A Simulation Optimization Method for Rail Transit Network under Partial Blockages

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Abstract. With the rapid development of urban rail transit, delays caused by equipment failures and other reasons are common occurrences. However, current operational adjustments primarily aim to recover the order of the line as quickly as possible without considering the changes in the spatiotemporal distribution of passengers on platforms and trains. To address this issue, this paper proposes a simulation optimization method for partial blockages in urban rail transit. Firstly, a fluid simulation model for urban rail transit is established, based on the passenger flow distribution in the network under normal operations, and the train schedules and passenger flow distribution of the affected lines are calculated according to the characteristics of the emergency. Subsequently, an optimization model for line capacity is developed, targeting the minimization of stranded passenger time costs and operational costs. The model examines the process and scope of the emergency's spread in the network before and after adjustments. Finally, a case network is analyzed through simulation modeling, and the results demonstrate that the line capacity optimization model can effectively reduce the time cost of stranded passengers, validating the effectiveness of the simulation optimization approach.

Keywords: Urban rail transit, Congestion propagation, Disruption management, Timetable rescheduling

1 INTRODUCTION

Urban rail transit is an essential component of the urban public transportation system, and its operational organization is a complex and extensive planning process. However, during daily operations, unexpected factors may affect or even disrupt the service, such as signal failures and foreign object intrusions, which severely impact the normal operational order. According to incomplete statistics, in 2023, there were more than 250 incidents of delays exceeding 5 minutes (including) but less than 15

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minutes in Chinese urban rail transit. It is evident that how to promptly and accurately handle delay incidents is a crucial issue in the daily operations of urban rail transit.

Urban rail transit networks are typical complex networks, where nodes can represent stations or platforms within the network, and edges can represent sections or transfer passages. In response to the issue of the spread of impacts from unexpected events within urban rail transit networks, scholars have conducted relevant studies on its mechanisms. These include the SIR infectious disease model[1], disaster spread dynamics model[2], dynamic passenger flow distribution model[3-4], graph-based cellular automata and improved ASIER model[5], and congestion dissipation propagation model based on cellular automata, etc. [6-8], analyzing the characteristics of crowd propagation under unexpected events in the network. In the research on operational adjustments under urban rail transit emergencies, current studies mainly focus on optimization objectives such as minimizing the total delay duration, maximizing transportation capacity, and minimizing the total waiting time for passengers [9-17]. The aforementioned research has made significant contributions to the emergency management and handling of urban rail transit. However, there are still areas that can be improved: (1) Existing network propagation models often emphasize the connectivity between nodes in the network, neglecting the impact of train operations on the spatiotemporal distribution of passenger flows. (2) Current research pays less attention to the impact of the number of passengers waiting on the platform on operational safety, especially in some stations built earlier with narrow platform widths, which are more prone to overcrowding, leading to accidents such as stampedes. Therefore, how to combine the spatiotemporal distribution of passenger flows to adjust transportation plans in a timely and accurate manner, reducing the impact of partial blockages, is an important issue in the daily operation of urban rail transit.

2 PROBLEM DESCRIPTION

Partial Blockages can significantly impact the operational order and passenger flow distribution of urban rail transit systems. As depicted in Figure 1, the solid blue line represents the train operation line executed according to the scheduled timetable, the dashed blue line indicates the planned operation line of trains affected by localized disruption events, and the solid black line denotes the adjusted train operation line. Following a localized disruption event in the S4-S3 section, the operation lines of trains t3, t4, and t5 were deflected; after a certain period of recovery, trains t6 and t7 were still able to operate according to the scheduled timetable without deflection. After the deflection of the operation lines, the train intervals at some stations along the line changed. Due to the increased intervals, the number of passengers waiting on the platform at stations s4, s3, and s2 exceeded the passenger capacity that the trains could accommodate when they arrived at these stations, resulting in passenger congestion.

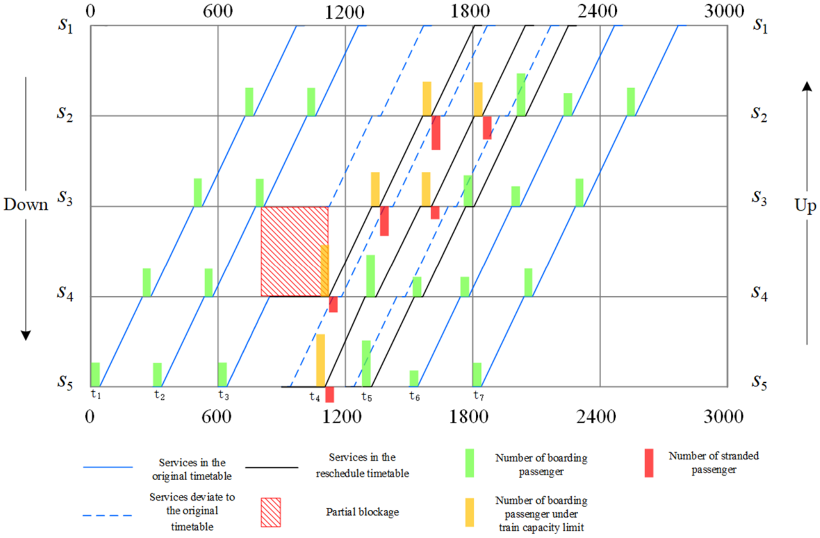


Fig. 1. Partial Blockages influence for train timetable and passenger number at platform

To ensure operational safety, it is essential to first consider limiting the maximum congestion levels at various sections within the network and the number of passengers stranded on platforms at transfer stations to within safe standards. To address this issue, the dynamic relationship between train operation frequencies on each line within the network, passenger flow at sections, and station platform capacities is considered. A macroscopic fluid dynamics model is established to describe the coupling relationship between passenger distribution and transport capacity within the network under normal operation and when disturbed. This model takes into account the development, propagation, and superposition of congestion, and quantitatively analyzes the new spatiotemporal transport capacity requirements of the network.

Based on the existing set of alternative routes, the number of trains allocated, and the transportation plan, the transportation plans for each line are optimized in coordination with the new network transport capacity requirements. This approach aims to reduce the impact of disturbances on the operational order of the network.

3 CONGESTION PROPAGATION MODEL

3.1 Assumptions

Assumption 1: Passengers traveling in all directions are uniformly distributed within the stations and trains.

Assumption 2: Trains stop at platforms corresponding to their travel direction at each station, with additional platforms not serving as waiting spaces.

Assumption 3: In the absence of localized disruption events, trains on all lines operate at uniform intervals and stop at each station

3.2 Simulation Model Construction

Urban rail transit networks are complex networks composed of numerous stations and sections. The propagation patterns of the impact of operational disturbances on passenger flow distribution within the network are influenced by factors such as platform area, buffer area, passenger flow into and out of stations, section headway, and train capacity. Therefore, by drawing an analogy to the principles of flow, pressure, and pressure wave variations within liquid transportation pipelines, a macroscopic fluid-based simulation model can be established. This model effectively simulates the impact of line disturbances on passenger distribution and their propagation patterns, while also enhancing the real-time nature of simulation calculations. Figure 2 illustrates the urban rail transit fluid simulation model established, where the lines are composed of station waiting platforms $p_j^{l,s,d}$, platform arrival valves $Varr_p^t$, platform departure valves $Vdep_p^t$, and sections e^l.

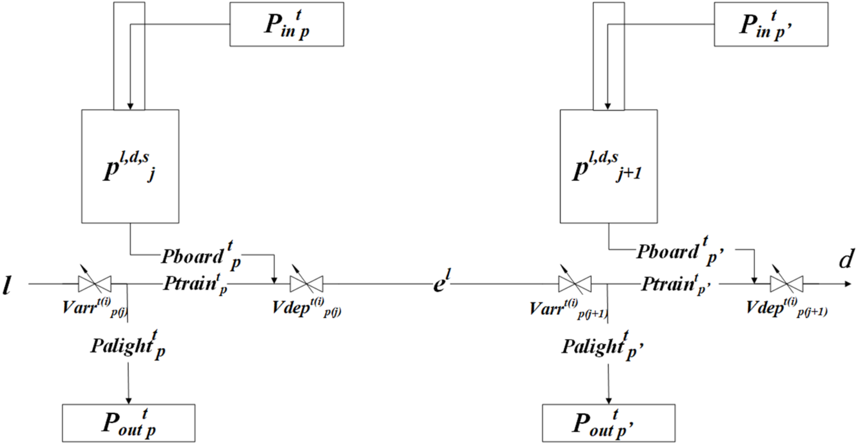


Fig. 2 Macroscopic fluid-based simulation model

In the station platform simulation process, passengers entering the waiting area in a given direction during a time period, denoted as $Pin_p^{t(i)}$, first enter the platform $p_j^{l,s,d}$to wait. Based on the number of passengers stranded on the platform from the previous time period, $Ppl_p^{t(i-1)}$,the current waiting passenger count is updated. According to the average train interval at the station, h_s^l, it is determined whether a train arrives during the time period. If a train arrives, $Varr_p^{t(i)}$is set to 1, and based on the flow balance constraint in the interval, the number of passengers on the arriving train, $Ptrain_p^{t(i)}$, and the number of passengers getting off, $Palight_p^{t(i)}$, are calculated, updating $Ptrain_p^{t(i)}$ accordingly.Similarly, it is determined whether a train departs during the time period. If a train departs, $Vdep_p^{t(i)}$is set to 1. It is then judged whether the current platform waiting passenger count, $Ppl_p^{t(i)}$, and the number of passengers on the train, $Ptrain_p^{t(i)}$, are less than the train's capacity. If so, it is assumed that the number of passengers boarding the platform, $Pboard_p^{t(i)}$, is equal to the platform waiting passenger count, with the waiting passenger count set to 0. Otherwise, the platform boarding passenger count is the remaining capacity of the train, and the passengers still on the platform are the original platform waiting passenger count minus the boarding passenger count. Finally, the values of $Ppl_p^{t(i)}$, $Pboard_p^{t(i)}$, $Ptrain_p^{t(i)}$, and $Palight_p^{t(i)}$ for the current time period are updated.

In the section e^l, passengers who board the train enter the section through the departure valve $Vdep_p^t$ of the platform at the front station in the section, which is in an open state, and travel at the average travel speed v^l of the line. After a section running time, they arrive at the arrival valve $Varr_p^t$ of the platform at the rear station in the section. If the arrival valve is open at this time, the passenger flow enters the platform $p_{j+1}^{l,s,d}$ and leaves the section e^l , completing the movement process in the section.

When a section disruption event occurs, causing the arrival or depart valve to fail to open normally, the flow velocity of the passenger flow within the section drops to 0, generating a pressure wave with the same flow velocity but in the opposite direction, which propagates in the reverse direction along the section. If the event causing the section disruption continues, the departure valve at the front station platform will remain closed until the disruption event at the rear station of the section is over before it can open normally.

4 URBAN RAIL TRANSIT NETWORK CAPACITY COORDINATION ADJUSTMENT METHOD

In networked operations, disturbances on a single line may lead to changes in the distribution of passenger flow across the network, potentially causing a mismatch between passenger demand and transport capacity on other lines. This can result in platform congestion and excessively high train occupancy rates, posing operational safety hazards. Therefore, to minimize the impact of disturbances on a single line on the overall network operation, it is necessary to adjust the transport capacity plans for the lines. The aim is to reduce the passenger congestion on platforms caused by partial blockages and, on this basis, to reduce the required train-kilometers and enhance the efficiency of transport capacity utilization.

4.1 Definition of Parameters and Variables.

Table 1 lists the relevant parameters and variables and their definitions.

Table 1. Parameters and Variables Definition

Notations	Definition
l	Line in a network
s^l	The station in line l
t_i	The *i*th time interval in study period, *i*=0,1,2...

t_s	The length of the time interval t_i, unit: s
C_t	Capacity of a train
n^l	Fleet size of rolling stocks in line *l*
r_k^l	The train route in line *l*, *k*=1,2...
$b_s^{r,l}$	0–1 variable, if service route *r* contains station *s* in line *l*, $b_s^{r,l}$ is 1, 0 otherwise
h_{min}	The minimum headway requirements of the line
h_{max}	The maximum headway requirements of the line
h_s^l	The average interval between trains in station *s* in line *l*, unit: s
d_r^l	The running distance of route r^l, unit: km
$Varr_p^t$	If a train arrive at platform *p* during time interval *t*, $Varr_p^t$ is 1, 0 otherwise
$Vdep_p^t$	If a train depart at platform *p* during time interval *t*, $Vdep_p^t$ is 1, 0 otherwise
ω_1	The weight of the platform overcrowded condition costs in the model objective function
ω_2	The weight of the operating distance costs in the model objective function
c_p	Passenger's dual waiting time cost per second, unit: CNY/minute;
c_v	Running cost of operating a train per kilometer in the study period, unit: CNY/ km;
x_r^l	0–1 variable, if service route *r* is adopted by line *l*, x_r^l is 1, 0 otherwise
h^l	Continuous variable, average interval between each route trains operating in line *l*, unit: s

4.2 Objective Function

Upon the occurrence of a blockage, the critical aspect of adjusting the line's transport capacity plan is to reduce passenger congestion on station platforms while meeting the transport capacity demands of the line, as indicated in Equation (1).

$$Z_1 = c_p \sum_{l\in L}\sum_{t_i\in T}\sum_{p\in P^l} Ppl_p^{t_i}\cdot t_s \tag{1}$$

Additionally, considering the constraints of rolling stock utilization costs, it is necessary to minimize the train-kilometers traveled while still meeting the transport capacity requirements, as shown in Equation (2).

$$Z_2 = c_v \sum_{l\in L}\sum_{t_i\in T}\sum_{r_1\in R} x_{r_1}^l\, d_{r_1}^l \frac{t_i}{\sum_{r_2\in R} x_{r_2}^l\, h^l} \tag{2}$$

In summary, the objective function of the optimization model is as shown in Equation (3).

$$\min Z = \omega_1 Z_1 + \omega_2 Z_2 \tag{3}$$

4.3 Constraints

Service Constraint. To ensure that every station is serviced, it must be covered by at least one train route.

$$\sum_{r\in \mathrm{R}} \mathrm{x}_{\mathrm{r}}^{l} b_{s}^{r,l} \geq 1 \qquad \forall\, l \in \mathrm{L}, \forall\, s \in \mathrm{S} \tag{4}$$

Train headway Constraint. To ensure the safe operation, a minimum headway time must be established based on the line's equipment capabilities. The headway between trains at all stations along the line should be greater than the minimum interval.

$$h_{s}^{l} = \frac{\sum_{r\in \mathrm{R}} \mathrm{x}_{\mathrm{r}}^{l}}{\sum_{r\in \mathrm{R}} \mathrm{x}_{\mathrm{r}}^{l} b_{s}^{r,l}} h^{l} \qquad \forall\, l \in \mathrm{L}, \forall\, s \in \mathrm{S} \tag{5}$$

$$h_{s}^{l} \geq h_{min} \qquad \forall\, l \in \mathrm{L}, \forall\, s \in \mathrm{S} \tag{6}$$

Service Frequency Constraint. To ensure a certain level of service quality on the line, the headway between trains at all stations should be less than the maximum service interval.

$$h_{s}^{l} \leq h_{max} \qquad \forall\, l \in \mathrm{L}, \forall\, s \in \mathrm{S} \tag{7}$$

Section Capacity Constraint. Considering the carrying capacity of the section, the sum of the number of passengers on board the train and the number of passengers boarding at the station should be less than the train's capacity multiplied by the number of trains operating during the time period.

$$Ptrain_{p}^{t} + Pboard_{p}^{t} \leq \frac{\mathrm{C}_{t} t_{s}}{h_{s}^{l}} \qquad \forall\, t \in \mathrm{T}, \forall\, l \in \mathrm{L}, \forall\, s \in \mathrm{S} \tag{8}$$

Number of Trains in Service Constraint. Considering the limitation on the number of trains assigned to the line, the total number of trains required for operating all routes should be less than or equal to the number of trains assigned to the line.

$$\sum_{r\in \mathrm{R}} f_{r}^{l} \leq n^{l} \qquad \forall\, l \in \mathrm{L} \tag{9}$$

$$f_{r}^{l} \geq \frac{t_{ta}^{r,l}}{\sum_{r\in \mathrm{R}} \mathrm{x}_{\mathrm{r}}^{l} h^{l}} \qquad \forall\, l \in \mathrm{L}, \forall\, r \in \mathrm{R} \tag{10}$$

Section Flow Balance Constraint. For any given section, the sum of the passengers on board and the number of passengers boarding the train entering the section should be equal to the sum of the passengers on board and the number of passengers alighting after the train has traveled through the section for the duration of the interval.

$$Ptrain_{p(j)}^{t} + Pboard_{p(j)}^{t} = Ptrain_{p(j+1)}^{t\prime} + Palight_{p(j+1)}^{t\prime} \qquad \forall\, t \in \mathrm{T}, \forall\, p \in \mathrm{P} \tag{11}$$

Platform Flow Balance Constraint. For any given station platform, the number of passengers on the platform during the current time period is equal to the number of passengers stranded from the previous time period, plus the number of passengers entering the station during this time period, minus the number of passengers boarding during this time period. If the platform is at a transfer station, the number of passengers transferring to this direction during this time period should also be added.

$$Ppl_p^{t(i)} = Ppl_p^{t(i-1)} + Pin_p^{t(i)} - Pboard_p^{t(i)} \quad \forall\, t \in \mathrm{T}, \forall\, p \in \mathrm{P} \tag{12}$$

Platform Train Capacity Constraint. For any given station platform, at most one train can be docked at a time.

$$0 \le Varr_p^t - Vdep_p^t \le 1 \qquad \forall\, t \in \mathrm{T}\,, \forall\, p \in \mathrm{P} \tag{13}$$

4.4 Algorithm

Step 1. Initialize the train operation schedule, passenger flow, line infrastructure information, and train routing data. At the onset of a partial blockage, adjust the timetable; invoke the congestion propagation simulation model to obtain the current passenger distribution and the operational demand at each station.
Step 2. Update the h_s^l for each station based on equations (6-8); at this point, the h^l for a single full-line route is equal to the minimum value of h_s^l, invoke the simulation model to calculate the Z value, denoted as Z_{min}.
Step 3. For the short-turn route r_k^l, set $\mathrm{x}_\mathrm{r}^l = 1$ and update h^l, then invoke the simulation model to calculate the Z value at this point.
Step 4. If Z<Z_{min}, update Z_{min}=Z; if all routes have been calculated, the algorithm terminates; otherwise, k=k+1 and repeat Step 3.

5 CASE STUDY

5.1 Case Description

Taking the sudden incident that occurred in the subway of a certain city in 2023 as an example, at 9:47 AM, the subway Line 13 was interrupted between LSQ Station and HY Station due to a switch failure, and the fault was repaired at 10:00 AM, with the operation order gradually recovered. The fault lasted for 13 minutes. The incident resulted in the suspension of 2 trains and the delay of 14 trains at their final destinations, with 4 of them delayed by more than 5 minutes.

The affected Line 8 and Line 27, which are near the fault section of Line 13, are selected to form the case network, as shown in Figure 3. The passenger capacity of each train on all lines is 1468 people, with a minimum headway of 150 seconds for Lines 13 and 27, and 120 seconds for Line 8. The maximum headway for all lines is 600 seconds. The study period is selected from 9:30 to 11:30, totaling 120 minutes, with the simulation step set to 60 seconds. The weights are set as ω1=0.5 and ω2=0.5, the unit kilometer travel cost for trains is 120 CNY/km, and the platform stranded passenger time cost is 0.51 CNY/minute.

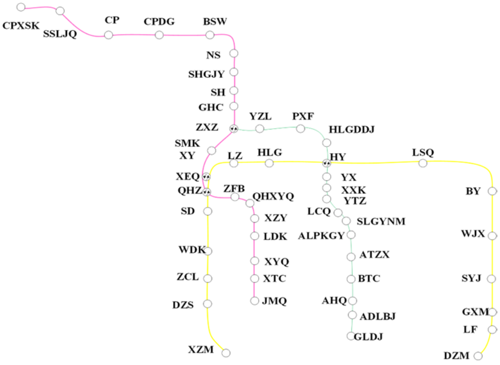


Fig. 3. Case network structure

5.2 Results Analysis

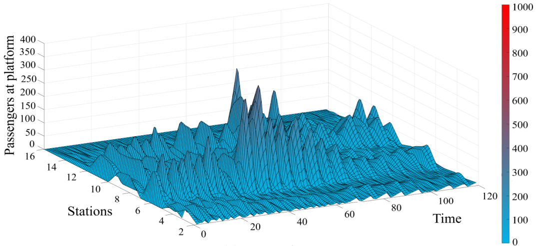
The proposed method is coded in Java 8 on an Intel Core i7 processor running on a system with Microsoft Windows 10 (64-bit) and 8 GB of RAM. The calculation time is within 45 seconds, which can meet the real-time requirements for the calculation of train operation adjustments in partial blockages situations.

Table 2 presents the operation plans and costs for Line 13 under various scenarios. In Scenario 1, where no disruption occurs, trains operate on a single full-line route r_1 with a 300-second headway, resulting in a total cost of 90,470.95. In Scenario 2, affected by a localized disruption, the train interval increases and the platform stranded passenger time cost increases by 48.9% compared to the normal situation, and the total cost also rises by 11.3%. Scenario 3 represents the optimized operation plan, which introduces the operation of short-turn routes r_2. Since the demand for capacity is concentrated in specific time periods, the short-turn route trains r_2 only operate during the 9:45-10:00, with the full-line route r_1 still in operation during other periods. Due to the limitation of the return depot capacity, the interval of the full-line route r_1 cannot be operated according to the optimized plan, resulting in a utilization of vehicle sets and train-kilometer cost that is not significantly different from Scenario 2, increasing by 9.2%. However, the platform stranded passenger time cost decreases by 23.7% compared to Scenario 2 and only increases by 13.6% compared to Scenario 1.

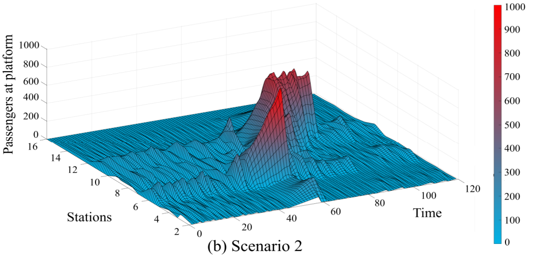
Table 2. Optimization results of the line plan for line 13

Scenario	Train routes	Departure and arrival stations	Interval	Period	Z_1	Z_2
1	r_1	XZM-DZM	300	9:45-10:45	61304.97	119637
2	r_1	XZM-DZM	327	9:45-10:45	91267.41	110066.04
3	r_1, r_2	XZM-DZM,XZM-HY	471	9:45-10:45,9:45-10:00	69667.38	120236.76

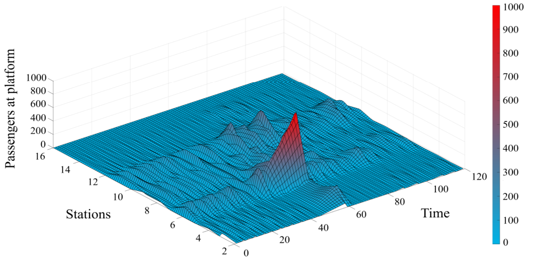
Figure 4 illustrates the number of passengers waiting on the platform at various times within each scenario, as obtained through simulation. Scenario 1 represents the normal operation of the line, showing the number of passengers waiting on the platforms at each station during different times. Scenario 2 depicts the situation during a partial blockages, Scenario 3 shows the situation after the implementation of the optimized operation plan during a localized disruption. Compared to Scenario 1, the maximum number of waiting passengers on the platforms at LSQ, XEQ, and QHZ stations during peak times in Scenario 2 all exceed 600, and all are transfer stations. After the optimized operation plan in Scenario 3, except for the LSQ station, which is not covered by the short-turn router_2 due to equipment failure, the maximum number of passengers waiting on other platforms is within the safe range, with the highest value at QHZ from 10:14 to 10:15, at 423 people, indicating that the optimized plan is significantly effective in controlling the maximum number of passengers waiting on the platform. Additionally, the simulation verified that in Scenario 3, the maximum number of passengers waiting on the platforms of the transfer stations connected to Lines 8 and 27 did not exceed the maximum platform capacity, so there was no need to adjust the operation plans for Lines 8 and 27.



(a) Scenario 1



(b) Scenario 2



(c) Scenario 3

Fig. 4. Number of passengers at platform under different scenarios\

In summary, by optimizing the operation plan, the cost of time passengers are stranded on the platform can be effectively reduced, while the increase in train-kilometer costs is not significant. The total cost has decreased by 6.7% compared to before the optimization, effectively validating the effectiveness of the simulation model and the operation plan adjustment model.

6 CONCLUSIONS

After the occurrence of partial blockages in urban rail transit, this paper designs a simulation model for passenger flow on the line from the perspective of reducing platform stranded passengers. The simulation calculates the changes in the number of passengers waiting on the platforms of various stations after partial blockages. The simulation results are used as input to establish an optimization model for the line's operation plan, aiming to reduce the cost of stranded passenger time and train-kilometer costs. An actual disruption event is taken as an example to verify the simulation and optimization models proposed in this paper. The optimization results prove that they can effectively reduce the cost of time passengers are stranded on the platform, alleviate the passenger flow pressure on the platform, and at the same time, the simulation verifies that partial blockages will not have a significant impact on the safe operation of adjacent lines.

In future research, the impact of local disruption events on passengers' travel path choice behavior can be further studied. Combined with different local disruption scenarios, passenger travel path allocation can be incorporated into the simulation model and applied to the passenger flow analysis and capacity plan adjustment of urban rail transit networks.

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