Received 30 September 2020
Revised 26 October 2020
Accepted 26 October 2020

Research on digital flow control model of urban rail transit under the situation of epidemic prevention and control

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Abstract

Purpose – Beijing rail transit can actively control the density of rail transit passenger flow, ensure travel facilities and provide a safe and comfortable riding atmosphere for rail transit passengers during the epidemic. The purpose of this paper is to efficiently monitor the flow of rail passengers, the first method is to regulate the flow of passengers by means of a coordinated connection between the stations of the railway line; the second method is to objectively distribute the inbound traffic quotas between stations to achieve the aim of accurate and reasonable control according to the actual number of people entering the station.

Design/methodology/approach – This paper analyzes the rules of rail transit passenger flow and updates the passenger flow prediction model in time according to the characteristics of passenger flow during the epidemic to solve the above-mentioned problems. Big data system analysis restores and refines the time and space distribution of the finely expected passenger flow and the train service plan of each route. Get information on the passenger travel chain from arriving, boarding, transferring, getting off and leaving, as well as the full load rate of each train.

Findings – A series of digital flow control models, based on the time and space composition of passengers on trains with congested sections, has been designed and developed to scientifically calculate the number of passengers entering the station and provide an operational basis for operating companies to accurately control flow.

Originality/value – This study can analyze the section where the highest full load occurs, the composition of passengers in this section and when and where passengers board the train, based on the measured train full load rate data. Then, this paper combines the full load rate control index to perform reverse deduction to calculate the inbound volume time-sharing indicators of each station and redistribute the time-sharing indicators for each station according to the actual situation of the inbound volume of each line during the epidemic. Finally, form the specified full load rate index digital time-sharing passenger flow control scheme.

Keywords Digital flow control, Inbound passenger flow control, Passenger flow prediction, Section full load rate, Train full load rate

Paper type Research paper

Smart and Resilient Transportation
Vol. 3 No. 1, 2021
pp. 78-92
Emerald Publishing Limited
e-ISSN: 2632-0495
p-ISSN: 2632-0487
DOI 10.1108/SRT-09-2020-0010

1. Introduction

In the context of the continuous advancement of urbanization, the urban rail transit system has become the main way for urban residents to travel. In recent years, due to the continuous improvement of the construction speed and the increasing demand for passenger flow, the urban rail transit system has gradually shown the characteristics of networked operating lines and complicated passenger flow components. In particular, the arrival of the new crown epidemic has caused significant changes in the rail transit passenger flow trends in major cities and has also placed more requirements on operation and management personnel. For example, the passenger flow of the Beijing rail transit network has continued to rise with the changes in the epidemic prevention and control situation and the deepening of the resumption of work and production since February 10, 2020. To ensure the epidemic control of rail transit and the stable order of the operation during the epidemic prevention and control period, Beijing rail transit takes "station congestion and train full load rate" as key indicators and proposes a standard that the train full load rate does not exceed 50% to strictly control rail transit passenger flow. Therefore, in the current situation, it has become a key issue to be urgently resolved how to accurately monitor the entry volume of each station in the road network to satisfy the full load rate requirements of the running trains in the road network.

To effectively control the density of rail transit passenger flow, meet the travel needs of citizens and provide passengers with safe and reliable rail transit travel services on the premise of meeting the full load rate control index, it is necessary to establish a passenger flow prediction model according to the characteristics of passenger flow and to predict passenger flow origin-destination (OD) time-sharing. Based on the predicted passenger flow data and the train schedule, we can deduce the whole process chain information of passengers entering the station, boarding, transferring, getting off and leaving the station and calculate the predicted full load rate data of the planned train. We can analyze the section where the highest full load occurs, the composition of passengers in this section and when and where passengers board the train, based on the measured train full load rate data. Then we combined the full load rate control index to perform reverse deduction to calculate the inbound volume time-sharing indicators of each station, and redistribute the time-sharing indicators for each station according to the actual situation of the inbound volume of each line during the epidemic. Finally form the specified full load rate index digital time-sharing passenger flow control scheme.

2. Literature review

The contradiction between the supply and demand of urban rail transit has attracted more and more attention from operators. Restricting passengers from entering stations and boarding trains to ensure the safe and orderly operation of rail transit systems has become the common method in major cities. The corresponding theories have also attracted more and more attention from researchers.

Passenger flow control methods are the first to be applied to road traffic. Operators often ensure the efficient operation of the bus system by adjusting the number of people boarding the bus at each bus stop (Ibarra-Rojas *et al.*, 2015). For example, Delgado *et al.* (2012) proposed a mathematical programming model to control the vehicles in the public transport network for minimizing delays. Within the framework of an iterative optimization, two optimization strategies were proposed: first, to control the speed of vehicles in each section of the road network; second, to impose restrictions on passengers at each station while controlling the speed of buses in designated sections. Simulation experiments in different scenarios verified the feasibility and effectiveness of the proposed method. The results showed that the method can reduce 77% of the extra waiting time in the road network. Akamatsu *et al.* (2015) proposed a method to analyze dynamic user balance, which converted the balance condition in the conventional "Eulerian coordinate system" into the "Lagrangian coordinate system" to evaluate the dynamic travel of the road section-time and made recommendations for current limiting. Wang *et al.* (2019) built a data-driven hybrid control framework for the public transportation system. The framework consisted of three components: a data-driven control module, a performance module and an optimization module. Among them, the data-driven control module used the random forest model to determine whether the vehicles currently running on the bus line need to have interfered. The performance module was used to calculate and describe the current operating state of the vehicle. The optimization module was used to calculate and generate the corresponding control strategy, that is, which vehicles to control and which control strategy (including acceleration strategy and deceleration strategy) should be adopted to minimize the total travel time of passengers in the road network. The framework proposed in this study was applied to the road network in Urumqi, China. The results showed that the framework could meet the needs of real-time control in complex traffic environments. Manasra and Toledo (2019) developed a control framework based on real-time simulation to coordinate the operation of public transportation services to achieve smoother transportation and maintain regular service. In this framework, the maintenance and change of bus speed were set as the solution to the optimization problem, and the optimization goal was to minimize the total travel time of passengers within the forecast range. The control framework was demonstrated using three BRT lines in Haifa, Israel as an example. The results showed that it was superior to traditional autonomous driving strategies in reducing the total travel time of passengers and improving punctuality. Yang *et al.* (2019) developed a passenger flow control model based on a network-level system, discretized the continuous movement of passengers through modeling methods and systematically considered traffic demand and strict vehicle capacity restrictions (including station passing capacity, platform carrying capacity and train transportation capacity). An integer linear programming model was established to minimize the total waiting time of passengers outside the station and on the platform. The method has been applied in the actual network of the Beijing subway system, and the results showed that the proposed flow control strategy could provide detailed information about the control station, control duration and control intensity and could effectively reduce passenger waiting time and lighten the number of stranded passengers in the subway network.

In the field of urban rail transit, researchers often started with the microscopic behavior of passengers, analyzed their movement laws and then designed control strategies for rail transit by referring to the current limiting experience of the bus system. In terms of passenger micro-behavior, Xu *et al.* (2014) established a station queuing network analysis model based on the M/G/C/C state-related queuing network and discrete-time Markov chain based on the collection and distribution process of subway passengers. The calculation of the capacity of the subway station layed the foundation for the formulation of passenger flow restriction strategies. Yang *et al.* (2019) proposed an improved social force model to study the influence of subway platform waiting area design on passengers' getting on and off behavior from a micro perspective. Liu and Chen (2019) calibrated the relevant parameters of pedestrian movement in crowded conditions through the pedestrian monitoring video data of the subway station during the peak hours and constructed a multi-agent-based pedestrian simulation system based on the calibration results. Furthermore, the simulation system was used to quantitatively analyze the correlation between the speed of pedestrian movement and the way of movement in the crowd and the degree of crowding.

Finally, a case analysis was carried out based on the pedestrian movement data of the Optics Valley Plaza Station of Wuhan Metro in China during the morning rush hours to verify the validity and accuracy of the model. Li *et al.* (2020) first defined a passenger violation, that is, when there are passengers in the carriage getting off, the passengers on the platform start to get on the train. Then, based on an improved social force model, a micro-pedestrian simulation model simulated the process of getting on and off the subway passengers and quantified the impact of passengers' violations on the efficiency of passengers getting on and off the train with the empirical analysis of the Hong Kong subway. On the basis of studying the micro-behavior of passengers, many methods for formulating flow restriction strategies have been proposed. For example, Jiang *et al.* (2017) considered both subway passenger flow demand and train capacity limitation and studied the subway passenger flow control problem . Specifically, taking the passenger flow control ratio and train stopping strategy as decision variables, and aiming at the maximum utility of passengers, a passenger flow control strategy generation model based on utility theory was constructed. Finally, the Beijing subway was taken as an example to verify its effectiveness. Furthermore, the researchers took into consideration the train schedule and station characteristics. Li *et al.* (2017) studied the joint optimization problem of train schedule and passenger flow control scheme coordination, and he developed a coupled state-space model for calculating the departure time and full load rate evolution of each train. Then, he transformed this problem into a set of quadratic programming problems and performed numerical calculations to give a joint optimal strategy, and used numerical examples to verify the convergence and effectiveness of the method. Liu *et al.* (2020) updated the method of the above research, further reconstructed her model into a mixed-integer linear programming model and introduced a method based on Lagrangian relaxation to solve this model. Based on automatic fare collection (AFC) data and considering two factors, passenger flow and spatial distance, Luo *et al.* (2017) proposed a clustering algorithm based on K-means to analyze the traffic travel demand of designated stations. A case study in the Haaglanden area of The Netherlands proved the method's effectiveness. Validity provides a theoretical basis for the analysis of passenger flow sources and the study of passenger flow control strategies. With the continuous development of networked subway operations, Xu *et al.* (2019) innovatively proposed a multi-station collaborative current limiting model, that is, simultaneous control of incoming passengers and transfers on multiple stations and lines. This model was a two-tier model. The upper model aimed to achieve optimal system performance through different passenger flow control strategies. The lower model used the passenger flow evolution model based on the Logit model to achieve balanced user distribution. The model was solved by an improved genetic algorithm and an actual case was used to verify its effectiveness. Furthermore, Yu *et al.* (2020) proposed a flow control strategy formulation method based on the Bayesian inference framework considering the traveling backward phenomenon. This method was used in the Beijing subway network and proved to be effective in reducing passengers' waiting time and travel time.

In summary, existing studies have conducted in-depth studies on the formulation and optimization of passenger flow control strategies in the field of urban rail transit. However, the targeted scenarios are often the morning and evening peaks under congested conditions. Research studies on passenger flow control under the form of epidemic prevention and control are still rarely. To do this, this paper analyzed the rules of rail transit passenger flow during the epidemic and adjusted the passenger flow prediction model in time according to the characteristics of the passenger flow during the epidemic. Combining the time and space distribution of the finely predicted passenger flow and the train operation plan of each line, the system was analyzed and restored by big data. The deduction obtains the travel chain information of the passengers from entering, boarding and disembarking and the full load rate of each train. We designed and developed a set of digital flow control models, which were based on the time and space composition of passengers on trains with congested sections scientifically obtained the number of controlled passengers entering the station and provided an operability basis for operating companies to accurately control flow.

3. Methodology

Digital flow control is a comprehensive and deepened application of rail transit passenger flow analysis. To accurately control the inbound passenger flow, the full load rate of the control line does not exceed the control index. First, it is necessary to analyze the historical rules of passenger flow, especially the historical rules of passenger flow during the epidemic, find the rules and establish a passenger flow prediction model suitable for the epidemic period and obtain the OD distribution law of rail transit on a certain day in the future. Second, it is necessary to adjust the parameters of the classification model currently used by Beijing rail transit to adapt to the passenger flow law during the epidemic. According to the predicted OD law combined with the planned train operation chart of the day, the passenger flow classification is required to obtain the predicted OD travel trajectory and obtain each train. The incoming station composition of each section. Finally, the inbound flow control algorithm described in this article is used to obtain the control indicators of the inbound stations at various times throughout the day, and they are distributed to all stations in the whole road network for the station's current limit reference. The overall process of the digital flow control method discussed in this article is shown in Figure 1.

3.1 Forecasting passenger flow in the form of epidemic prevention and control

The full load rate control during the epidemic requires comprehensive consideration of passenger travel needs and the full load rate control under the requirements of epidemic prevention. With the gradual advancement of resumption of work and production, passenger flow demand is gradually changing. Taking the Beijing Subway as an example,

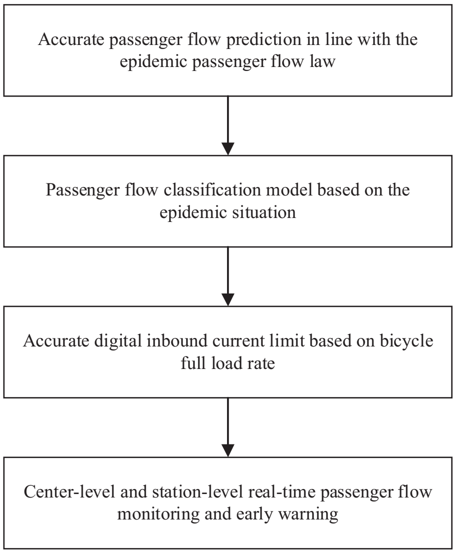

Figure 1.
The overall flow chart of the digital flow control method

there is a big difference between the passenger flow of the road network during the same time period in 2019 and 2020 (as shown in Tables 1 and 2). It is mainly as follows:

- During the epidemic period, the overall passenger flow in the road network decreased significantly;
- During the non-epidemic period, the passenger flow of different weeks tended to be stable, with passenger flow fluctuations of about 2%.

During the epidemic period, passenger flow fluctuated significantly and showed a weekly upward trend. The weekly increase rate is about 16%, but the passenger flow has stabilized in the same week. This feature is consistent with the progress of the resumption of work and production.

It can be found that due to the characteristics of passenger flow during the epidemic, the usual passenger flow prediction model will not be suitable. It is necessary to re-establish the passenger flow prediction model based on the passenger flow after the epidemic. The model processing flow is shown in Figure 2.

The entire forecast model adopts a top-down approach to gradually calculate the forecast daily passenger flow OD demand.

Step 1: Determine the growth rate of the daily passenger flow of the road network, which is determined here based on the experience value. With the resumption of work and production and the adjustment of the epidemic prevention and control level, the growth rate needs to be adjusted appropriately. After determining the growth rate, we use the similar day passenger flow on the forecast day last week and the growth rate to calculate the overall passenger flow of the forecast daily road network.

Step 2: After determining the overall passenger flow of the forecast day, we use the moving average method to calculate the passenger flow of the line. The formula is as follows: Percentage of line passenger flow = $((L_{d1} + L_{d2})/2 + \ldots + L_{dn})/2$.

Among them, L_{d1} is the proportion of passenger flow of line L on similar day d_1, L_{d2} is the proportion of passenger flow of line L on a similar day d_2, etc;

Week	The first week	The second week	The third week	The fourth week
Monday	102.86	119.12	143.29	166.07
Tuesday	100.16	119.82	141.77	164.35
Wednesday	101.31	122.66	141.92	167.80
Thursday	100.98	122.74	142.45	162.40
Friday	101.91	124.88	146.79	170.89

Table 1. Passenger flow in March 2020 (unit: 10,000 people)

Week	The first week	The second week	The third week	The fourth week
Monday	654.01	652.11	653.52	663.06
Tuesday	655.66	654.17	657.02	667.81
Wednesday	650.73	656.32	647.58	670.81
Thursday	654.67	648.12	652.99	654.87
Friday	716.14	692.61	701.53	692.29

Table 2. Passenger flow in March 2019 (unit: 10,000 people)

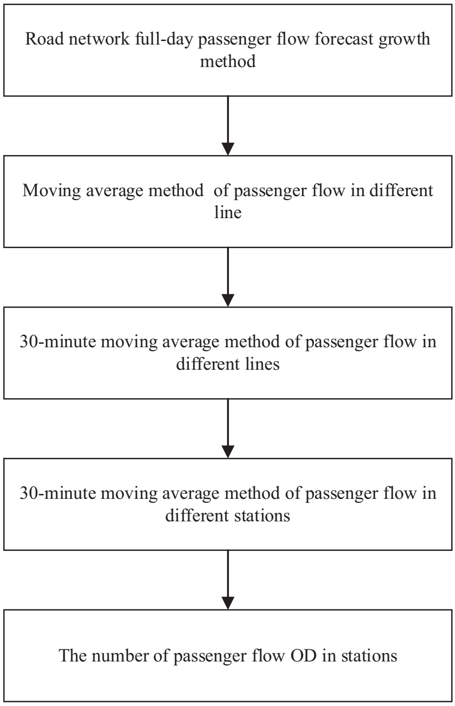

Figure 2.
Process of passenger flow prediction model processing during the epidemic

Step 3: After determined the total passenger flow of the predicted daily in different lines, it can be used the moving average method to calculate the 30-min passenger flow in the different lines and stations.

Step 4: According to the 30-min passenger flow in the different stations, it is used the historical daily average method to determine the allocation ratio of the destination station and calculate the 30-min OD of each station. Then, it is randomly allocated the 30-min OD to each minute. According to the original station time and the OD standard time (obtained through data cleaning through actual AFC transaction data), it is calculated the outbound time of the destination station and finally got the predicted OD details.

3.2 Calculating the maximum full load rate and the number of people on a single train

Based on the calculation results of the predicted passenger flow and passenger travel process, a two-dimensional array of the number of people getting on and off the single train is constructed. It is as shown in Table 3.

Then we find the highest section in the train S_m ($1 \leq$ m $< N_s$, N_s is the number of stations). Assuming that the number of people on the highest section car is γ_m, according to the threshold limit based on the full load rate of the section Pt ($0 \leq$ Pt $\leq 100\%$) and the rated number of passengers on the section $C_{r,m}$, the I_m is can be calculated in the S_m (If the number of people at the highest section exceeds the threshold limit, I is a negative number):

$$I_m = C_{r,m} \times P_t - \gamma_m$$

As no one gets on the train at the station, it does not contribute to the cross-section adjustment. To reduce this impact, the initial number of people boarding at each station $U_{m,s}$ is calculated is as follows:

$$U_{m,s} = \frac{I_m}{N_s - 1}$$

If the station has the number of people getting on the train, according to the distribution of the number of people getting off the station at the station $P_{off,i}$, the initial number of people getting on the train at stations U_s is allocated to each getting off station:

$$U_{off,s,i} = U_{m,s} P_{off,s,i}$$

Among them, $P_{off,s,i}$ represents the probability of passengers getting on the train from station s to get off at the i-th station and $U_{off,s,i}$ represents the initial number of passengers getting off the train at the i-th station. If there is no number of people on the train at the station, the initial number of people on the train is evenly distributed to the stations:

$$U_{off,s,i} = \frac{U_{m,s}}{N_{off,s}}$$

Among them, $N_{off,s}$ represents the number of getting off at the boarding station s and $U_{off,s,i}$ represents the initial number of getting off at the i-th getting off station. Taking into account the error caused by rounding, the number of people getting off at the last station $U_{off,s,N_{off}}$ is calculated using the following formula:

$$U_{off,s,N_{off}} = U_{m,s} - \sum_{i=1}^{N_{off,s}-1} U_{off,s,i}$$

3.3 Adjusting the number of people on a single train

Calculate the distribution probability $P_{on,m}$ of the number of people getting on the train from the source station at the highest cross-section S_m and assign the total increased number of people at the highest cross-section I_m to each source station. The increased number of people from each source station $I_{on,m}$ is as follows:

$$I_{on,m} = I_m P_{on,m}$$

Get on/off the station	*S2*	*S3*	*S4*	*S5*
S1	12	18	19	8
S2	0	8	14	3
S3	0	0	10	12
S4	0	0	0	5

Table 3. Two-dimensional array of the number of people getting on and off the train

Furthermore, the increased number of people from each source station $I_{on,m}$ is allocated to each drop-off station according to the distribution probability of the number of drop-off stations at that station $P_{off,s,i}$ and the increased number of drop-offs at the i-th drop-off station $I_{off,s,i}$:

$$I_{off,s,i} = I_{on,m}P_{off,s,i}$$

Therefore, for each station of the line, the number of people on the train after the increase is:

$$U_s = Ori_{on,s} + I_{on,m} + U_{m,s}$$

$Ori_{on,s}$ represents the original number of people on the train at the station s, $I_{on,m}$ represents the number of people on the train increased according to the highest section threshold and $U_{m,s}$ represents the initial number of people on the train. For each station of the line, the number of people getting off after the increase is:

$$D_{s,i} = Ori_{off,s,i} + I_{off,s,i} + U_{off,s,i}$$

$Ori_{off,s,i}$ represents the original number of alights at the station i, $I_{off,s,i}$ represents the number of alights increased according to the highest section threshold and $U_{off,s,i}$ represents the initial number of alights.

According to the number of people getting on and off the train at each station, count the number of people on each section of the train. After completing the adjustment of each source station before the highest section, search for the next highest section in order and increase the number of people on the train and the corresponding number of people alighting at the source station of the second-highest section after station D of the highest section according to the above method. Repeat the above process until the last two stations of the line are the source stations with high cross-section.

3.4 Converting the number of controlled boarding people into the number of controlled inflow people

The number of people boarding at ordinary stations is the same as the number of people entering the station. The number of people getting on the train after the increase is the number of people entering the station after the increase; the number of people getting on the train at the transfer station is the same as the number of people entering the station plus the number of people changing in. The transfer station needs to divide the increased number of passengers into the number of people entering the station and the number of people changing according to the proportion

Furthermore, the increased number of entrants and exchanged entrants will be allocated to different time periods according to the rule of 10 min granularity. Assuming that the number of people who get on the train number C after the increase in station A is $I_{on,C,A}$, according to the rules of boarding the train at station A on similar days/forecast days, these passengers are divided into K 10 min grain sizes before and after entering the station and the number of passengers entering the station at the k-th 10 min granularity can be expressed as follows:

$$I_{on,,C,A,k} = I_{on,C,A} \cdot \tau_{k,C,A}$$

Among them, $\tau_{k,C,A}$ represents the proportion of the k-th 10-min granularity among the number of people boarding the train at station A for train number C and $\sum_{1}^{K} \tau_{k,C,A} = 1$.

The total number of upward $E_{s,u}$ and downward $E_{s,d}$ inbound stops at each station following the change can be obtained by summarizing the 10-min granular inbound volume of all trains in each direction of the line.

Taking into account that there are certain rules for the up and down of station arrivals at each time period, for example, in the morning rush hour of Tiantongyuan Station, the number of people going down is significantly higher than that of people going up. Therefore, the number of people entering the station with a granularity of 10 min should be distributed according to this up and down redistribute regularly and then set the threshold. The analysis found that it is difficult to find stable upward and downward distribution rules from the 10 min grain size inbound traffic. Therefore, the 30 min inbound volume is used to redistribute the data.

Step 1: Set the up and down probabilities of station A to enter the station by swiping the card at a granularity of 30 min as $\xi_{u,A}$, $\xi_{d,A}$, $\xi_{u,A} + \xi_{d,A} = 1$.

Step 2: According to the previous calculation, the total number of incoming and outgoing arrivals $E_{s,u,A}$, $E_{s,d,A}$ at the granular level of 10 min after the adjustment of station A can be calculated:

$$E_{s,u,A} = \frac{E_{s,u,A}}{_{u,A}}, \quad E_{s,d,A} = \frac{E_{s,d,A}}{_{d,A}}$$

Step 3: To ensure that both the up and down trains can be within the threshold range, we take $min\{E_{s,u,A}, E_{s,d,A}\}$ as the final entry threshold for station A: $E_{s,A}$.

Step 4: Circulate all stations and calculate the 10-min granularity threshold for each station: E_s according to the above process.

For the transfer station, there are usually multiple gates belonging to different lines. Therefore, after calculating the threshold value of the inbound volume according to the up and down rules of the ordinary station, it is also necessary to split it according to the proportion of the 30-min incoming lines in the same period of the transfer station and to obtain the threshold value of the inbound volume of the transfer station belonging to different lines.

Step 1: Set the 30-min inbound rate of transfer station B under different lines as $\lambda_{B,i}$ (i is the line belonging to the transfer station, i >= 2).

Step 2: Transfer station B, according to the calculation of ordinary station, get the entry threshold of transfer station B: $E_{s,B}$.

Step 3: Calculate the entry threshold for each line of the transfer station according to the proportion of pit stops in 30 min, $E_{s,B,i} = \lambda_{B,i} \cdot E_{s,B}$.

Step 4: Calculate the thresholds for all transfer stations belonging to different lines according to the above process, and merge them to obtain the final thresholds for the transfer stations belonging to different lines.

Through the above four steps, under the premise of a given maximum section full load rate, the passenger flow restriction plan of each station in the road network can be created.

4. Case study and system display

4.1 Case study

Taking the passenger flow situation of Beijing Metro on March 30, 2020, as an example, the full load rate index of the rail transit section on that day was 50%. According to the passenger flow situation growth in March 2020, combined with the legal holiday (Ching Ming Festival) the week of March 30 before the holiday, the willingness of some employers to resume work was reduced and there was no updated stimulus policy in Beijing. It was judged that the passenger flow growth on March 30 was difficult to maintain the trend of the previous few weeks, and the growth rate was initially determined to be about 10% (16% in the previous weeks), the passenger flow on March 23 (last Monday) is used as the reference value to calculate the overall demand for passenger flow as shown in Table 4.

According to the passenger flow prediction results, combined with the adjusted comprehensive classification model to complete the calculation of the passenger travel chain, based on the digital inbound flow control calculation process to complete the inbound passenger flow control indicators of each station in the road network, as shown in Table 5.

According to the time control data of each station calculated by the model, real-time passenger flow comparison is carried out through the real-time passenger flow collection system of the Beijing Rail Transit AFC Monitoring Center. The personnel of each station implements the flow restriction measures outside the station based on the on-site situation and the comparison result. Passenger flow control is used to achieve the goal of full-load rate control. According to the actual passenger flow occurrence on March 30 and specific measures for current restriction, the following stations have carried out passenger flow control to ensure the full-load rate control requirements, as shown in Table 6.

After the current limit operation at the station, the maximum full load rate of each line on March 30 is shown in Table 7.

It can be seen from the above table that on March 30, the maximum full load rate of each line of the road network was controlled below 50% of the control index, including lines with large daily passenger flow such as Line 4, Line 5, Line 6 and Line 15. The full load rate of the highest section of the line, etc., is controlled below the control index 50%, reaching the control target.

4.2 System function display

To provide a scientific and reasonable flow control basis for the station site to control the full load rate of vehicles at the first time, the digital flow control model was designed and developed in the fastest time and was officially deployed in the Beijing Rail Transit AFC Monitoring Center on March 2, 2020, Launched, providing time-sharing flow control reference for each station for Beijing Metro Operation Company, Beijing-Hong Kong Metro Company and Rail Operation Company and formed a central-station-level system linkage.

Table 4.
Passenger flow forecast table on March 30, 2020

Similar day passenger flow	Growth rate(%)	Forecast passenger flow	Actual passenger flow	Deviation(%)
1,673,969	10	1,841,366	1,854,697	−0.72

Table 5.
The 10-min inbound flow control index of each station on March 30

Line	Station	Time period	Inbound volume index
Line 1	Ping Guoyuan	07:00–07:10	528
Line 1	Gu Chen	07:00–07:10	483
Line 1	Ba Jiaoyouleyuan	07:00–07:10	507
Line 1	Babaoshan	07:00–07:10	556
Line 1	Yuquan Road	07:00–07:10	295
Line 1	Wu Kesong	07:00–07:10	376
Line 1	Wanshou Road	07:00–07:10	164
...	...	...	...

Line	Station	Time period	Inbound volume index	The number of current limits
Line 15	Hou Shayu	07:50–08:00	313	7
Line 15	Hua Likan	08:00–08:10	208	39
Line 15	Nan Faxin	08:00–08:10	194	22
Line 5	Beiyuan Road North	08:00–08:10	164	4
Line 6	Haidian Wuluju	08:00–08:10	196	20
Line 6	Changying	08:00–08:10	417	3
Line 13	ShaoYaoju	08:00–08:10	102	0
Line 15	South Faxin	08:20–08:30	200	22
Line 15	South Faxin	08:50–09:00	213	7
Line 6	Da Lianpo	08:20–08:30	287	0
Line 6	Chang Ying	08:20–08:30	378	21
Line 6	South Faxin	08:30–08:40	202	34
Line15	Ma Quanying	08:10–08:20	199	4
Line15	Guo Zhan	08:10–08:20	113	0
Line15	Hua Likan	08:10–08:20	174	77
Line15	Hou Shayu	08:10–08:20	237	50
Line15	South Faxin	08:10–08:20	176	83
Line15	Shun Yi	08:10–08:20	446	35
Line15	Feng Bo	08:10–08:20	373	36
Line15	South Faxin	08:40–08:50	216	26
Line6	Chang Ying	08:10–08:20	385	25

Table 6. List of stations with a current limit on March 30

Both the center and the station site can trigger passenger flow over-limit warning for the first time It provides powerful data support for the accurate flow control of the station site and enables digital anti-epidemic through the background model. The digital flow control center-level, station-level system interface and the digital flow control model system station-level monitoring interface are shown in Figures 3, 4 and 5.

5. Conclusions

The digital flow control model discussed in this paper takes the full load ratio of the road network as the control target, and uses the passenger information of each train as the basic unit, which reduces the complexity of road network linkage; from the line train to the station, we can control the input from the source, which conforms to the actual law; in the actual application process, the secondary dynamic allocation correction can be made according to the current inbound volume at each station of the line, which is more consistent with the passenger flow law of the day and is more suitable for on-site personnel dispatch and command.

The precise prediction of future passenger movement and the accurate classification of the entire passenger travel process is the key to the digital flow control model for eventually achieving accurate on-site flow control. According to this article, it is precisely the precise grasp of the passenger flow law during the epidemic era. The passenger flow prediction model of the epidemic passenger flow law and the targeted adjustment of the passenger flow classification model has finally realized the effective control of the full load rate of each line of the road network.

It can be said that the full load rate control of transmission lines during the epidemic is an application of the digital flow control model in specific scenarios, and it has been proved that the theory of the digital flow control model is scientific and reasonable in practice. The essence of the digital flow control model is a set of methods for an in-depth study of the rules

Table 7.
30-min maximum full load rate of each line of the road network on March 30

Line	Maximum full load rate period	Maximum full load rate range	Interval passenger flow	Interval full load rate (%)
Line 1	08:00–08:30	Sihui-Dawang Road	6,792	29.73
Line 2	05:00–05:30	Beijing Railway Station-Jianguomen	235	16.46
Line 4	08:00–08:30	West Red Gate-New Palace	6,178	39.89
Line 5	08:00–08:30	Beiyuan Road North-Datun Road East	8,605	43.16
Line 6	09:00–09:30	Shilibao-Jintai Road	10,409	43.90
Line 7	08:00–08:30	Baiziwan-Dajiao Ting	3,542	22.59
Line 8	08:30–09:00	Huilongguan East Street-Huoying	5,650	32.25
Line 9	08:00–08:30	Qilizhuang-Liuliqiao	6,386	31.24
Line 10	08:00–08:30	Shuangjing-Guomao	9,272	42.11
Line 13	08:00–08:30	Xi Erqi-Qinghe	7,478	43.64
Line 14	09:00–09:30	Jintai Road-Chaoyang Park	6,507	43.73
Line 15	08:00–08:30	Ma Quanying-Cui Gezhuang	6,410	48.78
Line 16	08:00–08:30	Nongda South Road-Xiyuan	2,162	21.79
Line S1	08:00–08:30	Sidaoqiao-Jin'an Bridge	1,731	33.55
Batong Line	08:30–09:00	Communication University-Gao Beidian	6,493	37.89
Fangshan Line	08:00–08:30	Dao Tian-Dabaotai	6,709	38.29
Changping Line	08:00–08:30	Gonghua City-Zhu Xinzhuang	7,292	38.42
Yanfang Line	07:30–08:00	Zicaowu-Yancun East	693	12.03
Yizhuang Line	08:00–08:30	Xiaocun-Songjiazhuang	3,113	35.34
Capital Airport Line	15:00–15:30	T2Hangzhanlou-Sanyuan Bridge	170	12.65
Daxing Airport Line	07:30–08:00	Daxing New Town-Daxing Airport	71	3.90

Figure 3.
Digital flow control center-level system interface

当前时段: 13:10-13:20

线路	控制量	进站量	预警车站	超限车站	线路	控制量	进站量	预警车站	超限车站
1号线	3675	1269	1	0	14号线(东段)	5920	694	0	0
2号线	4258	1208	0	0	15号线	2527	506	0	0
4-大兴线	6652	2024	0	0	16号线	3309	112	0	0
5号线	4970	1243	0	0	大兴机场线	1987	153	0	0
6号线	5107	1389	0	1	S1线	1253	60	0	0
7号线	2833	704	0	0	燕房线	1665	31	0	0
8号线	6573	766	0	0	昌平线	2630	396	0	0
9号线	6410	602	0	0	房山线	1831	215	0	0
10号线	7889	1901	0	0	亦庄线	1642	339	0	0
13号线	2544	643	0	0	八通线	2236	297	0	0
14号线(西段)	1330	112	0	0	首都机场线	1054	71	0	0

进站量告警

6号线 东四 进站量告警，控制量25人，已进站40人

Figure 4.
Digital flow control station-level system interface

2号线宣武门分时进站客流监视

时段	限制最大进站量	当前进站量
14:10-14:20	61	
14:00-14:10	56	
13:50-14:00	43	
13:40-13:50	56	
13:30-13:40	64	
13:20-13:30	55	
13:10-13:20	**56**	**19**
13:00-13:10	65	39
12:50-13:00	78	44
12:40-12:50	57	31
12:30-12:40	42	26
当前时段累计	7229	3785

Figure 5.
Station-level monitoring interface of the digital flow control model system

on the composition of passenger flow, which can be applied to different scenarios for the study of passenger flow that need to be quantified such as accurate flow restriction of high-normal passenger flow stations after the epidemic has stabilized, traffic capacity matching analysis and other scenarios.

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