17, 18]. Zhang et al.'s hybrid model integrates these approaches to optimise simulation efficiency and enhance operational planning [19].

These studies often simplify passenger movements and lack realistic modelling of train operations, which impacts the accuracy of simulations. We address these issues with a mesoscopic triple simulation method that integrates stations, trains and passengers using discrete event simulation. This method maps detailed passenger journeys and constructs a system framework from these mappings. It models stations, trains and passengers separately but integrates them through discrete events for comprehensive urban rail transit simulations. Validated with real data from the Nanjing Metro, our method captures cross-sectional passenger flows effectively, highlighting its main contributions:

1) The paper presents a triple simulation method for urban rail transit that simulates station connections, train operations and passenger movements. This method integrates data interactions among stations, trains and passengers using discrete event-driven simulations to enhance individual passenger journeys. It includes an advanced train model that adjusts travel and waiting times based on real operational data and a station class that facilitates the movement of passengers between trains and stations in both time and space;
2) The system allows for the direct gathering of passenger flow distribution data in stations and on trains, with containers implemented in both trains and stations to monitor changes in passenger flows. This setup permits the immediate output of passenger flow data without the need for additional processing. The data can be utilised to evaluate advertising exposure levels across different stations and trains.

2. METHODOLOGY

We build the models based on passenger travel time. By unifying the three models, the passenger flow can be estimated accurately.

2.1 Fundamentals of travel time simulation

Passenger travel time refers to the total time from when a passenger swipes their card to enter the station until they swipe to exit, encompassing walking time (including entry, exit and transfer walking time), waiting time and train travel time (including train dwell time at platforms) [20, 21].

The network provides passengers transportation from any station O to station D. However, in complex networks, there are multiple path selection options from O to D. This means passengers may opt for different routes based on factors such as travel time and the comfort level of the route to transfer from O to D. When modelling passenger travel chains, it is assumed that passengers enter station O on route L_1, transfer to route L_2 at transfer station t_1, then transfer to route L_3 at transfer station t_2, and so forth, until they transfer to route L_n at transfer station t_{n-1} before finally exiting at station D on route L_n.

As depicted in *Figure 1*, it forms the passenger's travel chain, which describes the journey from station O to station D for passengers.

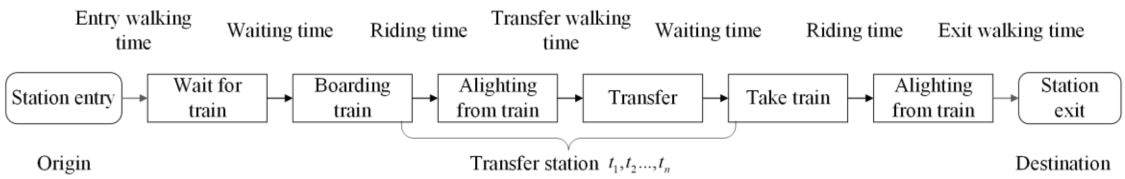


Figure 1 – Passenger travel time composition

The paper primarily examines the passenger travel process in terms of travel time; thus, it chooses to characterise the passenger travel process through travel time. For ease of subsequent exposition, variable notation as shown in *Table 1* is adopted to describe the timing of various events on the travel chain and the types of time involved. In the table, T_D as the ground truth of AFC data, is compared and validated against the simulated exit time $T_{\tilde{D}}$.

In the railway transit AFC system, the ticket gate card readers primarily used for user ticket information confirmation can only record the times when passenger P swipes the card to enter and exit, as indicated in the first two items of the table. The seventh item in the table represents the duration of the train's operation in the x to y section. The railway transit signal system records relevant information about the arrival and departure of vehicles, with retrievable data records available.

For passenger P with the travel chain $\chi = (O, t_1, t_2, \ldots, t_n, D)$, the calculation formula for exit time based on the travel chain is given as shown in *Equation 1*:

$$T_{\tilde{D}} = T_O + (\lambda_O + v_{O\to t_1} + \tau_{O\to t_1}) + (\lambda_{t_1} + v_{t_1\to t_2} + \tau_{t_1\to t_2}) \\ +(\lambda_{t_2} + v_{t_2\to t_3} + \tau_{t_2\to t_3}) + \cdots + (\lambda_{t_{n-1}} + v_{t_{n-1}\to t_n} + \tau_{t_{n-1}\to t_n}) + \lambda_D \quad (1)$$

Therefore, the travel time of the travel chain can be represented as

$$\Gamma(\chi) = T_D - T_O = (\lambda_O + v_{O\to t_1} + \tau_{O\to t_1}) + \sum_{i=1}^{n-1} (\lambda_{t_i} + v_{t_i\to t_{i+1}} + \tau_{t_i\to t_{i+1}}) + \lambda_D \quad (2)$$

Table 1 – Travel time variables

Parameters	Meaning	Data Source
T_o	Time of card swipe at entry	AFC system OD records
T_D	Time of card swipe at exit	AFC system OD records
λ_O	Passenger entry walking time	Simulation model generates
λ_D	Passenger exit walking time	Simulation model generates
λ_{tn}	Walking time for passengers transferring from L_i to L_{i+1} at station t_i	Simulation model generates
$v_{x\to y}$	Waiting time for passenger P on platform from station x to station y in the direction of the train	Simulation model generates
$\tau_{x\to y}$	Travel time of a train from station x to station y	Train scheduling system records
$T_{\tilde{D}}$	Simulated time of card swipe at exit	Simulation model generates

2.2 Simulation architecture

By incorporating interactive event attributes among the models of stations, trains and passengers, this research establishes a cohesive simulation framework. This integrative approach facilitates dynamic interconnections between these components, thereby augmenting the fidelity and interactive complexity of urban rail transit system simulations.

The passenger flow simulation system establishes three distinct classes to accurately simulate passengers, stations and trains. Stations manage the lines they operate, capturing and disseminating information about train arrivals and departures to passengers. The characteristics of the stations are detailed in *Table 2*. Passengers swiping in to enter the station and disembarking from the train increase the number of passengers at the station, while boarding the train and swiping out to exit decreases the number of passengers at the station. The walking time of the line generates the time variable needed for passengers to walk in stations. Each line operated by the station corresponds to a "train attributes of the line" to control train information.

Table 2 – Station attributes

Attributes	Description
Station ID	The unique identifier of the station
Number of station passengers	Used to store and record the number of passengers
Train attributes of line	The status of a train on a line operated by a station
Walking time of the line	The duration necessary for station entry/exit and transfer processes

The train line attributes of trains within the station's lines reflect the operational status on those lines, indicating whether trains have reached the current station. Accordingly, the train status subclass, as outlined in *Table 3*, furnishes passengers with train information through event completion and resetting. The train status within the line is controlled by two events, arrival and departure, which toggle between completed and uncompleted states, while the train stop event informs passengers whether the train is at the station.

Table 3 – Train attributes of line

Attributes	Description
ID of the train currently at the station	Entered through train operation
Train stop event	Received by passengers
Train attend event	Completed and reset by the arriving train
Train departure event	Completed and reset by the arriving train
Train departure and arrival process	Triggered by the departing train, which sets the event upon leaving the station

The attributes of trains detailed in *Table 4*, include travelling along designated routes and transmitting their ID to stations upon docking, enabling passenger boarding.

Table 4 – Train attributes

Attributes	Description
Train ID	The unique identifier of the train
Operating line	The stations that the train travels through
Current station	Used to record the current position of the train, initially set to the departure station
Departure time	The time when the train departs based on its schedule
Passenger count	Records the number of passengers on the train
Departure process	Departing the train according to the departure time
Travel process	Arriving at and departing from stations along the route based on travel time

Passengers' attributes listed in *Table 5*, incorporate OD data and travel chain details into their profiles, facilitating interactions with stations and trains. The travel chain includes OD stations, transfer stations and transfer lines for passenger travel. The simulation encompasses the full timeline of a passenger's journey, including arrival, entry, boarding wait, onboard travel, disembarkation, transfer, reboarding, travel, station exit and departure.

Table 5 – Passenger attributes

Attributes	Description
Passenger ID	The unique identifier of the passenger
OD time	The time of entry and exit while swiping in and out
Travel chain	The travel path of the passenger
Travel process	Implements the complete travel process of the passenger

2.3 Simulation models

By constructing the interactive logic among the station, train and passenger models, this study facilitates synergistic interactions among the models, thereby efficiently propelling the simulation system. This system is capable of capturing detailed changes in passengers across temporal and spatial dimensions, providing a comprehensive and nuanced perspective for analysing passenger flows.

Station simulation model

The simulation system connects stations to form a transportation network; therefore, stations are initially initialised in the system.

Station information such as name, operated lines, train stop times and travel time parameters are input into the station system for station construction. The Station class utilises the train status subclass of the line to create and manage the lines it operates, while the Line Travel Time subclass provides travel time information to the Passenger class. Within the train status subclass of the line, three events are created to transmit train arrival information: the train arrival event, the train at station event and the train departure event.

Figure 2 depicts the simulation logic of the train status subclass of the line. Upon a station's initialisation, it awaits the train arrival event, activated by trains on that line. After the event's completion, the subclass finalises the "train at station" event, allowing passengers to verify the train's presence and board. The subclass then prepares for the train departure event. Following the train's departure, it resets the "train at station" event, clears the station's train ID, and reinitiates the waiting period for the next arrival. The train's in-station status transitions are dictated by its arrival and departure events.

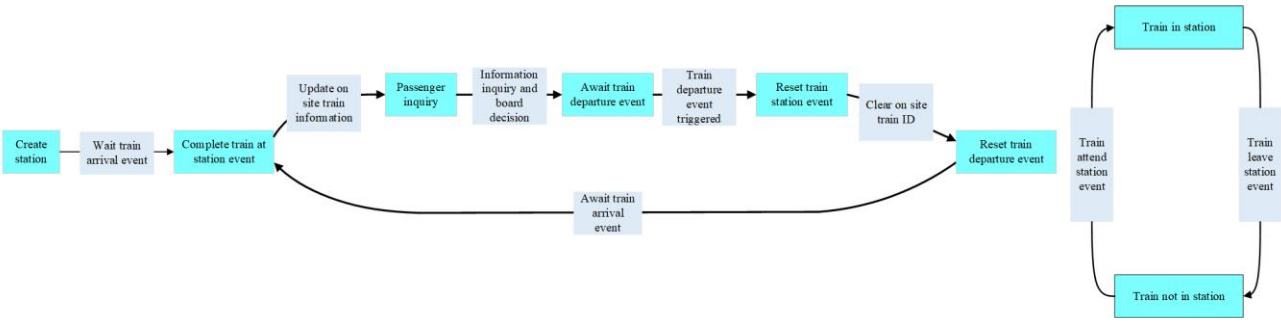


Figure 2 – Train state simulation logic for station lines

Train simulation model

The train model initialises train objects by incorporating actual and operational routes, along with departure times. Train simulation consists of two main phases: the departure process, where trains are dispatched to their starting station at the designated departure time, triggering train arrival notifications at the station; and the travel process, where trains proceed to stations along their actual route, based on inter-station travel times, also notifying stations of their arrival and departure. During these phases, trains communicate with stations through arrival and departure events, enabling passengers to retrieve relevant train information at stations.

Figure 3 illustrates the simulation logic of the train, which progresses with time to complete and reset events, facilitating the train's operation on the route.

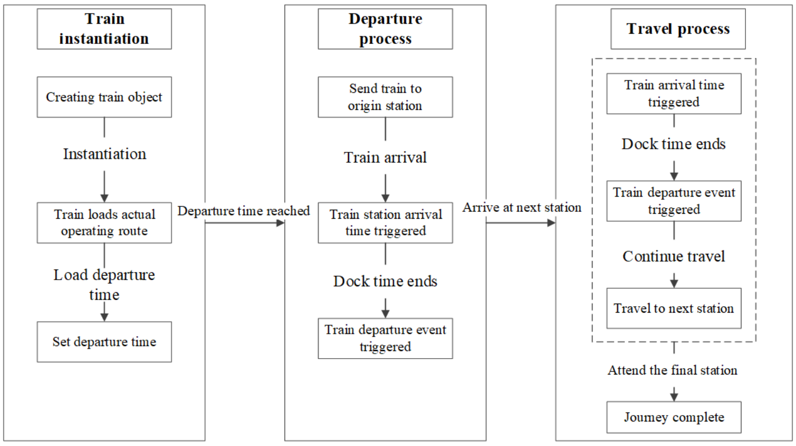


Figure 3 – Train simulation logic

Passenger simulation model

The passenger's travel process is a dynamic experience filled with changes in time and space. Therefore, the simulation of passenger travel revolves around time and space, enabling an accurate reproduction of the entire travel process and obtaining precise travel times by simulating the passage of time and changes in space.

The simulation process of passenger travel can be divided into six parts: entering the station, boarding, travelling, transferring, alighting and exiting the station. The functionalities of advancing time and spatial changes implemented in each part are illustrated in *Figure 4*.

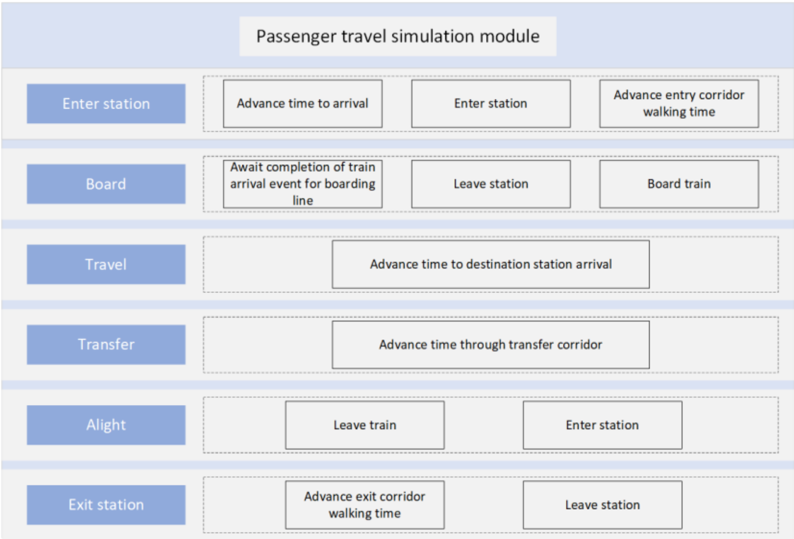


Figure 4 – Passenger travel simulation module

The entry module places passengers at the arrival time into the originating station, advances the passenger's travel time in the entry channel, and positions the passenger at the station platform at this time. The boarding module is responsible for boarding passengers onto the train. This module advances the waiting time of passengers by obtaining train arrival information from the station and changes the passenger's position from the station to the train.

In the travel module, the passenger's position changes along with the train. The system advances time until the passenger reaches the destination station, and the passenger's position is updated to the destination station.

Depending on the passenger's origin and destination stations, the passenger's journey can be categorised into single-line and multi-line journeys. Multi-line journeys involve transfer processes, as illustrated in *Figure 5* depicting the simulation process of the passenger's journey. In a single-line journey, there is no need for transfers; passengers only need to reach the destination station after boarding at the origin station. In multi-line journeys, if the origin and destination stations are not on the same line, the transfer station acts as the initial destination station. Upon alighting, passengers need to transfer according to the number of transfers, board again, and can only depart the station and complete their journey after all transfers are completed.

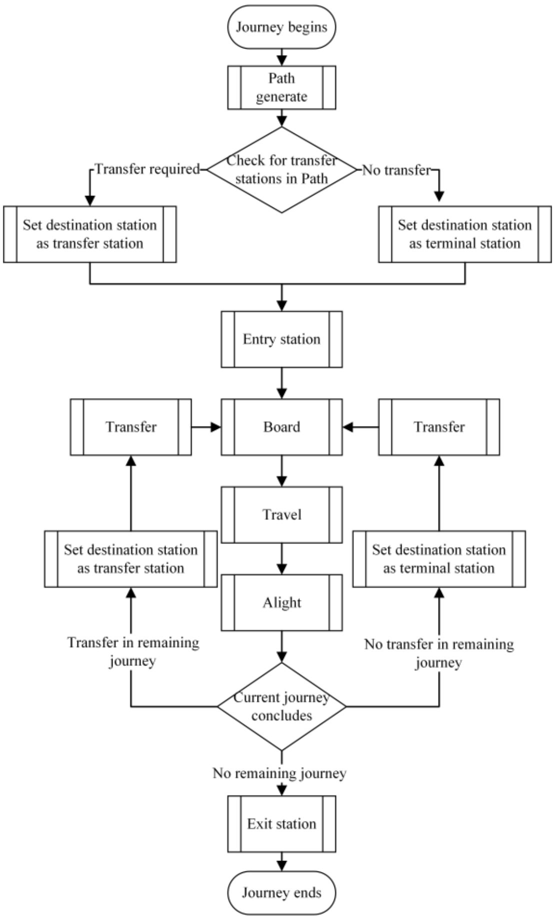


Figure 5 – Passenger travel simulation process

2.4 Simulation data set

OD (Origin-Destination) data are generated from processing AFC (Automatic Fare Collection) data, which capture detailed ticket or card information and record when passengers enter and exit stations [22]. These processed data then provide specific insights into travel times and station locations for passengers, effectively mapping their journeys [23]. The specific OD data are provided in *Table 6*.

Table 6 – OD data

Entry time	Exit time	Entry station number	Exit station number
15:03:26	15:17:22	47	46
14:29:40	14:51:31	50	46
14:30:22	15:31:14	17	46
……	……	……	……

In simulating passenger travel time, waiting and riding times can be controlled using the train timetable. However, a city's entire transportation network often comprises hundreds of subway stations, each constructed differently. Due to variations in geographical locations, passenger flow also differs, making it challenging to collect travel data for all stations. According to references [24, 25], through the travel time of passengers on the unique route, the real values of the passengers' travel time are calculated. These real travel time values were used to construct truncated normal functions for simulating passenger walking time in simulation experiments.

Figure 6 shows the diagram of the Nanjing metro network, this study selects Lines 2, 3 and 4 of the Nanjing metro as simulation targets. The selected network comprises 74 stations, and the simulation system operates from 6:00 to 23:00. On weekdays, there are approximately 1,263 trips of passenger trains in the system (with potential additional trains). For the simulation experiments, OD data from one day in 2022 were chosen. Preprocessing of the OD data involved removing entries and exits on different days, selecting data where both entry and exit occurred on these three lines, and excluding trips with the same entry and exit.

Figure 6 – Diagram of Nanjing metro network

The original OD data only include the entry time, entry location, exit time and exit location of passengers. In the simulation system, it is necessary to input the complete travel chain of passengers for simulation. This requires processing the OD data to include the entry route, exit route, transfer route and transfer station of passengers to determine the passenger's travel path. To construct a directed graph to model the network of routes, the subway line stations are listed, representing the sequences of stations on various routes in both directions. A directed graph object is initialised to store the stations and their interconnections. Stations from each subway line are added to this graph, and edges are created to connect adjacent stations, thereby constructing the directed graph of subway routes, where the nodes represent stations and the directed edges represent the routes and their directions. Then, the breadth-first search algorithm is used to obtain the possible travel paths for passengers.

3. SIMULATION RESULTS

The system is tested on real OD data from Nanjing Metro to validate its effectiveness. By gathering data on passenger presence within stations and cross-sectional flows on trains, and comparing these with incoming passenger flows, the analysis highlighted patterns and trends in passenger movement.

3.1 Verification of passenger travel time

The precision of the simulation model was assessed by comparing simulated travel times with actual travel times [19], the relevant error for each passenger is obtained from *Equation 3*:

$$Er = \frac{|T_{\tilde{D}} - T_D|}{T_D - T_O} \tag{3}$$

The relative errors are depicted in *Figure 7*. It is observed that 88.44% of passengers have simulated travel times with errors of less than 30% compared to their real travel times, indicating the high effectiveness of the simulation system in replicating passenger travel times.

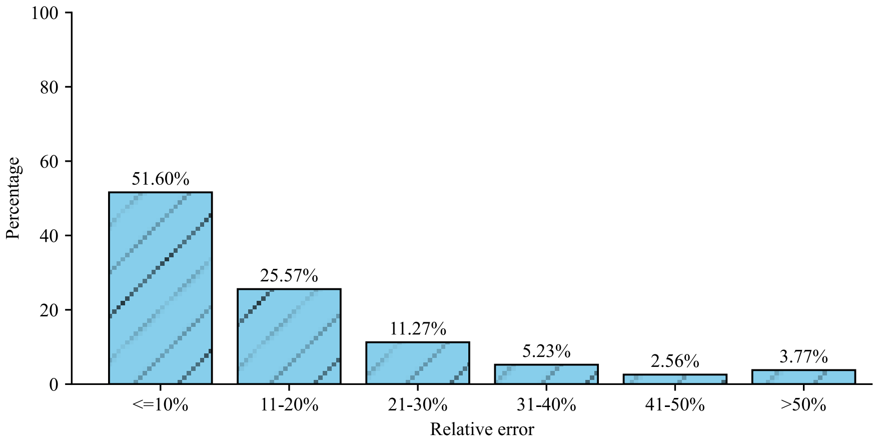


Figure 7 – Error distribution between the overall simulation time and the real-time

The DES simulation method is compared with four other methods using the Nanjing Metro's AFC dataset. The hybrid framework, optimised for efficiency, groups passengers by origin, destination and similar arrival times into 30-second batches, assuming identical travel behaviour, including shared walking times [19]. The multi-agent model used by literature [26] simulates passengers and trains but assigns uniform walking times for all, ignoring individual differences. The proximity boarding method allows passengers to board the nearest arriving train, synchronising their walking times for entry and exit. The fixed interval method controls train operations with a fixed timetable for departures, waits and travel times, without modelling individual trains.

Table 7 displays the comparative simulation results between our method and others, categorising performance at error thresholds of 10%, 20% and 30%. The results demonstrate that our method consistently outperforms others. Our approach generates walking times based on a distribution model, accurately reflecting passengers' actual walking paths. Additionally, the train class has been created to enable trains to operate independently according to a precise timetable. The resulting errors are primarily influenced by exit walking times, with fewer cases of passengers boarding incorrect trains.

Table 7 – Experimental results on Nanjing metro

Methods	**≤ 10%**	**≤ 20%**	**≤ 30%**
DES model	51.60	77.17	88.44
Hybrid framework	41.22	70.19	85.45
Multi-agent	39.20	68.45	84.42
Proximity board	37.53	62.35	76.49
Fixed interval	47.24	74.12	86.47

Nevertheless, no matter the method employed, some data will invariably show significant deviations from actual conditions. The reasons for this phenomenon may include:

1) Complex structures at transfer stations with multiple transfer channels, making it difficult for collected travel data to accurately reflect actual passenger movements [27];
2) Multiple travel paths during transfers not fully accounted for by the system [28];
3) The presence of travel time, resulting in passengers not necessarily catching the same train in the simulation system. Additionally, some lines have loops of different sizes, leading to significant differences in waiting times for passengers who miss or catch a specific train;
4) Some passengers linger at stations, resulting in their real travel times obtained from OD data far exceeding the required travel times for that segment of the line.

3.2 Passenger flow of the stations

Figure 8 shows the cross-sectional passenger flow from 6:00 to 23:00 at Liuzhou East Road Station and Xinjiekou Station. Both stations experience higher passenger flow during peak commuting hours. However, after these peak hours, the passenger flow decreases at Liuzhou East Road Station while Xinjiekou Station maintains a high passenger flow. This indicates a strong correlation between passenger flow at residential area stations and commuting patterns, while commercial area stations experience more stable and abundant passenger flow due to commercial activities.

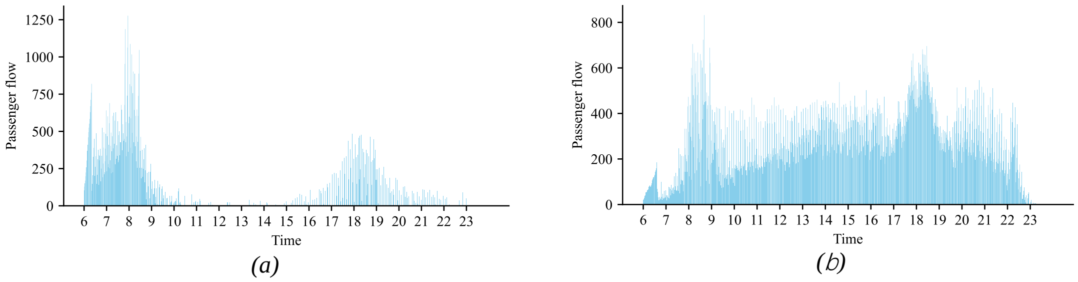


Figure 8 – Passenger float stations: a) Passenger flow at Liuzhoudonglu; b) Passenger flow at Xinjiekou

By stratifying advertising rates in accordance with the patterns of passenger flow, it is observed that Liuzhou East Road Station witnesses a substantial influx of commuters during peak hours, notably during the morning and evening rush. Consequently, advertising during these intervals offers pronounced value, notwithstanding diminished passenger numbers at other times, suggesting a potential for price adjustment to better reflect the fluctuating value of advertising opportunities. Conversely, Xinjiekou Station, situated within a commercial nexus, exhibits varied passenger traffic beyond conventional peak hours and, crucially, surpasses Liuzhou East Road Station in overall passenger volume. This disparity underscores the heightened advertising potential at Xinjiekou Station, warranting a premium on advertising rates to effectively tap into its larger audience base.

Besides analysing passenger flow during various time periods, this system also captures and quantifies the inflow of passengers at the station in the same manner as traditional methods, segmented by time intervals. Two stations are selected to reveal the difference between the passenger flow within the station and the passenger flow entering the station. We gathered data on passenger flow within the station and passenger flow entering the station from 6 AM to 11 PM in 1-minute intervals, as illustrated in *Figure 9*.

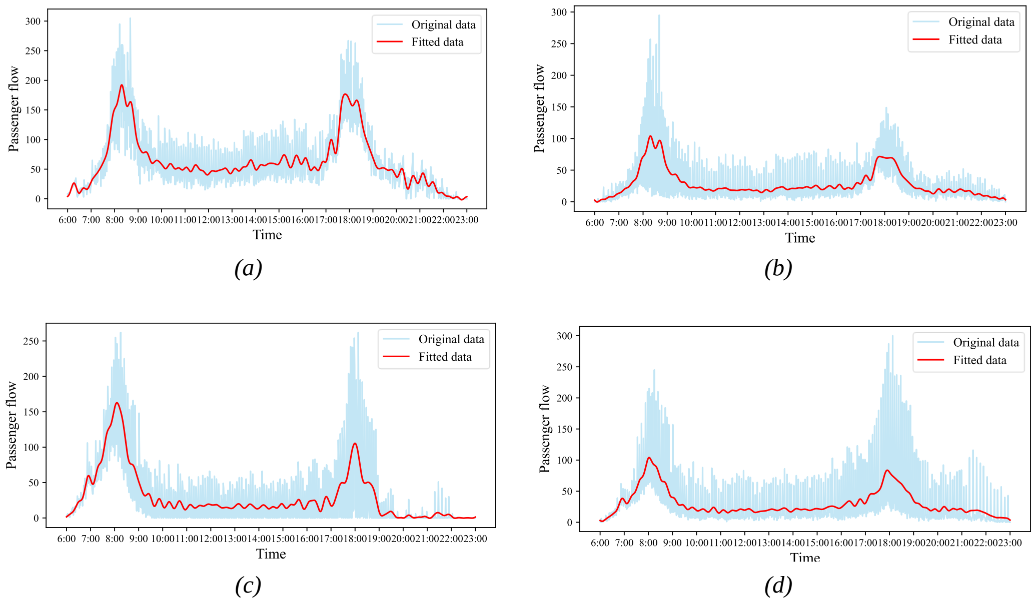


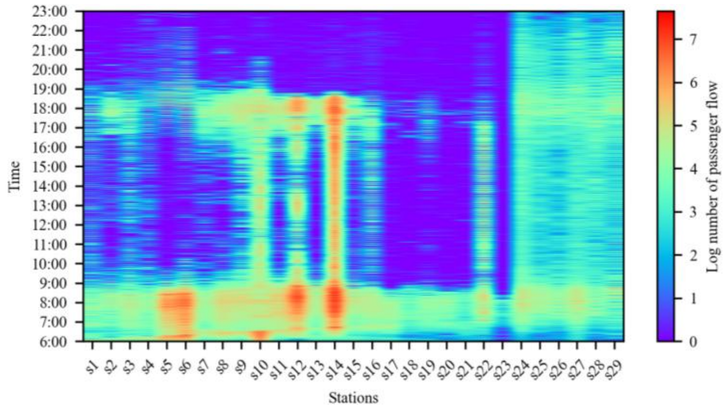
Figure 9 – Passenger flow within the stations and entering the stations: a) Passenger flow in the Aotidong station; b) Passenger flow entering the Aotidong station; c) Passenger flow in the Longjiang station; d) Passenger flow entering the Longjiang station

Two methodologies for tracking passenger flow within and flow entering metrics effectively illustrate the dynamics of station passenger movement. These approaches jointly highlight that the passenger volumes at the majority of stations are predominantly influenced by peak commuting periods, with traffic reaching its zenith during morning and evening rush hours in particular. Further data modelling and analysis reveal that flow within the station is more pronounced than the entering flow. This trend is manifest not only in the variations of passenger flow across different times but also in the disparities between peak and off-peak periods.

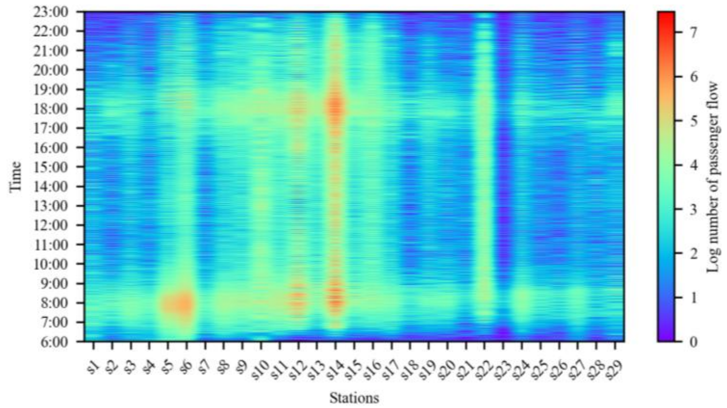
The variability in passenger flow within is more marked over time compared to entering flow, likely due to the nuanced capture of internal station movements within station flow within the station metrics. During peak times, the cumulative effect of passengers awaiting trains can significantly boost the volume of passenger flow. Conversely, during off-peak periods, enhanced passenger flow speeds may lead to a relative decrease in passenger volumes within the station. The heightened fluctuations, particularly the stark differences in traffic between peak and off-peak times, offer valuable insights for the thorough examination of station internal flows.

3.3 Passenger flow of the line

Figure 10 employs a heat map to vividly demonstrate the dynamic fluctuations in passenger flow within the station and passenger flow entering the station along the entirety of Line 3 throughout the day, presenting a novel viewpoint for this research area. S1 to S29 represent stations from Linchang to Mozhoudonglu.



(a)



(b)

Figure 10 – Heat map of station passenger flow for Line 3: a) Passenger flow in the stations of Line 3; b) Passenger flow entering the stations of Line 3

The variability in passenger volumes shows notable diversity across various times and stations, with surges exceeding 6,000 passengers within a mere 1-minute span during peak periods, underscoring the intense utilisation of certain areas or times. Nevertheless, this level of high traffic is not universally observed, as the passenger volumes at most stations fall significantly below this threshold. Acknowledging that the raw passenger data's direct depiction might result in visual imbalances due to varying traffic volumes, this research adopts a logarithmic transformation approach to balance the visualisation of traffic fluctuations. This method facilitates a more intuitive and recognisable contrast between areas of low and high passenger volumes.

Passenger flow data derived from simulation systems offer valuable business consultancy and exposure guidance for a wide array of organisations and individuals engaged in commercial activities at stations.

Passenger flow directly impacts the opportunities and outcomes of advertising exposures. Knowledge of passenger flow distribution enables advertisers and station administrators to establish more scientifically grounded and rational ad pricing strategies.

In addition to the notable impact on commercial deployments, data on passenger flow distribution within stations are crucial for managing a variety of emergency scenarios. The provision of rescue efforts in response to crises such as groundwater pipe leaks, rainwater backflow and fires needs to be calibrated according to the number of passengers present in the station. While traditional models primarily offer insights into passenger flow entering and exiting stations, the system introduced in this study directly outlines the distribution of passengers within the station, delivering accurate data support for emergency management officials. Such data enhance the precision and efficiency of safety planning and emergency response strategies. A profound understanding of passenger flow patterns during specific periods allows rail transit administrators and emergency services to devise detailed evacuation plans, optimise emergency passage and safety exit layouts, ensuring rapid and organised evacuation of passengers and staff in the event of fires, natural disasters or other emergencies.

3.4 Passenger flow transported by stations

Beyond the advertising revenue generated at stations, the income from advertisements on trains constitutes an integral part of the rail transit system's advertising earnings. The quantity of passengers transported by trains from stations at various times directly impacts the exposure level of advertisements. Traditionally, weighing trains has been used to estimate passenger numbers, a method constrained by the variability in passenger weight, notably between children and adults, as well as among different gender groups. Using train weighing to differentiate between individuals provides a crude approximation of passenger counts, as it fails to distinguish adequately among passengers. This system employs simulation to emulate the complete lifecycle of train operations, capturing interactions with the train at each passenger boarding and alighting point, thus accurately quantifying onboard passenger flow.

As illustrated in *Figure 11*, two stations have been chosen to display the passenger flows transported by trains in both directions as they traverse these locations. This method enables observation of the passenger flow dynamics within the transit line. At the same station, the passenger flow in both directions shows an almost mirror-like symmetry, particularly noticeable in the symmetric distribution of commuters during peak hours.

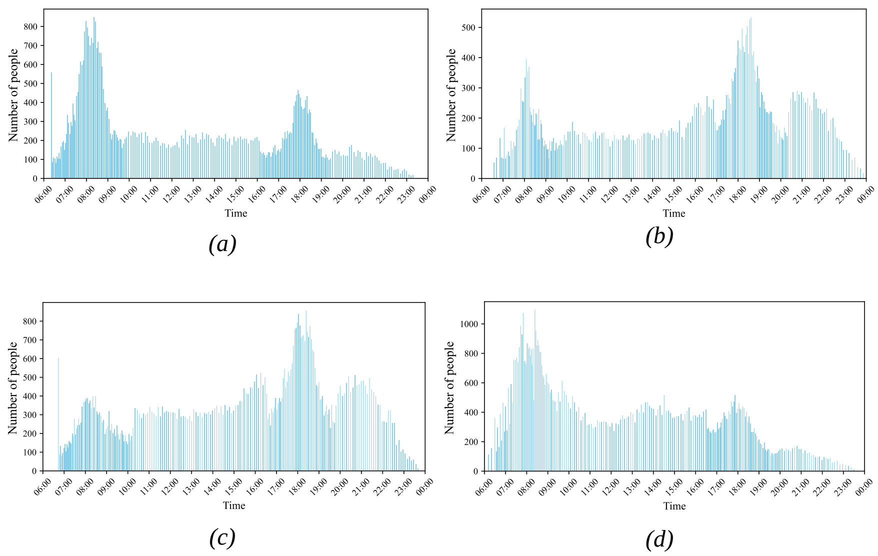


Figure 11 – The passenger flows transported by trains in both directions: a) Passenger flow transported by Aotidong station in the up direction; b) Passenger flow transported by Aotidong station in the down direction; c) Passenger flow transported by Minggugong station in the up direction; d) Passenger flow transported by Minggugong station in the down direction

Based on changes in passenger flow distribution during different train directions, rail transit system managers can strategically segment advertising prices on trains. For instance, at Aotidong Station, there is a higher passenger volume during the morning peak hours in the upward direction, and predominantly evening peak traffic in the downward direction. Such fluctuations in passenger flow offer operators a rationale for setting advertising prices based on varying time periods. This strategy allows for a more precise alignment of advertising prices with passenger flow, enhancing the appeal to advertisers. Moreover, this pricing adjustment not only boosts the allure of train advertisements but also significantly elevates their commercial value, resulting in increased revenue for operators. By refining and optimising the advertisement pricing model, operators can maximise the effectiveness of ads, while delivering more targeted and timely information to passengers.

4. DISCUSSION

A simulation system is designed for urban rail transit, modelled through travel time and discrete events. The system integrates the modelling of passengers, trains and stations, facilitating the flow of information throughout the entire transportation system. Coordination between trains and stations is employed to manage the travel time and spatial positioning of passengers. Experimental results indicate that this simulation system is capable of accurately estimating passenger travel times, and both stations and trains provide passenger flow data at specific intervals as required. Discrete event simulation is employed to replicate the journey of passengers within the rail transit system, simulating their movement through stations with walking time functions and utilising station and train models to track temporal and spatial changes, thus offering precise insights into passenger flows. The system not only captures traditional data on passenger flows into and out of stations but also monitors station traffic from two distinct perspectives, revealing the traffic conditions at individual stations and along the entire line, thus providing an additional viewpoint for observing urban rail transit flows. Furthermore, the system captures train transport passenger data, previously obtainable only through train weighing. By capturing passenger data as trains pass through stations, cross-sectional flow information for the trains is generated, offering management a novel method to assess vehicle capacity and passenger data.

The simulation of daily operations proves to be a critical tool in assessing the carrying capacity of specific railway lines or the entire network during both peak and off-peak periods. This analytical prowess is essential for making well-informed decisions concerning potential modifications in service frequency, the incorporation of trains with greater capacities or the expansion of infrastructure to meet rising passenger demands. By facilitating a comprehensive understanding of traffic patterns and capacity constraints, the simulation underpins strategic planning and operational adjustments that are targeted at improving service efficiency and enhancing passenger satisfaction. Furthermore, the simulation plays a pivotal role in evaluating the returns on investments by conducting thorough assessments of historical operational costs of trains, passenger revenue and other pertinent economic indicators such as maintenance expenditures and energy consumption. These evaluations establish a solid economic base for route planning and train scheduling decisions, harmonising financial management with operational strategies to optimise cost-efficiency and service quality.

Utilising historical data, the system enables the retrieval of detailed passenger flow data for specific stations and trains, thereby improving the granularity and accuracy of traffic analysis. These data are not only pivotal for routine operational planning but also prove invaluable in scenarios involving hypothetical emergencies, such as fires, earthquakes or other disasters. The system's capability to forecast the expected number of individuals affected in such emergencies facilitates the development of more effective safety measures and emergency response strategies. By proactively understanding potential impact areas and the magnitude of emergencies, transit authorities can formulate response plans that minimise risks to passengers and ensure rapid operational recovery, thus enhancing the resilience and safety of urban rail networks.

In the ongoing development of the urban rail transit simulation system, several enhancements are necessary to address its current limitations. The article mentions that walking times within the system are approximate estimates. Achieving more accurate and tailored walking time functions would enhance the generation of passenger walking times and improve the accuracy of simulations. Additionally, the simulation assumes that passengers do not engage in any extraneous activities while moving in and out of stations, thereby overlooking additional travel times incurred from activities such as using the restroom, waiting for others or taking wrong routes. The simulation system relies on processed AFC data, with travel paths generated by the breadth-first search algorithm. However, in real passenger journeys, path selection is not controlled by a single algorithm. Instead, the true path selection by passengers involves a complex estimation problem that incorporates multiple factors and dynamic decisions [29]. Furthermore, the study imposes constraints on train capacity and does not simulate scenarios where passengers cannot board due to full trains, assuming that all passengers successfully commence their planned journeys [30]. The impact of trains skipping stations when full is also not addressed in the article [31]. Moreover, the passenger flow data utilised in the simulation are historical and limited only to passengers who have recorded entries and exits via fare collection gates, which does not support real-time distribution analysis. Researching how to enhance the system to handle real-time inputs and outputs is worthwhile; furthermore, developing a digital twin for real-time simulation could significantly deepen the analysis of passenger flows. These improvements could address the inherent limitations and increase the robustness and applicability of the simulation system in urban rail transit planning and operations.

5. CONCLUSION

Given the prevalent approach of grouping passengers by similar arrival times and arranging their travel paths by proximity, this study introduces a novel method that integrates walking times into the simulation, ensuring individuality in passenger journeys. However, simulating passengers individually presents challenges in capturing the overall distribution of passenger flows, with the results influenced by predefined travel paths.

In this research, we have developed discrete event-based models for stations, trains and passengers, and established an interactive system among them, enabling a comprehensive simulation of the entire urban rail transit system that encompasses the full lifecycle of passenger travel. Experiments using historical AFC data have demonstrated that our method is highly accurate, with a deviation of less than 30% for 88.43% of passengers compared to real-time data, validating the reliability of the derived passenger flow distribution.

Our ultimate goal is to derive cross-sectional passenger flows for stations and trains using the system, apply these data to guide advertising pricing within the urban rail transit system using a data-driven approach, provide managers with detailed information on station and train distributions for thorough management and analysis of the urban rail system, and furnish data support for emergency management and vehicle scheduling.

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陈苏霄，刘光杰，高申，李继铭，吴娟

用于估算城市轨道交通乘客流量的离散事件仿真系统

摘要
建立仿真模型是分析城市轨道交通系统中乘客流量分布的一种广泛使用且有效的方法。最近，多智能体和基于离散事件的仿真模型在研究城市轨道交通系统内的乘客流量信息方面表现出色。尽管对乘客和列车的仿真通常能够产生令人满意的结果，但很少有模型能够捕捉到城市轨道交通系统的整体运行状态。车站、列车和乘客之间的复杂相互作用使得将这些要素整合到统一的系统框架中具有挑战性。本文介绍了一种三重仿真框架，将车站、列车和乘客作为基础要素进行全面整合，以仿真整个城市轨道交通系统，并观察总体乘客流量分布。实验结果表明，我们的系统超越了现有的先进仿真模型，在允许 30%偏差的情况下达到了 88.44%的准确率。为进一步说明我们框架在分析乘客流量方面的有效性，我们使用南京地铁自动售检票（AFC）数据集进行了实验，分析了车站和列车上的乘客流量分布。

关键词
城市轨道交通；事件驱动仿真；旅行时间；客流