

# Modelling the Selection of Waiting Areas on Subway Platforms Based on the Bacterial Chemotaxis Algorithm

Guang YUAN, Dewen KONG, Lishan SUN\*, Guangtong LIU, Yingda CHEN

**Abstract:** Based on the bacterial chemotaxis algorithm, a new waiting-area selection model (WASM) is proposed that predicts well the pedestrian distribution in subway waiting areas. WASM regards passengers waiting on a subway platform as two-dimensional points and adopts an essential rejection factor to determine the target waiting area. Based on WASM, three experiments were carried out to explore how passenger volume, waiting-area capacity, and staircase position affect the number and distribution of waiting passengers. The experimental results show the following. 1) Regardless of the passenger flow, passengers prefer waiting areas that are between the stairs. 2) Setting proper capacity limits on waiting areas can help to improve subway transportation efficiency when passenger flow is relatively high. 3) The experimental results show that the closer the staircases, the more passengers are left stranded on the platform.

**Keywords:** bacterial chemotaxis algorithm; pedestrian distribution; subway platform; waiting area selection

## 1 INTRODUCTION

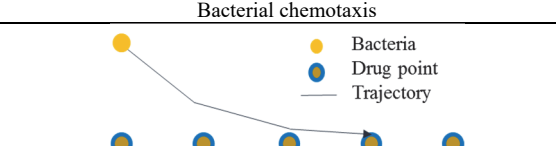
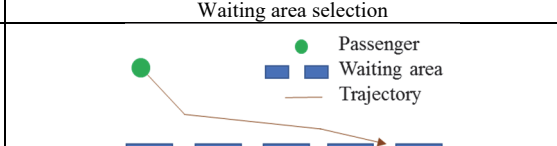
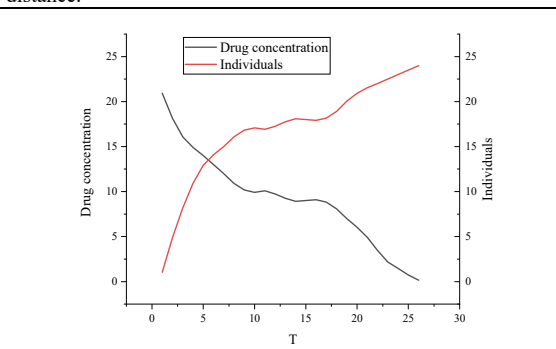
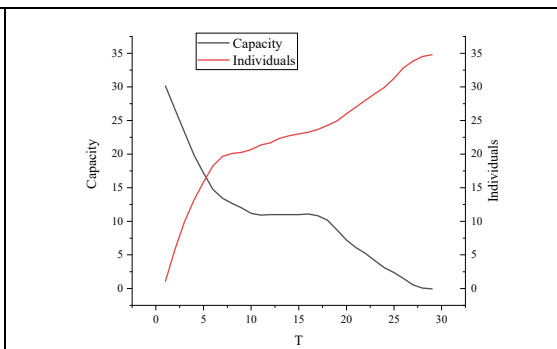
Allowing passengers to board and alight, platforms are key components of subway stations [1]. For boarding, passengers usually move purposefully on the platform to avoid obstacles, shorten their walking distance, and walk quickly to their chosen waiting area (WA). Previous studies of how passengers move on subway platforms are relatively rich [2, 3]. Yang et al. [4] focused on how passengers are distributed on the platform and found that (i) they are distributed unevenly and (ii) walking distance is the main factor in individual WA selection. Dell'asin and Hool [5] studied the characteristics of passengers getting on and off a train and found that the process by which passengers select WAs has a significant effect on platform efficiency; for example, selecting WAs reasonably reduces the number of passengers who are stranded on the platform. However, this process is very complex and is affected by many factors, such as walking distance, available platform area, passenger psychology, the intensity of boarding and alighting activities, and the positions of facilities [6]. Affected by these factors, passengers tend to choose sub-optimal WAs based on their minds and actual situation, which causes unbalanced passengers' distribution of WA. In conclusion, most previous studies analyzed the relationship between passenger WA selection and the factors influencing that selection, but still to be completed are (i) how to predict the distribution of passengers on the platform based on these factors and (ii) the formation mechanism of unbalanced passenger distribution.

Simulations and field experiments are often used to analyze the variation of passenger flows on platforms. Field experiments are more direct, but they are expensive and offer less control of external factors. Simulations have no such problems, but their accuracy is highly dependent on model calibration. To date, serial-type simulation models for crowd evacuation have been proposed [2, 7], of which the most commonly used are the social force model (SFM) and cellular automata (CA) model [8]. The SFM is a classic continuous-space microscopic model that allows the observation of pedestrian flow characteristics [9]. Xiao et al. [10] used several experiments to calibrate the basic characteristic time of the SFM, and they used the calibrated

model to study exit evacuation strategies. Sticco et al. [11] used experiments to study friction in the SFM and how it affects pedestrian aggregation. Broadly speaking, the SFM is very complex because it involves the interactions among pedestrians and requires those interactions to be quantified as forces. By contrast, the CA model is a discrete model that comprises a regular grid of many cells, the states of which are updated using the same rule [12]. Zhou et al. [2] used the CA model to simulate pedestrians at different speeds, but they ignored any environmental changes. Müller et al. [13] used an extended CA model to study the evacuation processes of pedestrian crowds containing different interacting groups, but their model lacked mechanisms for group formation for comparison with actual conditions. Based on the CA model, Zheng et al. [7] studied the characteristics of pedestrian evacuation influenced by flooding, but the main disadvantage of the CA model for WA selection by subway passengers is its lack of adaptability to the complicated and changing environment of a subway platform.

To predict accurately the distribution of passengers on a platform under different conditions, it is important to understand the process whereby passengers select target WAs. Upon arriving at the subway platform, passengers tend to search for target WAs based on the actual surroundings and quickly choose the WAs that they deem the most suitable, which is similar to a bacterium engaged in dynamic chemotaxis (see Tab. 1). A suitable WA can be regarded as a strong drug: just as a strong drug attracts more bacteria, so a WA with good conditions attracts more passengers. Therefore, the aim in the present study is to use the bacterial chemotaxis algorithm (BCA) to predict the distribution of passengers on the platform. The BCA was first summarized by [14] on the basis of biological research results, the aim being to optimize the multimodal function by using the movement behaviour of bacteria in a chemical attractant environment. In the BCA, agents move to areas with stronger attractions based on external temptations and internal intentions; see [15, 16] for the detailed principles. In the field of transportation, the BCA has been used mainly for bus scheduling [17] but rarely for passenger selection. Its potential to predict the distribution of passengers on a platform is noteworthy and is verified in the present study.

**Table 1** Analysis of bacterial chemotaxis and selection of waiting area (WA) by subway passenger

	Bacterial chemotaxis	Waiting area selection
Process of individual selecting its target	 <p>Both a bacterium and a passenger tend to determine a target before selection. They may change target according to the actual situation around the former targets and their subjective feelings, but once the final target is determined, they move toward it in the shortest distance.</p>	
Temporal distribution of volume at a certain point at a certain time		 <p>Similar to the drug concentration of certain points in bacterial chemotaxis, the available WA capacity decreases as the number of individuals increases. Based on the temporal distributions of volume (drug concentration, available capacity, and individuals) at a certain point, four phases can be obtained for both drug point and WA. Phase 1: drug concentration at drug point or WA capacity decrease quickly, while the number of individuals increases quickly, because the drug and space are abundant and individuals head toward it quickly at the beginning of the cycle time. Phase 2: the changes of all items are quite small, which means that fewer individuals choose this point or some individuals may change targets at this stage. Phase 3: drug concentration and available WA capacity decrease, while the number of individuals increases quickly, but not as fast as in phase 1. In the latter half of the cycle time, the number of individuals increases quickly, and they accumulate rapidly in the WAs. Phase 4: drug concentration and WA capacity drop to zero, but the number of individuals still increases slowly. It can be speculated that the train is about to leave and passengers are trying to squeeze onto it.</p>

To better describe the characteristics of the selection of WAs by subway passengers, a new WA selection model (WASM) is proposed based on the BCA. Compared with the disadvantages of the commonly used model on complex process and multiple factors on WAs selection, WASM considers the similarity between WA selection and bacterial chemotaxis, and it can quantify the complex processes by parameter updating and describe the procedure of WA selection more accurately. Additionally, WASM can adjust the target WA dynamically according to the surroundings, and it incorporates subjective factors in the choice of WAs by passengers. WiFi data acquisition technology is used to obtain the movements of passengers on the platform, which in turn can provide a reliable data base for model construction and are used for model calibration and verification. The present study shows that WASM improves the accuracy of predicting the distribution of passengers on a platform and describes well the distribution and characteristics of those passengers, thereby providing guidelines for the operational management and layout of facilities at subway stations.

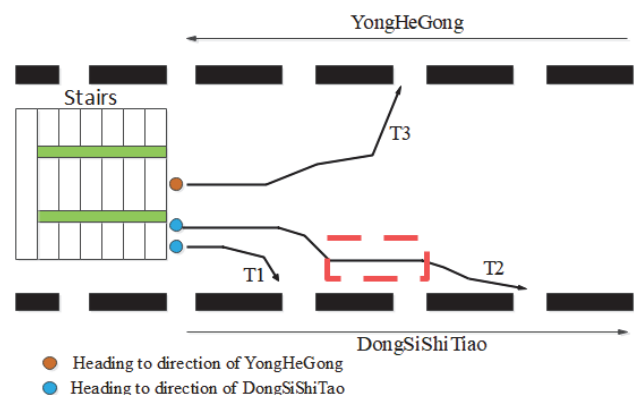
The rest of this paper is organized as follows. Section 2 presents the data sources, Section 3 introduces the construction of WASM, and Section 4 reports on three experiments to explore how different factors influence WA selection. Conclusions are presented in Section 5.

## 2 DATA SOURCES

WiFi data and questionnaire data were used in this study. The WiFi probes collected passenger flow data and trajectories of passengers on the platform, which were used for model construction, calibration, and validation. The questionnaire survey was used to determine the main factors influencing passenger WA choice.

### 2.1 WiFi Data

Field data were collected at Dongzhimen subway station, an island platform on Line 2 of the Beijing subway, during evening peak time (17:00-19:00) on May 15, 2019. In this paper, it is assumed that each passenger has only one mobile terminal device. The two probes obtained 18 901 and 32 350 items of data, respectively, in the 10 cycles, giving 12 499 items of effective data after data cleaning, fluctuation data eliminating and revising based on the video data. Besides, the position distribution of passengers can be measured through their angle and distance to WiFi probes.



**Figure 1** Map of sample passenger trajectories

The trajectories and video show that after entering the platform, passengers tend to avoid queues and go directly to the target WA, and the passenger's track is basically a straight line. When the target WA changes, the change of angle determines the trajectory, but the angle of the

trajectory shows no large change. For example, during the sample trajectories shown in Fig. 1, the target WA changes as the surrounding environment changes; the red dashed box segment in trajectory T2 indicates that the passenger on T2 changes the target WA and walks quickly to a new WA. The movement of a passenger on the platform can be abstracted as a particle movement. Its movement process can also be represented by lines.

The distribution of passengers among the WAs was obtained based on the data collected from the WiFi probes. The results of one cycle are shown in Fig. 2. The main features of the distribution are as follows. 1) The further a WA is from the stairs, the fewer passengers it contains (the stairs are next to doors 7 and 20) [Fig. 2a]. 2) In different periods, passengers are willing to choose various WAs, which resembles bacteria changing their areas according to the prevailing drug concentration. 3) In the first 40 s of the cycle (i.e., just after a train has departed), passengers tend to stop at the WAs that are relatively close to the stairs. In the second 40 s, passengers tend to walk between the two stairs, but in the third 40 s, passengers choose WAs randomly (Fig. 2b-d).

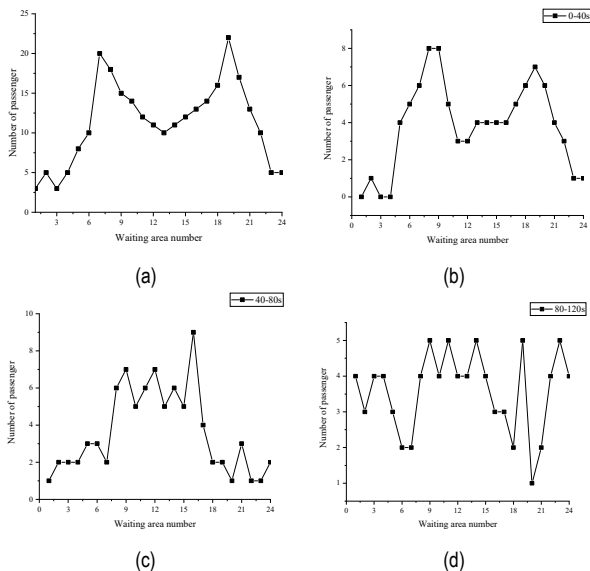


Figure 2 Passenger distributions in waiting areas (WAs) in different periods: (a) one cycle; (b) 0-40 s; (c) 40-80 s; (d) 80-120 s.

According to the results in Figs. 1 and 2, the number of passengers in each WA differs at different time intervals in one cycle. Passengers tend to choose WAs that are close to the stairs. Also, passengers can change their target WA with their surroundings while in motion. The movements are also affected by both subjective and objective factors in target changing. The features show that the process whereby passengers select WAs on the subway platform is very similar to the motion of bacteria (see Tab. 1). Therefore, it is certainly rational and feasible to use the theory of bacterial chemotaxis algorithm (BCA) to predict the distribution of passengers on the platform.

## 2.2 Questionnaire Data

To determine the main factors that affect the passengers' choice of platform WA, an online questionnaire and a field survey questionnaire were distributed. The questionnaire consisted of 15 questions,

including a passenger background survey and factors that may affect WA selection. The participants known factors' positive or negative impacts on WA selection then ranked them. Between May 1 and June 1 of 2019, 800 questionnaires were sent and 717 were collected. After excluding 42 questionnaires that were either incomplete or contained incorrect data, 675 valid questionnaires were obtained, which met the basic requirements of normal social surveys [18].

From the questionnaire results given in Tab. 2, when asked about the factors that contribute the most to WA selection, 86% of respondents chose the WAs closest to the stairs, and the proportions of passengers who preferred to choose WAs with shorter queues and larger capacity were 82% and 77%, respectively. The rest of the factors have proportions that are less than 70%, and a small number of passengers choose WAs either based on personal preference or unintentionally.

According to the results, the top three factors are walking distance at origin, queue length, and WA capacity. The first two are negative, and WA capacity is positive, which is helpful for the modelling. The three main factors obtained in the questionnaire are consistent with the impact characteristics reflected in the field observation data.

Table 2 Ranking statistics of influencing factors.

Node	Factor	Proportion	Rank	Impact
F5	Walking distance at origin	86%	1	Negative
F4	Queue length	82%	2	Negative
F2	Waiting area capacity	77%	3	Positive
F3	Number of people in each carriage	66%	4	Negative
F1	Number of passengers getting off the subway	65%	5	Positive
F6	Walking distance at destination	57%	6	Negative
F7	Personal preference	37%	7	Positive
F8	Choose a position unintentionally	33%	8	Negative

## 3 CONSTRUCTION OF WASM

Presented here is the WASM for predicting the distribution of passengers on the platform. Proposed in the model is a new element known as the rejection factor (RF), which is used as an essential judgment for WA selection.

### 3.1 Logic of Model

The logic of WASM consists of the input unit, the operation unit, and the update unit (Fig. 3). The input unit inputs particles representing passengers into the system, the operation unit calculates the times and angles of the passengers' movement trajectories, and the update unit renews all the parameters in the system based on the results of the operation unit. In the model, objective factors are represented by parameters, and subjective factors are represented via parameter updating.

For subway passengers, the WA selection process extends from entering the platform to arriving at their final WAs. The specific steps are as follows: (i) entering the platform via stairs and determining which side of the platform to go to; (ii) observing the queue length, available space, and walking distance of all the WAs on the chosen side; (iii) selecting the target WA based on observation and

preference, and then moving toward it; (iv) in the process of moving, the target WA may change with the changing queue length in each WA; (v) arriving at the WA and completing its selection; (vi) other individuals repeat the above process.

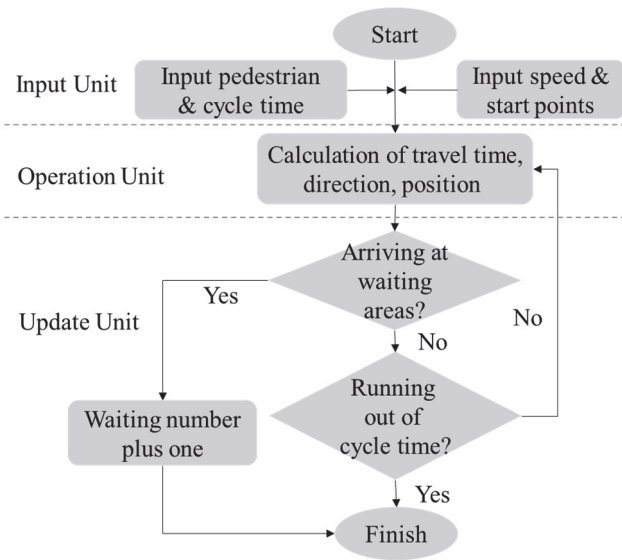


Figure 3 Model logic

According to the field survey and [19, 20], the following requirements are used in WASM for passenger WA selection.

- 1) The passengers arriving at the platform are treated as particles.
- 2) Each passenger moves to a target with a constant velocity. The trajectory, which comprises a series of links, is determined by the velocity, direction, and moving time.
- 3) Passengers have equal probability of turning left or right when they plan to change direction.
- 4) The moving time and angle of each trajectory are determined by the probability distribution of WA selection, which is affected by walking distance, queue length, and WA capacity.
- 5) Because each trajectory is independent and comprises a series of moving links, the time cost in a passenger's trajectory follows an exponential distribution that decreases gradually.
- 6) The probability distribution of the time of each trajectory and that of the angle between adjacent trajectories are two independent parameters because the trajectories vary with time.

### 3.2 Scenario Setting

Taking the platform as a planar rectangular coordinate system (unit: meter), the two edges (parallel or perpendicular to the platform) of the platform are the  $X$  and  $Y$  axes of the coordinate system, respectively, and the intersection point of the two edges is the coordinate origin (see Fig. 4). The WAs are separate regions of the same size with the train doors as their centers, but the WAs at the head and tail of the platform are slightly smaller because of toilets and other facilities. The abscissa corresponds to the WA order (each WA is assigned a different number for identification), and the ordinate range of the WAs is 5 m;

for example, the coordinates of the first and fourth WAs in Fig. 4 are (1, 5) and (4, 5), respectively.

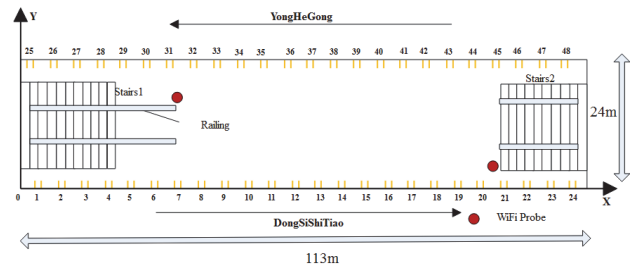


Figure 4 Positions of probes on platform

In this study, only one side of the platform is considered, and passengers in the system only walk toward the downside WAs in the analysis. When a passenger enters the range of WAs, the passenger stops moving and the number of waiting passengers in this area increases by one. In WASM, the same number of passengers enter the platform through each of the two staircases in each calculation step, and the speed of every passenger is constant. Passenger number and speed are controlled by parameters in WASM, and the model stops running when one cycle time ends up.

### 3.3 Basic Algorithm

The RF, proposed innovatively based on the BCA, is designed based on three main factors with the greatest impact on the WA selection in this paper. The core of the BCA involves decomposing the movement of bacterial individuals into three parameters: speed, time, and rotation angle. Consequently, the movements of passengers on the platform can be controlled by parameters in WASM. The parameter processing involves the following procedures. 1) When passenger  $k$  enters the platform at time  $t$ , data are collected about the distance from her/his position to each WA, the number of people in each WA (queue length), and the capacity of each WA. 2) Based on the data collected in step 1, the RF of each WA is calculated, and the target WA is the one with the smallest RF  $\varepsilon_{i\min}(t)$ . 3) Passenger  $k$  moves toward the target WA, and WASM updates  $\bar{p}_{new}$ . There are several steps in this procedure as follows.

Step 1: Constructing the rejection factor  $\varepsilon_i$

Each passenger has an RF for each door, which shows the passenger's degree of rejection for this WA. After each passenger either enters the platform or reaches the new position, the RFs of all doors are recalculated and the smallest one is selected.

According to the present research, the factors that contribute the most are walking distance from the starting point (F5), WA queue length (F4), and WA capacity (F2). According to the questionnaire results, the RF is correlated negatively with F5 and F4 and positively with RF. Therefore, in WASM the degree of rejection is represented by

$$\varepsilon_i = \frac{\alpha * D_i(t) * \beta^{d * N_i(t)}}{L_i^\gamma} \quad (1)$$

Step 2: Determining the moving time  $t_i$

The moving time is calculated according to the minimum RF and [19, 20]. The time of each moving track compiles with the exponential distribution of parameter  $T_0$ . The moving time is determined by the minimum average moving time  $T_0 T_0$ , so the moving time  $t_i$  is equal to a random integer value in that distribution, i.e.,

$$P(x = \tau) = \frac{1}{T_0} e^{-\frac{\tau}{T_0}} \quad (2)$$

Here,  $t_i$  is a random rounding of the result of

$$T_{0k}(t) = \varepsilon_{i\min}(t)^{0.30} \times 10^{-1.73} \quad (3)$$

where  $T_0$  is the minimum moving time,  $T_0 = \varepsilon^{0.03} \times 10^{-1.73}$ .

Step 3: Determining the rotation angle  $\theta(t)$

The passenger direction depends on the angle  $\theta(t)$  of the trajectory at time  $t\alpha(t)$ . The rotation angle is obtained by taking a random number under the probability distribution, which is described as follows:

$$P(x = \theta, v = \mu) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left[-\frac{(\theta - v)^2}{2\sigma^2}\right] \quad (4a)$$

$$P(x = \theta, v = -\mu) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left[-\frac{(\theta - v)^2}{2\sigma^2}\right] \quad (4b)$$

where  $\mu$  and  $\sigma$  are parameters that must be calibrated. The angle is equal to the random value ranges from zero to  $90^\circ$ .

Step 4: Updating the new position  $\bar{p}_{\text{new}}$

In WASM, the next time point of moving,  $t_{\text{cur}}$ , equals the sum of the last time point of moving,  $t_{\text{pr}}$ , and the moving time on the track of this time,  $t_i$ . As time goes on, the model judges whether the next time point equals  $t_{\text{cur}}$ : if so, then the passenger position is updated according to Eq. (5); if not, then the position is not updated until the next time point equals  $t_{\text{cur}}$ . The new position is determined by the moving time and direction:

$$\bar{p}_{\text{new}} = \bar{p}_{\text{pre}} + v \times t_i \quad (5)$$

where  $\bar{p}_{\text{new}}$  consists of  $X$  and  $Y$ :

$$X = \bar{X}_{\text{pre}} + v \times t_i \times \cos \alpha \quad (6a)$$

$$Y = \bar{Y}_{\text{pre}} + v \times t_i \times \sin \alpha \quad (6b)$$

Step 5: Judging whether the WA has been reached

When the vertical distance from the passenger to the platform edge line is less than 5 m, it is considered that the passenger has arrived at the WA. When the passenger data are updated, WASM judges whether the passenger has reached the WA. If the passenger moves into this area, then the passenger stops moving and the number of passengers

in this area increases by one. If the passenger does not arrive at the target area, then the time, rotation angle, and other parameters at the current position are recalculated, and the calculation of the next movement is carried out until reaching either the WA or the end of the cycle time.

### 3.4 Parameter Calibration and Model Testing

WASM is calibrated to ensure the accuracy of the prediction of the distribution of passengers on the platform. The actual data regarding the queue length in each area are used to calibrate the parameters by numerous experiments with different value settings [21]. However, because of the limited data collection, WASM is calibrated and validated by the leave-P-out method [22]. The advantage of this method is that all observations are used for training and testing. In addition, three approaches are proposed to test the performance of WASM, namely, feasibility of model, model output regression, and model comparison.

#### 3.4.1 Parameter Calibration

According to the leave-P-out method and field data of 10 cycles, the datasets of seven cycles are selected randomly for calibration, the remaining three datasets are validated, and the parameter combination with the least error is selected as the result. The parameters of  $\alpha$ ,  $\beta$ ,  $\gamma$ ,  $d$  in Eq. (1) and the angle  $\mu$  and variance  $\sigma$  of WASM are calibrated by the leave-P-out method in this section, and the trial-and-error method is used to calibrate these parameters. According to the structure of the BCA, the initial ranges of the parameters are set beforehand, with  $\alpha$  and  $\beta$  in the range [1, 10],  $\gamma$  in the range [0, 0.1], and  $d$  in the range [0, 100] [20, 23]. For the parameters  $\mu$  and  $\sigma$ , which equal  $62^\circ$  and  $26^\circ$ , respectively, in the initial BCA, their range is  $[0^\circ, 90^\circ]$  [20, 23]. The interval of  $\alpha$ ,  $\beta$ ,  $\gamma$  is 1, that of  $d$  is 0.01, and that of  $\mu$  and  $\sigma$  is  $1^\circ$ . Results of all the above values permutations and combinations, which are put into the model for calibration. Based on the absolute and percentage errors of the number of people in each WA, the combination with the least error is selected as the final parameter calibration result. The experiment showed  $\alpha = 7$ ,  $\beta = 5$ ,  $\gamma = 0.09$ ,  $d = 10$ ,  $\mu = 69^\circ$  and  $\sigma = 30^\circ$  to be the most suitable combination of parameters.

#### 3.4.2 Model Testing

Three approaches are used to test the performance of WASM based on three field datasets that differ from the one used in Section 3.4.1. The three methods are model feasibility, model output regression, and model comparison. The average walking speed of young and middle-aged passengers is set as 1.4 m/s, and the average passenger flow for each stair is two people per second.

##### 1) Model feasibility

The WASM output is obtained, and the field data and model output in each WA are compared. The passenger distributions given by the field data and model output are shown in Fig. 5, from which it can be seen that the two distributions are basically consistent. In addition, the absolute, percentage, and average errors of the passenger flows in the 24 WAs are calculated (see Tab. 3), according to which the average, positive, and negative errors are less

than 2, and in particular the absolute error less than 3. The average absolute percentage error is less than 13%, which shows that WASM accurately reflects the process of

passenger WA selection, and so the results of WASM are reasonable and acceptable.

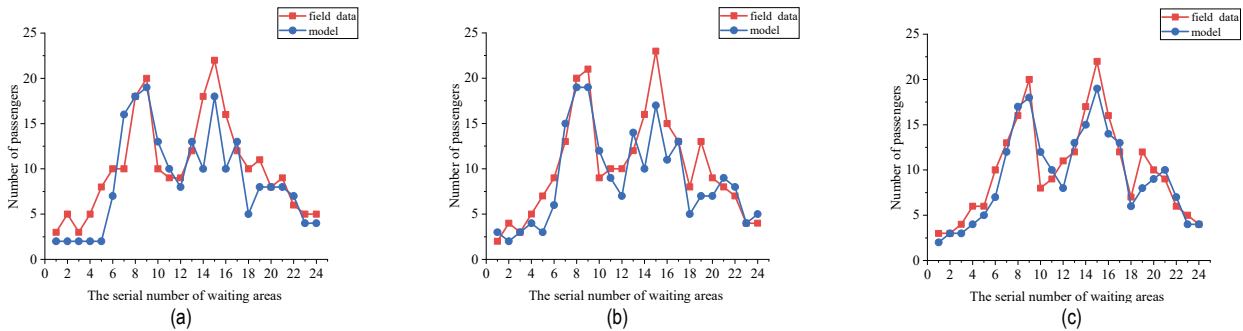


Figure 5 Passenger distributions in each waiting area (WA) from field data and model output: (a) no. 1; (b) no. 2; (c) no. 3.

Table 3 Errors of field data and model output.

No.	Absolute error	Percentage error	Average error	Positive error	Negative error
1	2.38	-18.88%	-1.13	0.63	-1.75
2	1.54	8.49%	0.77	1.09	-0.45
3	1.67	11.57%	1.17	1.42	-0.25

2) Model output regression

Taking the field data as the ordinate and the model output as the abscissa for regression analysis, the results are shown in Fig. 6. The model output is linear to the field data, and the regression function is  $Y = 1.11124 \cdot X + 0.51993$ . The slope is close to unity, the intercept is close to zero, and the  $R^2$  value is 0.81447. Therefore, the regression results of Fig. 6 show that the model output is consistent with the field data. In summary, the proposed WASM accurately reflects the processing of passenger WA selection.

3) Model comparison

To test the performance of WASM from the perspective of model performance comparison, the total absolute error  $E$  of this platform is presented here. Comparing the total absolute errors of WASM ( $E_{Model}$ ) in the WAs and those of the SFM ( $E_{SF}$ ) with the field data in this paper, both models are operated under three actual passenger-volume conditions based on field observations.

The absolute error distributions of each WA for the two models are shown in Fig. 7. As can be seen, when the passenger flow is low (Fig. 7a), the errors of the two

models are similar, and the total absolute error of the difference between the two models is 12. When  $N = 155$  (i.e., the total number of passengers),  $E_{SF}$  is 72 and  $E_{Model}$  is 51, which are higher than the actual situation; when  $N = 175$ , the respective values become 65 and 91, also higher than the actual situation. With the increase of passenger flow, the growth of  $E_{SF}$  is 35 (from 56 to 91) and the growth of  $E_{Model}$  is 21 (from 44 to 65). Therefore, the error growth of WASM is lower than that of the SFM, and the accuracy of the SFM is weaker than that of WASM ( $E_{Model}$ ).

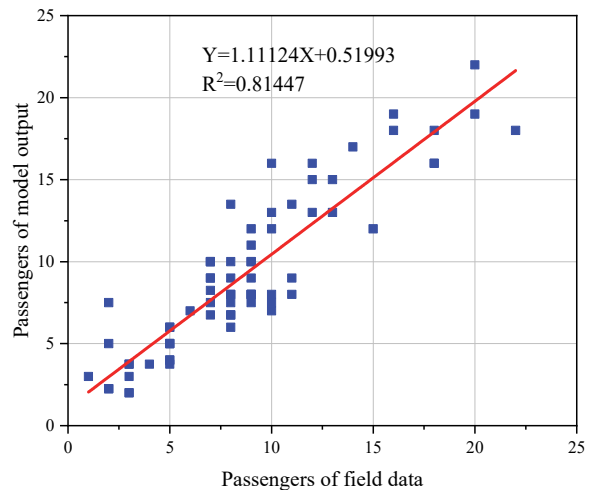


Figure 6 Results of regression analysis

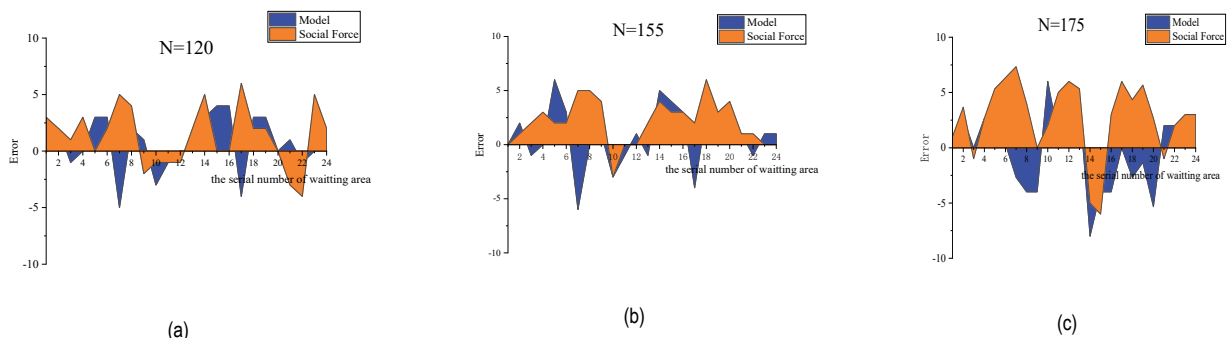


Figure 7 Distributions of absolute errors of waiting-area selection model (WASM) and social force model (SFM) in each WA: (a)  $E_{Model} = 44, E_{SF} = 56$ ; (b)  $E_{Model} = 51, E_{SF} = 72$ ; (c)  $E_{Model} = 65, E_{SF} = 91$

Based on the three methods of model testing, it can be concluded that (i) the results of WASM are reasonable and acceptable, (ii) WASM's output is consistent with the field data, and (iii) the error growth of WASM is lower than that

of the SFM and the accuracy of the SFM is weaker than that of WASM. In summary, the reliability of WASM is verified by testing.

## 4 EXPERIMENTS

To explore the characteristics of the three main factors affecting WA selection, three experiments were conducted based on WASM under the same parameters, in which only the control parameters were changed. According to the field data, the range of passenger flow is from 123 to 235 in 10 cycles; therefore, the number of entering passengers was set as 120, 180, and 240 in the experiments. The control parameter was passenger flow in experiment 1, WA capacity in experiment 2, and staircase position in experiment 3, and the time step was 1 s.

### 4.1 Effect of Passenger Volume

In this experiment, the spatiotemporal distribution of waiting passengers was recorded, as shown in Fig. 8. The WAs of doors 5-8 and 17-20 are close to a staircase, and these have the highest passenger densities, whereas those at the ends of the platform (doors 1-4 and 21-24) have the lowest passenger densities. Likewise, when the volume is larger ( $N = 180, 240$  in Fig. 8b and c), the crowded areas extend to the doors near the staircases. The crowded areas

and degree become much larger and higher, respectively, with increasing passenger flow. Furthermore, with increasing volume ( $N$  from 120 to 240), passengers prefer to go to the middle of the platform instead of its ends. In addition, when  $N$  is increased from 120 to 180, the volume increases at the platform ends are more obvious than those when  $N$  is increased from 180 to 240. The increase in passenger flow at the middle of the platform when  $N$  is increased from 180 to 240 is more obvious than that when  $N$  is increased from 120 to 180. These features show that passengers tend to head to the platform ends when the passenger flow is low but to between the two staircases when the passenger flow is high. Therefore, low passenger volume causes the areas near the staircases to become crowded quickly because of the low passenger flow at the platform ends. With increasing passenger flow at both ends of the platform, passengers walk farther to the WAs between the entrances under large passenger flow. In practice, diversion measures must be set to make passengers walk farther to balance the distribution of passengers on the platform and so improve efficiency when there is larger flow.

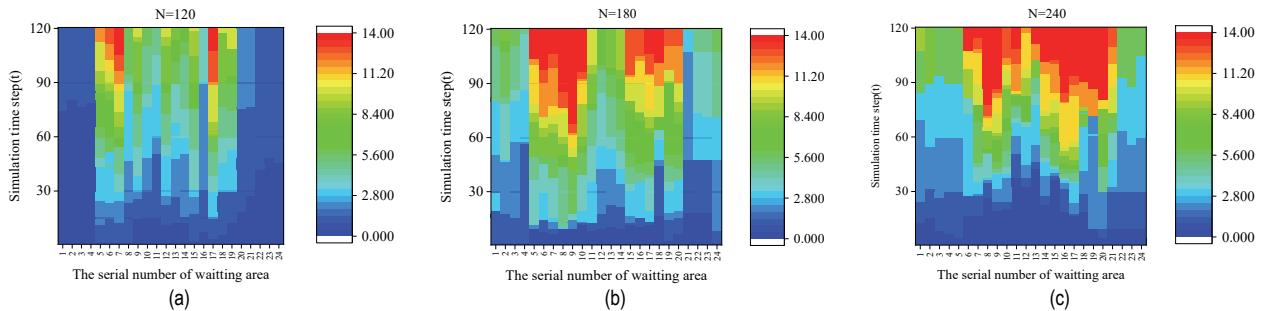


Figure 8 Spatiotemporal maps of passenger distribution for  $N =$  (a) 120; (b) 180 and (c) 240

Fig. 8 shows the passenger distributions for  $N = 120, 180,$  and  $240,$  for which the standard deviations are 0.029, 0.026, and 0.015, respectively. These results indicate that passengers tend to form a balanced distribution of WAs between the stairs when  $N$  is higher, which also means that passengers prefer to avoid crowds. Because more choices can be made when the passenger flow is low, the passenger distribution between the staircases on the platform is uneven when  $N = 120,$  but the difference diminishes when  $N = 180.$  When  $N = 240,$  the overall passenger flow on the platform is relatively high. The proportion of passengers in the two end areas increases significantly, and the proportional distribution is more balanced. In summary, with increasing passenger flow, passengers tend to avoid WAs with long queues and so tend to choose WAs between the two staircases.

### 4.2 Effect of Waiting-Area Capacity

According to experiment 1, passengers tend to wait between the two staircases (doors 7-20), especially near the stairs; this causes heavy passenger density in the middle area, and some passengers may be unable to board the train in a certain cycle time. Therefore, balancing the distribution of passenger flow by limiting the WA capacity may improve the transportation efficiency. An experiment involving limited WA capacity was conducted on doors 7-

13 without considering the load of the subway train. According to the field survey, the mean maximum number of boarders during door opening is 18, and some passengers cannot board the train when the number of passengers in a WA exceeds 18, therefore the WA capacity was set from 5 to 20 in this experiment. The WAs had a fixed capacity of 18 passengers for doors 5-6 and 14-20, and 8 passengers for doors 1-4 and 21-24 because there is less waiting space there. The experiment was conducted under different passenger volumes, and passengers chose adjacent uncrowded areas when the limit was reached in the restricted areas.

Fig. 9 shows the results for limited and unlimited capacity. Fig. 9b shows that the total number of boarding passengers does not change significantly when the passenger flow is  $N = 120.$  However, there are peaks when  $N = 180$  and  $240,$  and these appear at different capacity limits, namely 16 for  $N = 240$  compared to the lower value of 14 for  $N = 180.$  Fig. 9b shows that limiting the WA capacity when  $N$  is relatively low has less impact than doing so when  $N$  is higher. When  $N$  is relatively high, proper limited capacity at proper WAs helps to increase the total number of boarding passengers. This is because limiting the WA capacity balances the distribution of passengers on the platform, thereby avoiding partial congestion and improving transportation efficiency. Therefore, it is necessary to provide a higher capacity limit

to improve the transportation efficiency when the passenger flow is high. For example, for the WAs between the stairs, a proper capacity limit is 14 when  $N = 180$  and 16 when  $N = 240$ . Moreover, when  $N = 240$  with a relatively high capacity limit (see Fig. 9c; e.g., the limit is 16 when the peak appears), the total number of boarding passengers is larger than that with unlimited capacity.

Compared to the unlimited situation, in the case of limited capacity, the number of boarding passengers for  $N = 120$ , 180, and 240 is increased by 0.8%, 6.5%, and 9.2%, respectively. In summary, imposing proper capacity limits according to the prevailing passenger flow has a considerable effect on improving the transportation efficiency.

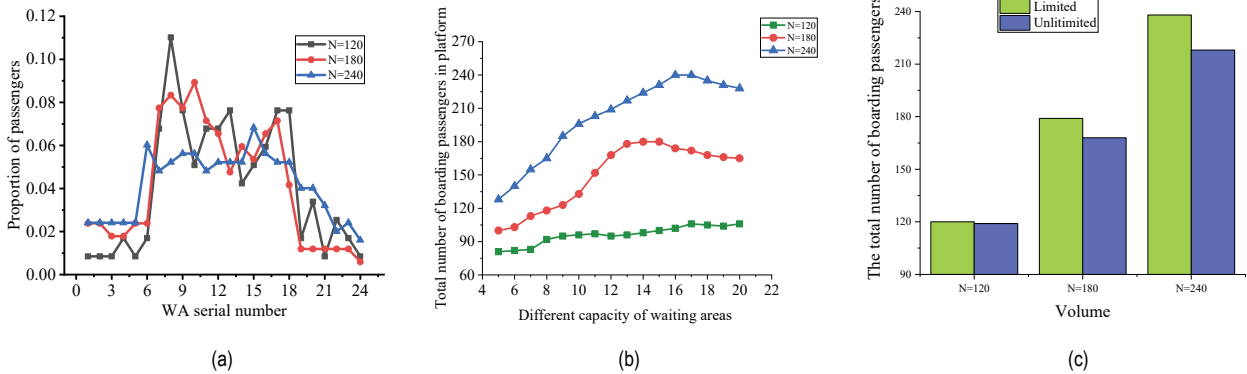


Figure 9 Results of experiments with limited (doors 7-13) and unlimited capacity: (a) proportion of passengers in each WA for different passenger volumes; (b) total number of boarding passengers on platform with various inputs for different capacity limits; (c) total number of boarding passengers with limited and unlimited capacity

### 4.3 Effect of Staircase Position

Because transportation efficiency is impacted greatly by the layout of platform facilities, positioning the stairs reasonably is very important for easing congestion in subway stations. Therefore, it is necessary to study the influence of stairs on transportation efficiency. According to the present field survey and the code for metro design in China [24], three different stair positions were set in this experiment (Fig. 10a). In the planar rectangular coordinate system, the stairs are positioned at (20, 14) and (92, 14) (configuration 1), (30, 14) and (82, 14) (configuration 2), and (40, 14) and (72, 14) (configuration 3). The experimental results obtained under different inputs ( $N = 120, 180, \text{ and } 240$ ) are shown in Fig. 10b. The results show that the closer the stairs, the fewer the boarding passengers. For example, with  $N = 240$ , the numbers of boarding passengers are 194, 179, and 163 for configurations 1-3, respectively. When the passenger density on the platform is low, the number of passengers for each configuration is close to the input data, and there is basically no passenger retention. With increasing passenger density, configuration 1 still guarantees that most passengers get on the train, but configurations 2 and 3 begin to have more stranded passengers because the difference between the number of boarding passengers and the input in configuration 1 is the lowest among the three configurations. Moreover, as the stairs become closer, the ratio of boarding passengers to total passengers on this side is lower with high passenger flow. This is because passengers tend to line up between doors, and a longer distance between stairway entrances provides more waiting space, which decreases the density of these areas and benefits the process of boarding. In summary, higher passenger flow requires a longer distance for passengers to get to the WAs; the closer the two staircases, the more passengers are stranded. It is therefore necessary to either design entrances separated by different distances or adopt different flow-limiting measures according to passenger flow, which will help to improve the passenger transport efficiency of subway stations.

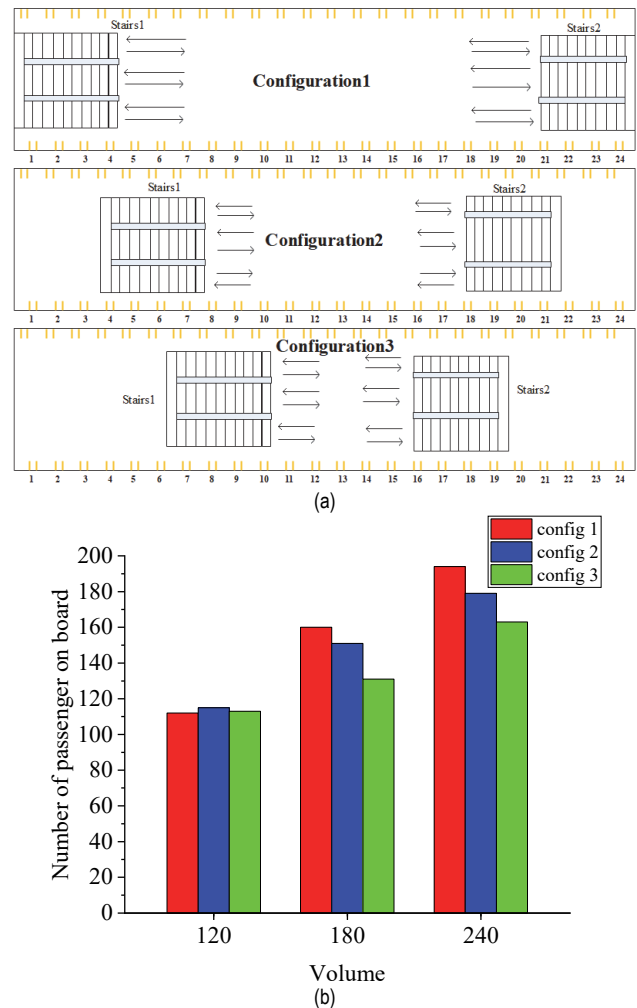


Figure 10 Results of experiments with staircase position: (a) configurations of staircase positions; (b) number of boarding passengers for various inputs

## 5 CONCLUSIONS

In this study, WASM for the distribution of passengers on a platform was proposed based on the BCA. In WASM,



queue length, capacity, and distance are taken as the main factors in selecting the WAs for subway passengers. Based on field data from the Dongzhimen subway station in Beijing, WASM was calibrated and shown to have sufficient predictive accuracy, as well as considerable advantages for predicting how passengers select WAs. Moreover, three experiments were conducted based on WASM, the aim being to explore how passenger volume, WA capacity, and staircase position affect WA selection. The main conclusions of this paper are as follows.

Based on the data collected by the WiFi probes and questionnaire survey, the main factors affecting WA selection are passenger flow, WA capacity, and position of stairs on the platform. Moreover, four characteristics of subway passenger movement were concluded: (i) the process of WA selection for subway passengers is very similar to bacterial chemotaxis; (ii) the further a WA is from the stairs, the fewer passengers it contains; (iii) the number of passengers in a WA with more queues rises slowly; (iv) the WAs at the ends of the platform contain the fewest people because of the restricted space there.

According to the characteristics of subway passengers on the platform and the principle of the BCA, WASM was constructed in this paper. The velocity, moving time, and rotation angle were represented by parameters in WASM. An essential element of WASM, namely the RF, was presented based on the three main factors (queue length, capacity, and distance) that affect WA selection. Moreover, the parameters of WASM were verified by field data. WASM is acceptably accurate and its practical significance is apparent, thereby providing the modelling basis for its application in WA selection. Also, WASM has a good application in designing of new terminals or capacity limiting of some subway terminals.

According to the experimental results, low passenger volume causes the WAs that are close to the staircases to become crowded quickly. With increasing passenger flow, passengers tend to avoid WAs with long queues. Furthermore, limiting WA capacity according to passenger flow is very important for improving transportation efficiency. Consequently, proper capacity restriction helps to improve the efficiency of subway transportation under higher passenger flow on the platform. In addition, having proper walking distances for passengers under high passenger flow improves the transportation efficiency of subway stations.

The process of WA selection for subway passengers is undoubtedly very complex. In this study, WASM simplifies that complex process with parameters and focuses only on the results based on the characteristics of passengers waiting on the platform. In terms of an exploratory article, there are also insufficient researches such as the minimum number of experiments was only three and WASM's popularization and application in deriving the spatial traffic capacity need to be promoted. For future research, the influence of conflicts between alighting and boarding passengers, and more experiments will be considered in WASM. Moreover, the simplified rules and the factors of passenger movement in modelling must be more specific in future work, such as the randomness of passengers and changing WA after the train has arrived.

## Acknowledgments

This work was supported by the Beijing Natural Science Foundation under Grant 9214022 and L201008; the Beijing Municipal Education Commission Science and Technology Program General Project under Grant KM202110005002; the National Natural Science Foundation of China under Grant 52002008; Science and Technology Planning Project of Beijing Municipal Commission of Communications (11000022210200021338-XM001); and the Basic Research Foundation Project of BJUT under Grant 038000546319519.

## 6 REFERENCES

- [1] Daamen, W., Lee, Y. C., & Wigenraad, P. (2008). Boarding and alighting experiments: overview of setup and performance and some preliminary results. *Transportation Research Record Journal of the Transportation Research Board*, 2042(2042), 71-81. <https://doi.org/10.3141/2042-08>
- [2] Zhou, X., Hu, J., Ji, X., & Xiao, X. (2019). Cellular automaton simulation of pedestrian flow considering vision and multi-velocity. *Physica A: Statistical Mechanics and its Applications*, 514, 982-992. <https://doi.org/10.1016/j.physa.2018.09.041>
- [3] Szolnoki, A. & Perc, M. (2017). Evolutionary dynamics of cooperation in neutral populations. *New Journal of Physics*, 20(1). <https://doi.org/10.1088/1367-2630/aa9fd2>
- [4] Yang, X., Dong, H., & Yao, X. (2017). Passenger distribution modelling at the subway platform based on ant colony optimization algorithm. *Simulation Modelling Practice and Theory*, 77, 228-244. <https://doi.org/10.1016/j.simpat.2017.03.005>
- [5] Dell'Asin, G. & Hool, J. (2018). Pedestrian patterns at railway platforms during boarding: evidence from a case study in switzerland. *Journal of Advanced Transportation*, 2018, 1-11. <https://doi.org/10.1155/2018/4079230>
- [6] Kang, Z., Zhang, L., & Li, K. (2019). An improved social force model for pedestrian dynamics in shipwrecks. *Applied Mathematics and Computation*, 348, 355-362. <https://doi.org/10.1016/j.amc.2018.12.001>
- [7] Zheng, Y., Li, X. G., Jia, B., & Jiang, R. (2019). Simulation of pedestrians' evacuation dynamics with underground flood spreading based on cellular automaton. *Simulation Modelling Practice and Theory*, 94, 149-161. <https://doi.org/10.1016/j.simpat.2019.03.001>
- [8] Jiang, Y., Chen, B., Li, X., & Ding, Z. (2020). Dynamic navigation field in the social force model for pedestrian evacuation. *Applied Mathematical Modelling*, 80, 815-826. <https://doi.org/10.1016/j.apm.2019.10.016>
- [9] Jiang, Y. Q., Chen, B. K., Wang, B. H., Wong, W. F., & Cao, B. Y. (2017). Extended social force model with a dynamic navigation field for bidirectional pedestrian flow. *Frontiers of Physics*, 12(5), 1-9. <https://doi.org/10.1007/s11467-017-0689-3>
- [10] Song, X., Sun, J., Xie, H., Li, Q., Wang, Z., & Han, D. (2018). Characteristic time based social force model improvement and exit assignment strategy for pedestrian evacuation. *Physica A: Statistical Mechanics and its Applications*, 505, 530-548. <https://doi.org/10.1016/j.physa.2018.03.085>
- [11] Sticco, I. M., Frank, G. A., Cornes, F. E., & Dorso, C. O. (2020). A re-examination of the role of friction in the original Social Force Model. *Safety science*, 121, 42-53. <https://doi.org/10.1016/j.ssci.2019.08.041>
- [12] Kaji, M. & Inohara, T. (2017). Cellular automaton simulation of unidirectional pedestrians flow in a corridor to reproduce the unique velocity profile of Hagen-Poiseuille

- flow. *Physica A: Statistical Mechanics and its Applications*, 467, 85-95. <https://doi.org/10.1016/j.physa.2016.09.062>
- [13] Müller, F., Wohak, O., & Schadschneider, A. (2014). Study of influence of groups on evacuation dynamics using a cellular automaton model. *Transportation Research Procedia*, 2, 168-176. <https://doi.org/10.1016/j.trpro.2014.09.022>
- [14] Muller, S. D., Marchetto, J., Airaghi, S., & Koumoutsakos, P. (2002). Optimization based on bacterial chemotaxis. *IEEE transactions on Evolutionary Computation*, 6(1), 16-29. <https://doi.org/10.1109/4235.985689>
- [15] Lu, Z. G., Zhao, H., Xiao, H. F., Wang, H. R., & Wang, H. J. (2015). An improved multi-objective bacteria colony chemotaxis algorithm and convergence analysis. *Applied soft computing*, 31, 274-292. <https://doi.org/10.1016/j.asoc.2015.02.046>
- [16] Lu, Z., Feng, T., & Liu, Z. (2014). A Multiobjective Optimization Algorithm Based on Discrete Bacterial Colony Chemotaxis. *Mathematical Problems in Engineering*, 2014(1), 339-353. <https://doi.org/10.1155/2014/569580>
- [17] Wei, M., Chen, X. W., & Sun, B. (2015). Model and algorithm of schedule coordination in regional bus transit with multiple transport modes. *Journal of Highway and Transportation Research and Development (English Edition)*, 9(3), 78-84. <https://doi.org/10.1061/JHTRCQ.0000460>
- [18] Fowler, F. J. (2014). *Survey research methods*. Sage Publications.
- [19] Cao, L. (2006). Development on Bacterial Chemotaxis Optimization Theory and its Application. *Computer Engineering and Applications*, 42(1), 44-46. [https://doi.org/10.1016/S1872-2040\(06\)60029-7](https://doi.org/10.1016/S1872-2040(06)60029-7)
- [20] Müller, S., Airaghi, S., Marchetto, J., & Koumoutsakos, P. (2000). Optimization algorithms based on a model of bacterial chemotaxis. *Proceedings of Sixth International Conference Simulation of Adaptive Behavior: From Animals to Animats*. <https://doi.org/10.1.1.18.3046>
- [21] Cheng, Q., Wang, S., Liu, Z., & Yuan, Y. (2019). Surrogate-based simulation optimization approach for day-to-day dynamics model calibration with real data. *Transportation Research Part C: Emerging Technologies*, 105, 422-438. <https://doi.org/10.1016/j.trc.2019.06.009>
- [22] Shao, J. (1993). Linear model selection by cross-validation. *Journal of the American statistical Association*, 88(422), 486-494. <https://doi.org/10.1080/01621459.1993.10476299>
- [23] Li, W. W., Wang, H., Zou, Z. J., & Qian, J. X. (2005). Function optimization method based on bacterial colony chemotaxis. *Journal of Circuits and Systems*, 10(1), 58-63.
- [24] China Construction Industry Press. (2014). GB50157-2013 Code for Design of Metro. China Construction Industry Press.

#### Contact information:

##### Guang YUAN, PhD

1) Beijing Key Laboratory of Traffic Engineering, Beijing University of Technology  
 2) Engineering Research Center of Digital Community, Ministry of Education, Beijing University of Technology  
 3) Beijing Laboratory for Urban Mass Transit, Beijing University of Technology, 100 Pingleyuan, Chaoyang District, Beijing 100124, China  
 4) Beijing Institute of Economic and Social Development, 55 Yunhe East St, Tongzhou District, Beijing 101160, China  
 E-mail: yuanguang@fazhan.net.cn

##### Dewen KONG, Lecture

1) Beijing Key Laboratory of Traffic Engineering, Beijing University of Technology  
 2) Engineering Research Center of Digital Community, Ministry of Education, Beijing University of Technology  
 3) Beijing Laboratory for Urban Mass Transit, Beijing University of Technology, 100 Pingleyuan, Chaoyang District, Beijing 100124, China  
 E-mail: kongdw@bjut.edu.cn

##### Lishan SUN, Professor

(Corresponding Author)

1) Beijing Key Laboratory of Traffic Engineering, Beijing University of Technology;  
 2) Engineering Research Center of Digital Community, Ministry of Education, Beijing University of Technology  
 3) Beijing Laboratory for Urban Mass Transit, Beijing University of Technology, 100 Pingleyuan, Chaoyang District, Beijing 100124, China  
 E-mail: lssun@bjut.edu.cn

##### Guangtong LIU, Traffic Engineer

Qingdao Municipal Engineering Design Research Institute, 222 Shenzhen Road, Laoshan District, Qingdao, 266100, China  
 E-mail: liukrongton@126.com

##### Yingda CHEN, PhD Student

1) Beijing Key Laboratory of Traffic Engineering, Beijing University of Technology  
 2) Engineering Research Center of Digital Community, Ministry of Education, Beijing University of Technology  
 3) Beijing Laboratory for Urban Mass Transit, Beijing University of Technology, 100 Pingleyuan, Chaoyang District, Beijing 100124, China  
 4) Tongji University, Ministry of Education, The Key Laboratory of Road & Traffic Engineering, 4800 Caoyang Road, Jiading District, Shanghai 201804, China  
 E-mail: alvincheny@163.com

#### Notation

$v$	Passenger velocity (constant throughout the whole process of the model)
$\varepsilon$	Rejection factor (the possibility of passengers not choosing a WA)
$i$	WA serial number
$\varepsilon_{\min}(t)$	Smallest rejection factor of all WAs
$D(t)$	Distance between a passenger and WA $i$ at time $t$
$N_i(t)$	Queue length (passenger flow) of WA $i$
$L$	Capacity of WA $i$
$\alpha, \beta, \gamma, d$	Parameters to be calibrated
$T_0$	Minimum average moving time
$k$	Passenger serial number
$\mu, \sigma$	Expectation and variance of passenger's moving trajectory angle
$\tau$	Time of a trajectory
$t_{pr}$	Last time point of passenger movement
$t_i$	Moving time of a trajectory (integer)
$t_{cur}$	Next time point of passenger movement
$\vec{p}_{new}$	Passenger's new position
$\vec{x}_{pre}$	Passenger's previous position
$X$	Abscissa of passenger's new position
$Y$	Ordinate of passenger's current position
$\theta$	Included angle of passenger moving trajectory