Modeling boundedly rational route choice in crowd evacuation process

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Abstract

With the development of modern information technologies, advanced evacuation guidance systems have been widely installed to provide updated route information, aiming to optimize the evacuation process. However, although pedestrians may know the information of the building and its surrounding environment, they sometimes still use the non-optimal evacuation route, that is to say, their decision-making process is rather boundedly rational. To understand the dynamics underlying such behavior, we present a new model where we consider two important factors affecting pedestrians' route estimation, i.e., distance and congestion. By introducing the *Congestion Sensitivity* and the *Conservative Level*, a bounded rationality route choice model is proposed to describe the route estimation and route change behavior. The proposed model is then validated, after which, detailed simulation studies have been performed to discuss the influence of those two factors. Results show that for small and open spaces, the influence of the free walking time on pedestrians' route choice is higher than the congestion queuing time. Moreover pedestrians prefer to change route in order to save the completion time. For a large virtual building, pedestrians with high *Conservative Level* and low *Congestion Sensitivity* tend to choose the global shortest route, which will result in an unbalanced usage of routes, while low *Conservative Level* and high *Congestion Sensitivity* will result in a significant detour behavior, which increases the evacuation time. This boundedly rational route choice feature results in distinct importance rank of evacuation facilities when considering their failures. The present study deepens our understanding of pedestrian route choice considering bounded rationality and provide a basis for crowd management in building evacuation.

Keywords: route choice, bounded rationality, conservative level, congestion sensitivity

1. Introduction

Studies on pedestrian dynamics have made considerable progress over the past few decades. Some interesting self-organization phenomena, such as lane formation [1], stop-and-go waves [2] and crowd turbulent flow [3], have been observed. To uncover the behavioral mechanisms underlying these phenomena, well-structured experiments and field surveys have been designed and performed considering varying factors e.g flow directions, pedestrian compositions, boundary conditions, etc. [4, 5, 6, 7, 8]. Based on these empirical insights, many simulation models have been proposed to reproduce realistic pedestrian movement features [9, 10, 11, 12].

Considering that a pedestrian's movement is influenced by its activity, a hierarchical activity scheduling model was proposed [13] to simulate daily pedestrian's traffic. Three levels, i.e., strategic level, tactical level and operational level were designed to accomplish activity pattern choice, route choice, and locomotion, respectively. The evacuation process is a special pedestrian traffic scenario, within which individual route choice has a significant impact on the overall evacuation efficiency, especially in complex buildings. Therefore, more and more attention has been paid to this topic lately aiming at understanding pedestrians' route choice behavior through experiment and modeling.

An early theoretical study from Senevarante and Morall shows that pedestrians appear to frequently choose the shortest route [14]. Some pieces of evidence also show that other factors such as pleasantness, habit, safety, also have an important influence on pedestrian's route preference [15]. Based on these studies, various mathematical models were developed

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to describe pedestrian route choice behavior [16, 17, 18, 19]. For crowd evacuation in a single room with multiple exits, Guo [20, 21] proposed a discrete lattice space method using a potential field to describe the route choice behavior. The potential of each lattice is directly proportional to its distance to the exit and the degree of congestion, and inversely proportional to the route capacity. Pedestrians flow from high potential positions to lower potential positions. During an evacuation, the potential field was dynamically updated and severed as a route guider providing pedestrian agent necessary route information. Except for the influence of distance and congestion, Haghani [22] additionally takes into account the effect of the visual field and the herding behavior during the crowd evacuation process and proposes an exit selecting model. Simulation results show that herding among evacuees significantly reduces evacuation efficiency.

It is noticed that the above-mentioned exit choice models describe fairly well exit-selecting processes in single room scenarios. However, in complex scenarios such as multi-floor buildings or train stations, pedestrians need to go across rooms or floors sequentially before they arrive at the safety area [23]. In these cases it is necessary to be able to choose a new route in intersections leading to several different destinations. As a consequence, some other important information should be taken into account to select an evacuation route. To handle such scenarios, various pedestrian route choice models were proposed in recent years. Wagoum et al. [24] built a decision-making model based on finding shortest and "quickest" paths between nodes in a network, which represents a building. The spatial structures such as rooms were considered as decision areas, and the doors connecting two decision areas were abstracted as a node. Hence, the route choice algorithm was reduced to optimization of evacuation costs on a graph. In terms of route selection, factors including route length, congestion, velocity, limited pedestrian visual field and patient time in the decision areas should be considered. Crociani et al. [25] argues that microscopic decisions on the actual steps can follow a high-level definition of a sequence of intermediate destinations.Based on this, they developed a route choice model and incorporated it into a cellular automaton. In their model, a pedestrian firstly chooses routes by evaluating the travel time, the congestion level and following behavior has also been considered. Zhou et al. [26] developed a model based on a graph which took speed reduction on future route into account.

Summarizing these studies, it can be noted that these models assume that pedestrians possess comprehensive knowledge of their neighborhood and can accurately evaluate and compare the evacuation route information such as route length and evacuation time. Based on this evaluation, a pedestrian will select the route to maximize a defined utility function. However, according to Simon [27, 28], people are boundedly rational in their decision-making processes and tend to seek a satisfactory choice solution instead. Based on his developed boundedly rational theory, travel behavioral modeling and escape dynamics have been explored recently [29, 30, 31]. Considering that route selection is a typical decision-making process, during an evacuation, people can only observe neighborhood directly in their vicinity (geometry and pedestrians). Hence, they can hardly predict the usage of the route out of sight, thus the route choice is believed to be boundedly rational. Therefore, sometimes people would rather deviate from what seems to be the most expected route [32, 33]. We investigate such boundedly rational pedestrian route choice behavior by means of a new model, considering the influence of distance and congestion.

The rest of the present paper is organized as follows: the boundedly rational pedestrian route choice model will be presented in Section 2. In Section 3, the model is validated and calibrated. The influence of factors affecting pedestrian route choice behavior will be detailed and discussed in Section 4. Evacuation efficiency considering route failure is further discussed in Section 5. At last, we conclude our study with a discussion of the results and limitations.

2. Model development

In this section, we introduce a model to simulate pedestrians' evacuation in a general scenario. Here, the route choice behavior will be emphasized while the locomotion features will be described by the foot step model [34]. To model the tactical level route choice behavior, we firstly need provide navigation information to each pedestrian based on the building configuration and pedestrians' locations.

2.1. Configuration and pedestrian location-based graph

Since the proposed algorithm is graph-based, the building and the pedestrians are mapped to a directed graph. The graph $G = G(V, E)$ is defined by a set of nodes V and a set of edges E .Firstly, the evacuation scenario should be divided into a series of "zones", such as rooms and corridors, we define as Z_i. The safety area is also considered as a zone which helps to define the node. Further, a facility node connects two adjacent zones, e.g. doors and exits.

For m facility nodes N_j, we define $FN = \{N_j|1 \leq j \leq m\}$. For the convenience of route length calculation, pedestrians are considered as "movable nodes", hence we define the set of source nodes as $SN = \{p_k|1 \leq k \leq n\}$. Thus, the set of the graph's nodes is defined as $V = FN \cup SN$.

Given two nodes x and y we define the set of edges as:

$$E = \{e(x, y)|\ x, y \text{ share } Z_i, x \neq y, x \in V, y \in FN\}. \tag{1}$$

Here, "x, y share Z_i" means x and y are contained in Z_i, and a path from x to y in Z_i exists. If two nodes share two different zones, the zone with shorter distance path will be selected. Note that an edge always ends with a facility node, while it can start from a source node.

Taking the multi-room layout in Figure 1 as an example, the scenario is divided into four rooms (1-4) and the outside. Pedestrian k, located in Room 3, can complete the evacuation either from Exit 1 or Exit 2. The scenario can be mapped to its equivalent graph as shown in Figure 2. In the graph G, V includes N_1, N_2, N_3, N_4, N_5 and p_k, which stands for Door 1, Door 2, Door 3, Exit 1, Exit 2 and pedestrian k, respectively.

It should be mentioned that the graph formed by the facility nodes is static, while with crowds moving towards to the exit, pedestrians would arrive in a new room, the graph consisted by SN will also change. That is to say, during the evacuation, the graph's topology should be updated every time step.

2.2. Route evaluation

When selecting an evacuation route to a destination, a pedestrian would be affected by different factors including route length, congestion level and its familiarity with the building.

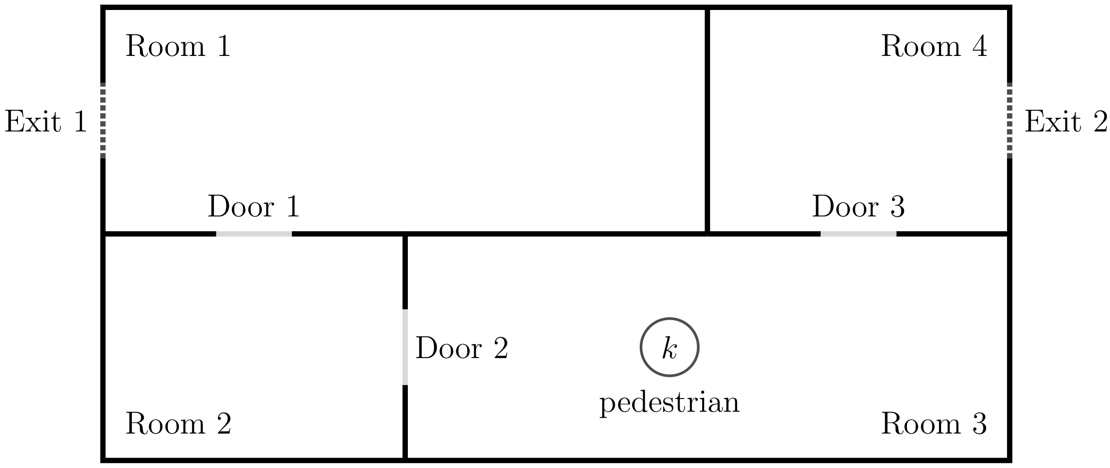


Figure 1: An example of a geometry with three rooms and two exits. The geometry is internally translated into a comprehensive graph structure.

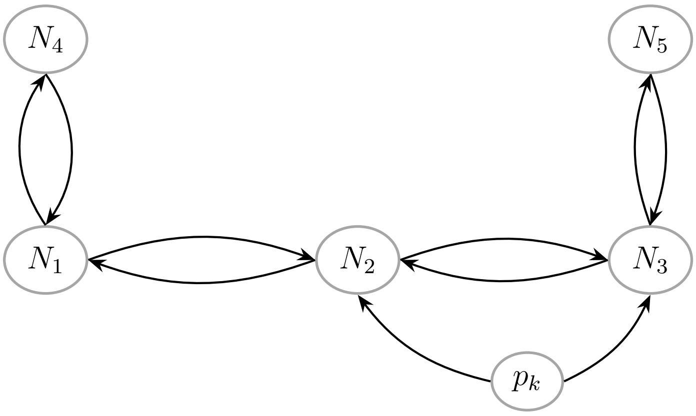


Figure 2: The complete navigation graph generated from the floor plan.

It has been long noticed that route length and congestion have strong impact on evacuation time. Therefore, in the present study free walking time and queuing time of each route would be considered in route evaluation.

The free walking time of an evacuation route is mainly determined by the route length and pedestrian free movement speed. Meanwhile, the pedestrian's level of knowledge about the building layout will also affect the way-finding process [35]. Here, we assume that pedestrians are familiar with the evacuation routes and do not need to explore their environment to search for evacuation routes. That is also to say, pedestrians in our model could estimate the length of each evacuation route. In the proposed model, after a pedestrian determines the next destination, it will move to there following shortest path in the shared zone. Therefore, the distance of each edge can be obtained from the distance field of each facility node, which is solved by the fast marching algorithm [36] in initialization. The advantage of this method is that the influence of obstacles on route length has already been taken into account.

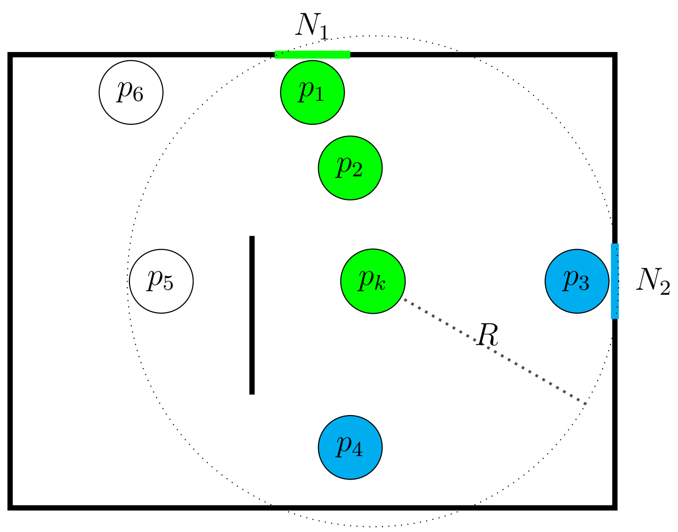


Figure 3: Schematic diagram of perceptual field. For p_k, p_5 can not be perceived due to the obstacle and p_6 can not be perceived since it is outside the visibility range.

The queuing time is mainly determined by other pedestrians' positions and route choices. Generally, a pedestrian can observe the distribution of the other pedestrians in it visual range, but can hardly know the congestion level of route segments outside its visual range.

Hence, individual perceptual field should be considered when estimating the queuing time. In the model, whether two pedestrians could perceive each other is determined by perceptual range and the walls or other obstacles. We model the pedestrians' visibility with a circle with radius R. If the distance between two pedestrians is smaller than R and their visual sights are not covered by any walls or obstacles, they could perceive each other, this also means that they know each other's positions and next destinations. As shown in Figure 3, the circle with dotted boundary denotes p_k's perceptual range, pedestrian colored with green or blue can be perceived by p_k.

In this study, R is set as 10 m. With the total number of pedestrians who have the same destination node with pedestrian k, the queuing time can be estimated. Normally, adding up the free walking time and queuing time could result in an estimation of the evacuation time of an evacuation route. Comparing the evacuation time of each route, a quickest route can be found. However, according to the boundedly rational decision-making theory [27, 28], pedestrians do not always make perfectly rational decisions when estimating the evacuation time for each route: some of the pedestrians would prefer evacuation routes with shorter free walking time, while others may prefer the ones with shorter queuing time. As a consequence, it is proposed that we set different weights of an edge for different pedestrians considering these two factors. Further referring to the empirical evacuation time calculation method proposed by Togawa [37], for pedestrian k, the time this pedestrian spends on the edge linking node x and node y can be calculated as follows:

$$T^k_{e(x,y)} = (1 - \beta_k)\frac{d_{e(x,y)}}{v^0_k} + \beta_k \frac{n^k_{e(x,y)}}{CW_b}. \tag{2}$$

Here, the time cost consists of the free walking travel time $\frac{d_{e(x,y)}}{v^0_k}$ and queuing time $\frac{n^k_{e(x,y)}}{CW_b}$. $d_{e(x,y)}$ denotes the path distance from x to y , v^0_k is the desired velocity of k. $\beta_k \in [0, 1]$ is the *Congestion Sensitivity* parameter to describe the boundedly rational route evaluation. C is a constant representing the specific flow rate of a door or an exit. Its value could refer to empirical observations. W_b is the width of that door or exit. $n^k_{e(x,y)}$ is the size of the set

$J^k_{e(x,y)}$, which can be obtained as follows,

$$J^k_{e(x,y)} = \{p_i \in SN | \mathrm{P}(p_k, p_i) = \mathrm{True} \wedge nd(p_i) = y \wedge d_{e(p_i,y)} < d_{e(p_k,y)}\} \tag{3}$$

where $\mathrm{P}(p_k, p_i)$ is the function to judge whether p_i could be perceived by p_k, $nd(p_i)$ is p_i's next destination, Taking the scenario in Figure 3 as an example, p_1, p_2, p_3 and p_4 could be perceived by p_k. The color filled on a pedestrian is consistent with the color of its next destination. Thus, $J^k_{e(p_k,N_1)} = \{p_1, p_2\}$ and $J^k_{e(p_k,N_2)} = \{p_3\}$.

Consequently, based on Floyd-Warshall algorithm [38], the quickest route to safety zone at time t for pedestrian k can be estimated from the directed graph. After finding out the quickest route, all intermediate nodes which consist the quickest route are set as pedestrian k's sequential destinations.

2.3. Route decision-making

When a new quickest route emerges, a pedestrian will compare it with the current route to decide whether to switch to the new route or not. If the saved evacuation time of the new route reaches a threshold, the new route is believed to be a satisfactory choice. In order to quantify the degree of satisfaction to the new route, we define satisfaction parameter q as the saved evacuation time on top of the current route evacuation time. For pedestrian k, its value can be calculated according to the following equation,

$$q_k = \frac{T^c_k - T^n_k}{T^c_k}, \tag{4}$$

where T^c_k denotes the estimated evacuation time of pedestrian k's current route, T^n_k denotes the estimated evacuation time of the new route. According to this definition, the range of q_k is between 0 and 1. The greater q_k and the lower conservative level of k is, the easier the new route becomes k's satisfactory choice.

Thus, the threshold can be seen as pedestrian k's *Conservative Level*, which is denoted as μ_k hereinafter. We further define P^t_k as the probability that pedestrian k choose the new route at time t, it can be calculated by Gaussian cumulative distribution function as follows,

$$P^t_k = \frac{1}{\sigma\sqrt{2\pi}} \int_{-\infty}^{q^t_k} e^{-\frac{(x-u_k)^2}{2\sigma^2_k}} dx. \tag{5}$$

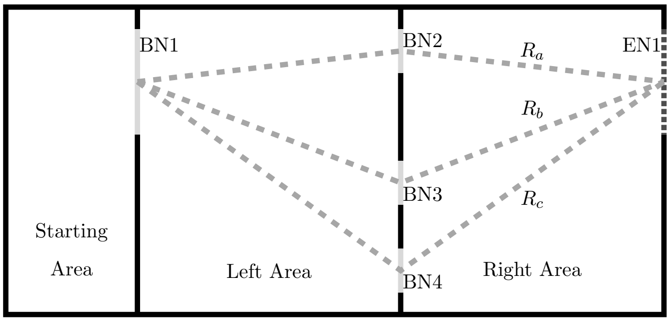
Here, when $\mu_k \to -\infty$,$P_k^t \to 1$, it indicates when a new evacuation route which costs less evacuation time emerges, pedestrian k will switch to it with a probability of 100%; When $\mu_k \to +\infty$, $P_k^t \to 0$, it means the pedestrian will reject all other routes and continue to evacuate following the original evacuation route, i.e., the pedestrian k is a extremely conservative person. σ_k is the deviation of the Gaussian distribution, in the model it is used to reflect the increase rate of P_k^t with the increase of q_k, it is set as 0.05 for each person in the present study. In our daily life, we have the experience that once a decision is made, we barely change it immediately. As a consequence, we assume that the pedestrian k will not consider other new routes again within δt_k seconds once he/she has switched to a new route. The route choice interval δt in the present paper follows a uniform distribution $U(1, 3)$.

3. Model validation

In November 2015, a pedestrian route choice experiment has been organized at University of Tokyo [25]. Here, we use the experiment data to validate the proposed route choice model. The experiment scenario is shown in Figure 4(a). From Figure 4(b) we can see the plan of the origin experimental settings. In total 46 participators initially distributed in the starting area. After they heard the instruction of start, they go through a door BN1 to a zone with a size of $12\,\mathrm{m}\times 7.2\,\mathrm{m}$. The whole area is separated in the middle with three doors: BN2, BN3, and BN4, as shown in Figure 4(b). Each individual selects one of the doors, then moves from the left area to the right area, finally reaches the destination EN1. The width of BN1 and EN1 was 2.4m, and the width of BN2, BN3, BN4 were all 1m. The routes from BN1 to EN1 which get through BN2, BN3, and BN4 are defined as R_a, R_b and R_c, respectively. 4 scenarios has been considered in their experiments. Under each scenario, 4 experimental tests were conducted. The scenario setting and experiment results are shown in Table 1 .

To validate the model we proposed in the present study, the above four scenarios were simulated. Due to the participators are Asians, the pedestrians' radius in the model was set as the random value from $0.2\,\mathrm{m}$ to $0.23\,\mathrm{m}$, and the flow rate C was chosen to be $1.8\,\mathrm{m}^{-1}\,\mathrm{s}^{-1}$. Considering the obstructions and walls used in the experiment cannot block the participants' sight, they could detect each other in the simulation as long as the distance between

(a)



(b)

Figure 4: Route choice experiment. (a) A snapshot of the original experiment in November 2015 [25]; (b) The plan of the complex scenario settings;

Scenario	Description	R_a	R_b	R_c	Completion time (s)
1	BN3 and BN4 closed	46	0	0	24.305
2	BN4 closed	23.25	22.75	0	19.42
3	BN3 closed	28	0	18	19.55
4	All gates opened	20.75	18	7.25	19.06

Table 1: Average size of participators choosing each route and completion times observed in the experiment [25]

them is less than perceptual radius. We further assume that all pedestrians have the same $ConservativeLevel$ and $CongestionSensitivity$ and let $\mu = 0$, $\beta = 0.45$ in the simulation. Here, $\mu = 0$ indicates that the participants are more willing to switch to a better route, and $\beta = 0.45$ means the participants prefer short distance and less queuing when evacuation. Each pedestrian has a desired velocity of $v_0 = 1.65\,\mathrm{m\,s^{-1}}$. To eliminate the effect of random initial pedestrian distribution, each scenario has been simulated 20 times, the completion times and the number of pedestrians choosing each route are averaged. Simulation results are shown in Figure 5.

Comparing the experiment results with the simulation results, we can find that the differences in the number of pedestrians choosing each route on average are very small in all scenarios. Meanwhile, with the increase of available routes, the experiment results show the larger standard deviation, indicating that pedestrians show stochastic feature in selecting routes. From the simulation results, we can also find this phenomenon, but not as significant as the experiment. The reason might be that in the simulations all pedestrians have the same route choice feature while in the experiments participants have some difference. When we further examine the averaged completion time, the simulation and experiment results are also very close, the differences between them are less than 1 s in all scenarios. In the experiment, the average completion time of Scenario 2 is almost the same as Scenario 3, which is only 0.5 s longer than Scenario 4. Meantime, the simulation results show a slightly different: the average completion time of Scenario 2 is about 1s longer than Scenario 3, and 2 s longer than Scenario 4. Considering that we do not know all the details about the experiment, we can only hypothesis that the participants' physical condition had a slight decrease after they finished the experiment Scenario1 and Scenario 2, leading to a lower desired velocity in the experiment Scenario 3 and Scenario 4. Replacing $v_0 = 1.65\,\mathrm{m\,s^{-1}}$ with a smaller desired speed, simulation results became more close to experiment results.

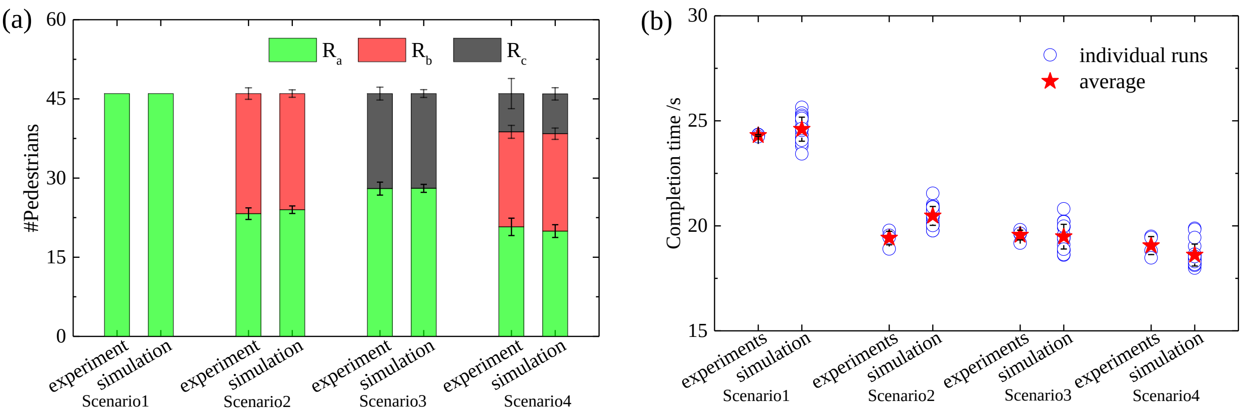


Figure 5: Simulation results of each Scenario compared with the experiment. (a) Average size of pedestrians choosing each route ; (b) Completion time of the 4 individual runs in the experiment and 20 individual runs in simulation.

Actually, we found that the combination of μ and β in this section resulted in balanced pedestrian loads on each route, and simulation results show that pedestrian route choices are almost perfectly rational, i.e., the completion time is very closed to the shortest time compared to other group of parameters. The reason might be that the experiment was conducted in a small space and the perceptual field was not covered by obstacles, participators could get all information of others, besides, participates were not in a high pressure environment, such as an emergency. As a consequence, dynamics of pedestrian route choice behavior should be further explored based on simulations.

4. Simulation results and discussion

A virtual building which has more available routes and different widths of nodes compared to the experimental scenario above is designed here in this section to perform simulation studies on the dynamics of pedestrian route choice behavior. The configuration of the building is shown in Figure 6. 100 pedestrians randomly distributed in these rooms can evacuate into the Center Corridor (CC), through which they can either go the the Left Corridor (LC) or to the Right Corridor (RC). Four final safety exits are designed, EN1, EN2, EN3 and EN4, with the former two in the RC and the later two in LC. Their initial evacuation routes are the global shortest distance route according to their positions. When the last pedestrian reaches the exit, the evacuation ends. Here, we designed three scenarios with the different pedestrian's distribution to compare the parameter sensitivity on evacuation results:

- Scenario 1 (S1), all pedestrians randomly distribute in Bottom Room (BR).
- Scenario 2 (S2), 80 pedestrians randomly distribute on the right side of Top Room (TR), and 20 pedestrians randomly distribute on the left side.
- Scenario 3 (S3), 50 pedestrians randomly distribute in TR and the rest of them randomly distribute in BR.

The influence of *Conservative Level* μ, *Congestion Sensitivity* β on route choice behavior and evacuation results will be presented and discussed. Other parameters will be set as the same values in Section 3. For each group of parameters in different scenarios, simulations were repeated 20 times. It should be pointed out that here the initial positions of pedestrians in each repeated run were kept the same to focus on the effect of μ and β.

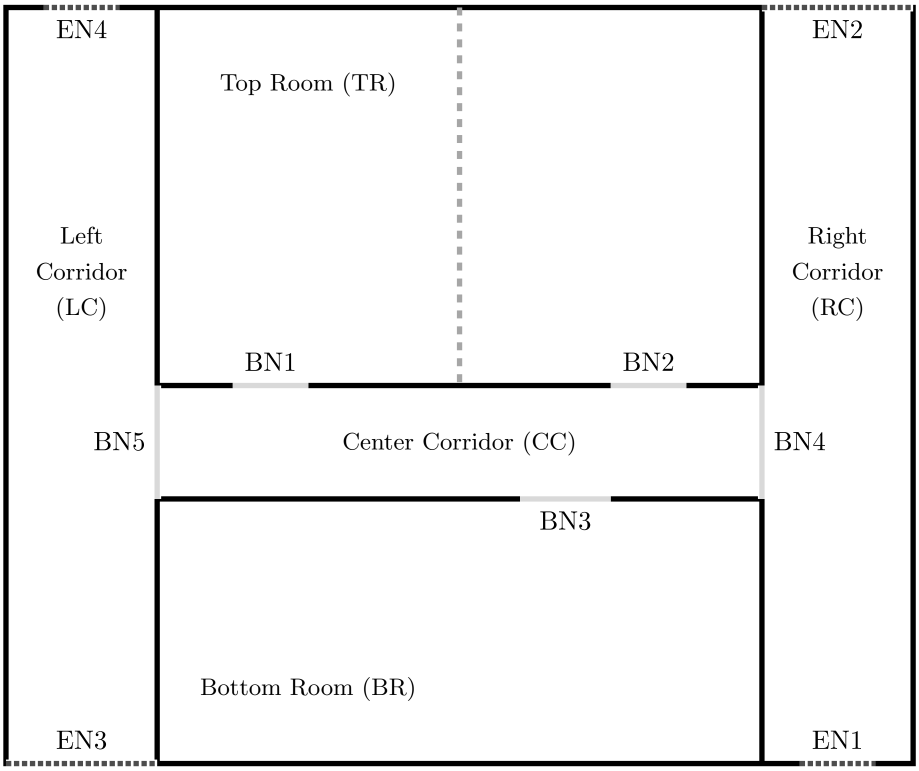


Figure 6: Configuration of the virtual building. The width of BN1, BN2, EN1 and EN4 are all 1 m, the width of BN3 is 1.2 m, the width of EN2 and EN3 are 2 m. The dashed line in the middle of Top Room divides the room to the left side and right side, it does not represent any wall or obstacle.

4.1. Effect of Conservative Level

Here, we set β=0.45, which is in consistent with the value used in Section 3. Considering that the range of time saving degree q is 0 to 1, we investigated the effect of μ on the evacuation with the range of 0 to 1. Typical evacuation scenarios at $t = 15\,\mathrm{s}$ for different μ values in S1 can be found in Figure 7. The color of an pedestrian's trajectory represents its final destination. The positions, at which the pedestrians change their destinations, are marked with black dots.

As can be observed in Figure 7, in S1 the initial destinations of the pedestrians are all EN1. Different μ resulted in different evacuation pattern, i.e., the pedestrian distribution on each evacuation route was different. When $\mu = 0$, pedestrians in the bottom room uses all the four exits to evacuate (Figure 7(a)). With the increase of μ, the total number of exits

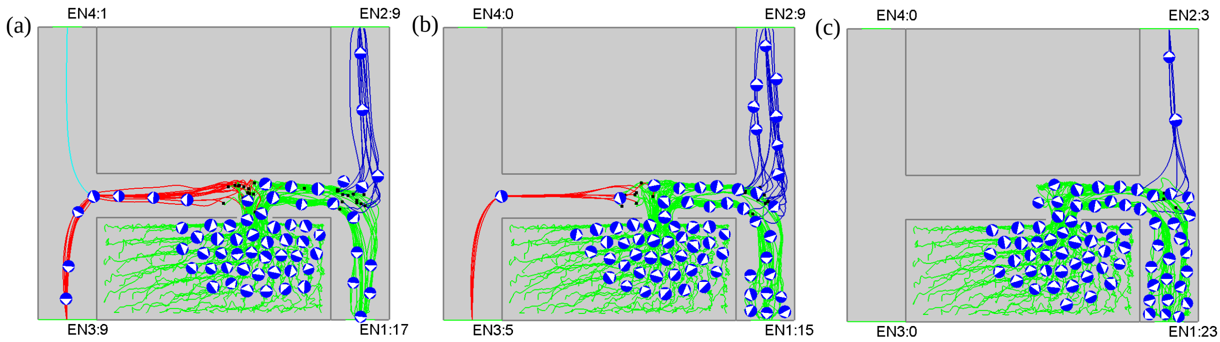


Figure 7: Simulation snapshots in S1. (a) μ=0, t=15 s; (b) μ=0.3, t=15 s; (c) μ=0.6, t=15 s.

used decreases. When $\mu = 0.6$, only the two nearest exits, i.e., EN1 and EN2 were used. From Figure 7 it can also be found that the pedestrian evacuation rate was also different. The number of pedestrians evacuated from each exit and the evacuation time in the three designed scenarios are shown in Figure 8.

From Figure 8(a), it can be found when $\mu = 0$, the sum number of pedestrians exited from EN1 and EN2 is approximate 76, and 24 pedestrians selected LC after they reached CC due to the congestion. For those who chose the RC, 31 pedestrians selected EN2 to avoid the congestion and to reduce the queuing time. It should be noticed that not all 31 pedestrians selected EN2 at the same time. They made the route choice decision according to the exit widths and queue sizes of EN1 and EN2 dynamically. The 24 pedestrians who entered into LC almost all evacuated through EN3. The reason is that the distance to EN3 is shorter than EN4, what is more, EN3 is 2 m wide which provides sufficient capacity to avoid congestion near the exit.

When $0 < \mu < 0.4$, it can be found in Figure 8(a) and Figure 7(b) that with the increase of μ, the proportion of pedestrians changed route from the initial routes decreases, while the number of people exited from EN2 keeps almost constant, which indicates the increased pedestrians exited from EN1 are those people who did not change their routes to LC. When $\mu > 0.5$, pedestrians will not change their routes unless the new route can save nearly half of evacuation time. As we can observe in Figure 8(c), no one chooses LC anymore and the number of people changed to EN2 also decreased significantly. Moreover, congestion and

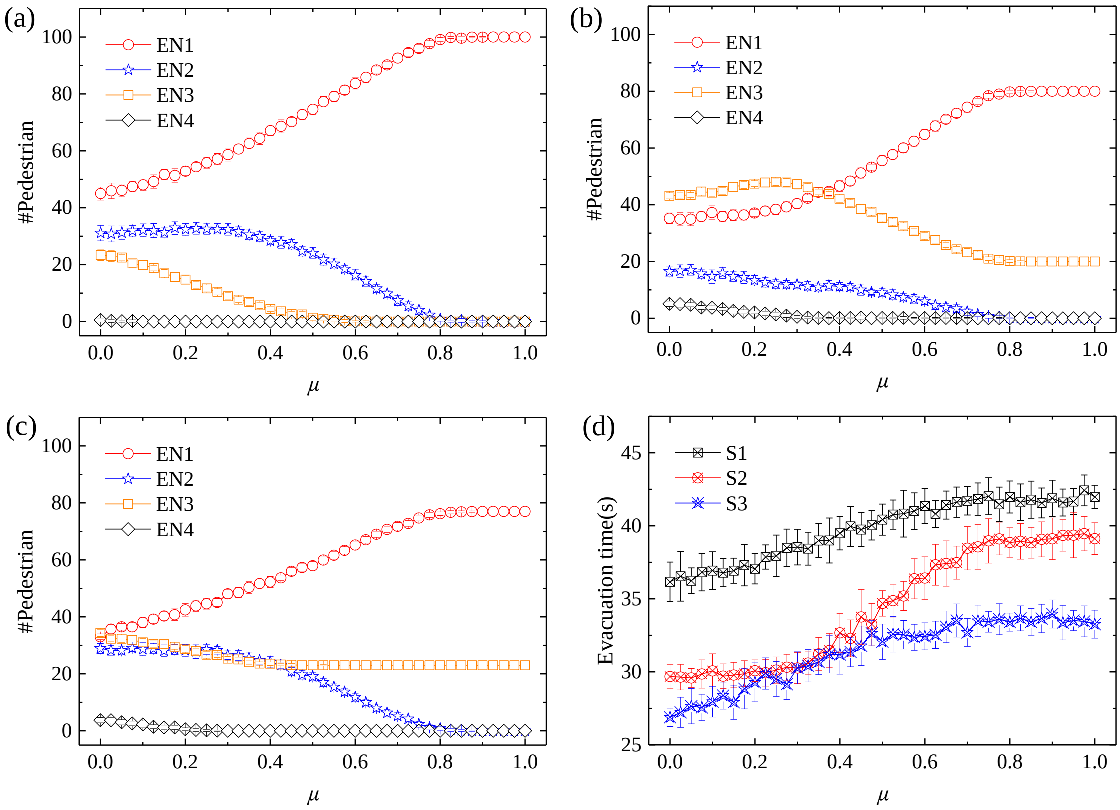


Figure 8: Simulation results under different irrational level. (a) number of people exited from each exit in S1; (b) number of people exited from each exit in S2; (c) number of people exited from each exit in S3; (d) evacuation time of S1, S2, and S3.

queuing formed near EN1. When μ reaches 0.8, no pedestrian chooses EN2 anymore. In fact, the routing behavior of pedestrians when $\mu > 0.8$ is comparable to the global shortest route strategy: individuals only select the exit which is shortest to its initial position during the evacuation process. When the exit's capacity can not fulfill pedestrian evacuation demand, the global shortest route strategy will result in serious congestion and the longest evacuation time. Therefore, the $ConservativeLevel$ play a critical role in affecting the evacuation efficiency. A lower conservative route choice would help in improving evacuation efficiency, otherwise, a lot of people will accumulate on the shortest route while the other evacuation routes and exits cannot reasonably be used.

In the second scenario S2, the building layout is symmetric, but the initial distribution of the pedestrian is different. Therefore, for the pedestrians located in the left side of TR, their global shortest route is to evacuate through BN1, while for those who were in the right side of TR, their global shortest route is to evacuate through BN2. Simulation snapshots can be found in Figure 9. As we can observe, when $\mu = 0$, 48 pedestrians in TR selected BN1 and 52 selected BN2 to evacuate. This result means that 28 number of pedestrians gave up the route BN2→BN4→EN1 and chose BN1 to evacuate. Comparing those who changed their routes with the one who did not on the right side of TR, we can find that the ones who were at the end of the queue moving to BN2 changed their evacuation route to BN1, although their distance to BN2 is shorter. The reason why they made such a decision was that the pedestrians would like to travel a little big longer distance rather than waiting in the queue. When $0 < \mu < 0.3$, as shown in Figure 9(b), although pedestrians become more conservative, the extra free travel time required to change to BN1 is still much less than the time spend in queuing. Therefore, when $\mu < 0.3$, the number of people chosen BN1 and BN2 maintained at around 50. However, similar to S1, in RC, the proportion of people who choose EN2 slightly decreased with the increase of μ. The same phenomenon can also be observed in LC. With the increase of μ, taking Figure 9(b) as an example, pedestrians tend to stick to their initial route choices, BN1 can only be the satisfactory choice for few people who located at the most disadvantage positions away from BN2. Accordingly, the number of people who exited from LC decreases, and the number of people chosen LC increases, while the number of people exited from EN2 also decrease due to the high *Conservative Level*. In this case, congestion occurred near EN1 led to the significant increase of evacuation time. When $\mu > 0.8$, the high conservative level makes all pedestrians evacuate according to the initial global shortest route. The evacuation under such scenarios as a consequence keeps increasing, as shown in Figure 8(d).

In the third scenario S3, 50 people were randomly distributed in TR and BR, respectively. For the TR, 23 pedestrians located on the left side and 27 pedestrians located on the right side. Typical simulation snapshots can be found in Figure 10. As can be found in Figure 10(a), When $\mu = 0$, two pedestrians were initially located in the right side of TR and changed their route. They were at the end of the queue escaping towards BN2 and then found that there were some other people (from BR) escaping through the right side of CC.

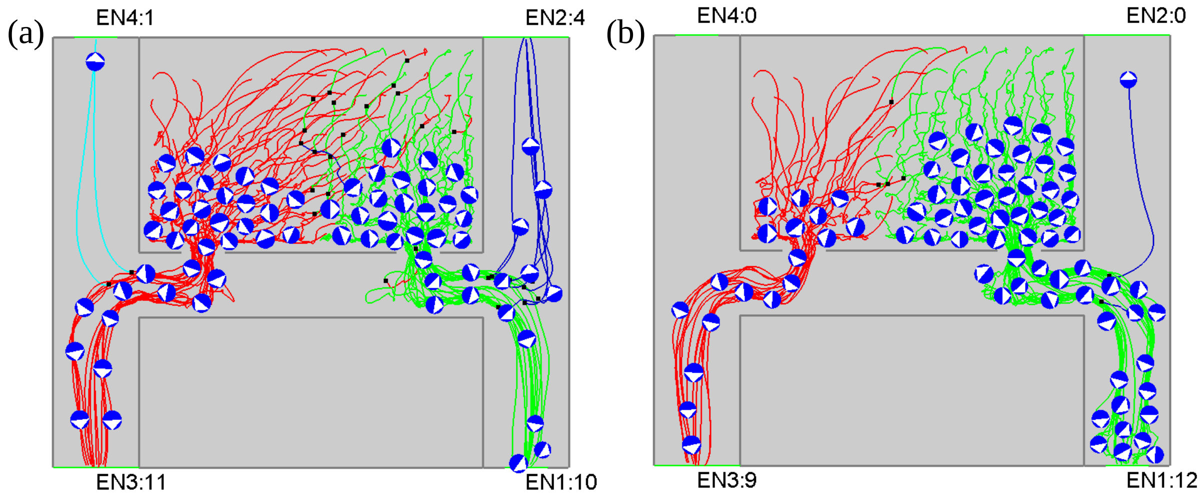


Figure 9: Simulation snapshots in S2. (a) μ=0, t=10 s; (b) μ=0.6, t=10 s.

Those people increased the congestion level of the original evacuation route and resulted in longer queuing time. As a consequence, even though they had waited some time near BN2, they decided to change to BN1. For similar reasons, these people who arrived CC from BN3 also decided to change their original intermittent destination RC to LC. when facing the merging pedestrian flow in CC. Summarizing the features of switching to the new route, we can see that although the new route usually has a longer travel distance, those who were at the end of the queue would like to change route. As shown in Figure 8(c), EN3 and EN4 evacuated a total of 38 people when $\mu = 0$. Reviewing the simulation we can see that about 5 pedestrians changed to BN1 in TR, 8 pedestrians from BN3 changed to LC, and no one from BN2 changed to LC. When μ increases to 0.2, it can be found in Figure 10(b), similar phenomenon can also be observed, but the number of people who changed to BN1 in TR decrease to 2, and about 5 pedestrians from BN3 changed to LC. Therefore, the route changing behaviors that happen in CC are more affected by μ than in TR. When $\mu > 0.45$, as shown in Figure 10(c), route changing phenomenons in TR and CC all disappeared. Just like S1 and S2, μ only affects the route choice of those people who has already arrived in LC and RC.

Further comparing the route choice behavior and evacuation time under different μ in the

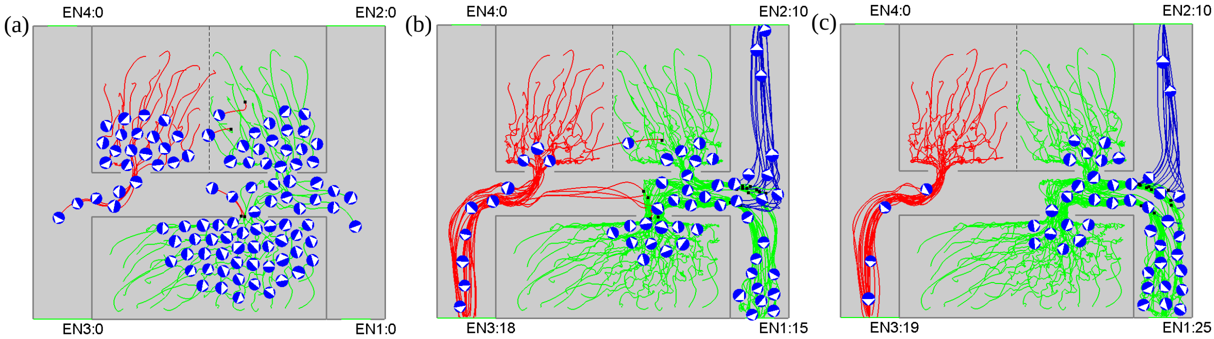


Figure 10: Simulation snapshots in S3. (a) μ=0, t=3.25 s; (b) μ=0.2, t=13.75 s; (c) μ=0.45, t=16 s.

three designed evacuation scenarios, we found that with the increase of $ConservativeLevel$ μ, the route and exit usage become more and more unbalanced, which results in serious congestion. Figure 8(d) also demonstrates that the the evacuation time increased with the increase of μ. It should be noted that people in real evacuation scenarios may have little information about the evacuation situation of the subsequent route segments, it makes sense for them to hold a higher $ConservativeLevel$.

4.2. Effect of Congestion Sensitivity

As pointed out in Section 3, the range of *Congestion Sensitivity* β is from 0 to 1. When $\beta = 0$, pedestrians only pay attention to the length of the route without considering the queuing time. With the increase of β, the influence of the dynamic positions of the pedestrians becomes more and more obvious on individual's route choice. When $\beta = 1$, the route length will be neglected, and route choice decision is only determined by the estimated queuing time of each route. In this section, we set $\mu = 0$ and change the value of β to perform simulation studies. Figure 11 shows the number of people who escaped from each exit with different β. It can be found that with the increase of β, pedestrians gradually transferred from the shortest route with high load to those routes with higher available capacity.

In S1, when $\beta = 0.3$, 54 pedestrians escaped from EN1, 34 pedestrians escaped from EN2, the rest of them escaped from EN3. This result is similar to the result with $\mu = 0.25$ and $\beta = 0.45$. The parameter combination of $\mu = 0$ and $\beta = 0.3$ here means that free walking time is still more important than queuing time, thus the routes with lower pedestrian load

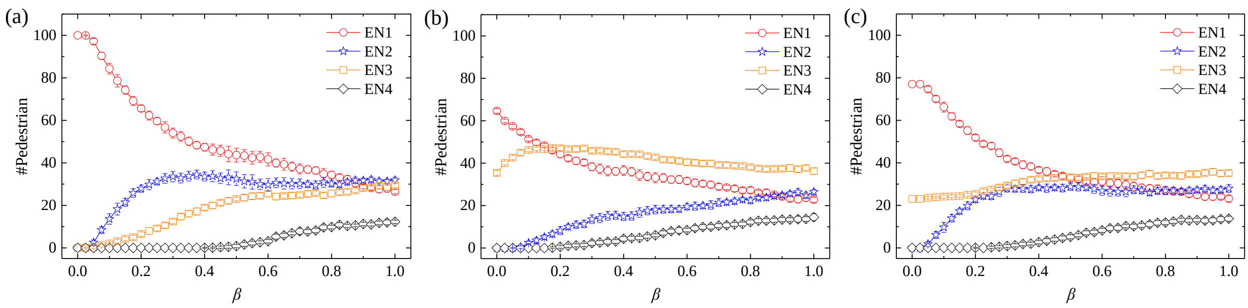


Figure 11: Relationship between the number of escaped people from each exit and β in scenarios (a) S1, (b) S2, (c) S3, respectively.

had little chance to be chosen as a quicker route. The parameter combination of $\mu = 0.25$ and $\beta = 0.45$ stands for the situation that the new route is easier to be selected as a quicker route, but the probability of people changing to it will be small unless the cost time is less than 75% cost of the current route. Comparing these results it can be found that higher μ and lower β reduced the probability to change to a new route. For this reason, the trend of the number of pedestrians escaped from each exit when β increases from 0 to 0.5 for the case $\mu = 0$ is similar to the trend of μ decreasing from 1 to 0 with $\beta = 0.45$.

When $\beta > 0.5$, the queuing time becomes the most important factor which affects a pedestrian's route decision. Under these circumstances, the ones who changed their routes resulted in the route-changing behavior of other pedestrians, which finally triggers the increase of the number of route changes. For the convenient of illustration, all route change positions were recorded in Figure 12 to analyze route change times and locations during evacuation process. It can be found from Figure 12(a), when $\beta = 0.5$, route changing places were almost near the door BN3 or intersections of BN4 and BN5. When $\beta > 0.7$, the number of route changes increased and some pedestrians near BN3 presented a short-distance detour phenomenon, i.e., pedestrians oscillated at points as their decisions switched back and forth between two or multiple choices. From Figure 12(b) it can be found that although the route change times increase, the positions are still around the doors and intersections. When $\beta = 1$, route change times increase significantly, and the route change points can be found in all the available routes in S1. That is to say, pedestrians ignore the lengths of the routes, and only consider the congestion information would resulted in long-distance detour and increase the evacuation time, as can be found in Figure 14.

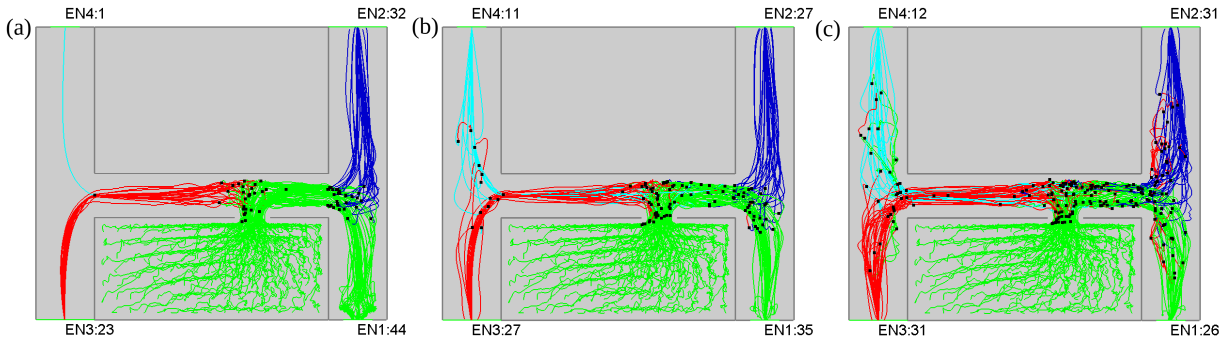


Figure 12: Simulation snapshots in S1 with (a) β=0.5, (b) β=0.8, and (c) β=1.

In S2, taking $\beta = 0$ in Figure 11(b) as an example, 65 people escaped from EN1, and 35 people escaped from EN3. That means 15 people from the right side of TR changed their route to BN2. This is different from the result of global shortest route strategy. Plotting the trajectories of all the pedestrians in Figure 13, it can found the trajectories are quite different from the ones in Figure 9(a). In Figure 9(a), the pedestrians' trajectories directly pointed to BN1, meaning that they changed to BN1 at the beginning of the evacuation. While in Figure 13(a), the ones in the right side of TR had a destination of EN1, thus they firstly moved towards BN2, however, due to the insufficient space, they were squeezed to the left side by other pedestrians, forming the curved trajectories. Then, after evaluation, EN3 became their shortest exit, and they changed their routes. Therefore, the route change positions were all located on the left side of TR. As mentioned in former sections, $\mu = 0$ means people would like to change routes, and thus when $\beta = 0$, a pedestrian follows dynamic global shortest route. Under this parameter combination, people will search for the shortest route during the evacuation based on their current positions. On the contrast, $\mu = 1$ and $\beta = 0$ denotes that a pedestrian follows a static global shortest route strategy, i.e., its route choice decision is only determined by their initial positions.

With the increase of β, similar to S1, more people changed to the route with the longer distance to avoid congestion. When β reaches 0.05, route change behaviors were found near

BN4, EN2 started to be chosen by pedestrians. When $0 < \beta < 0.2$, more people would like to change to BN1 from the right side of TR, which caused the number of pedestrians escaped from EN3 increases, as shown in Figure 11(b). After $\beta > 0.2$, we can found that due to the symmetric layout, the number of people escaped from LC and RC were almost 50 pedestrians each. Meantime, route change positions were found near BN5, people started to escape to EN4, which makes the number of pedestrians escaped from EN3 decrease slightly. When $\beta > 0.6$, detour phenomenon appeared, route changes from one side to the other side could be observed in CC as shown in Figure 13(b).

In S3, we found similar route choice decision features when increasing β, so its influence will not be detailed.

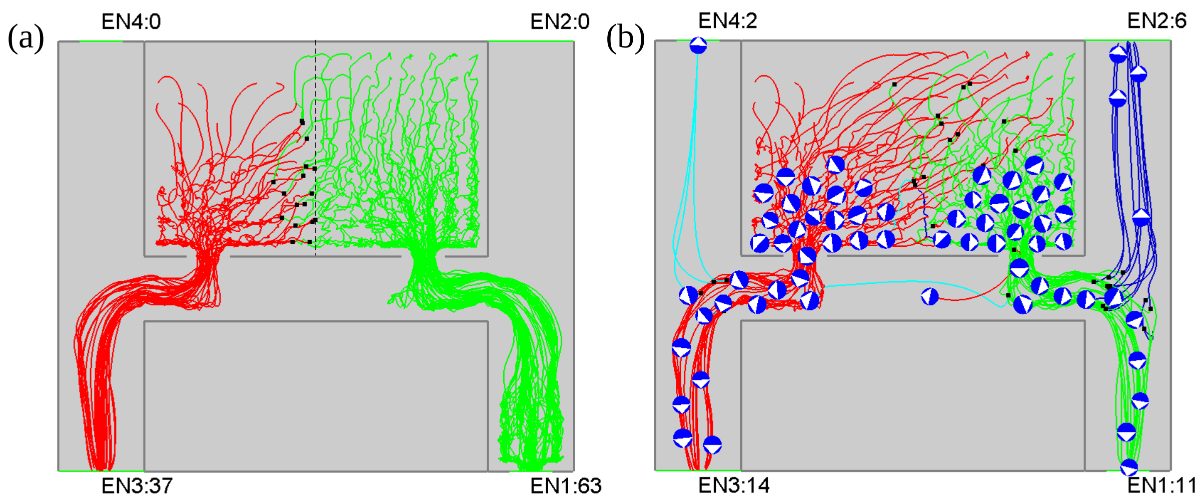


Figure 13: Simulation snapshots of S2 with (a) β=0 at the time when the evacuation finished and (b) β=0.6, t=11.8 s.

Further comparing the number of escaped pedestrians from each exit in Figure 11, it can be found that the number of escaped pedestrians from of the same exit in three scenarios were approximate the same when $\beta = 1$. This feature indicates that the number of people escaped from an exit is mainly decided by its width, but not its location. Obviously, this phenomenon deviates from our daily experiences.

To explore the dynamics behind this phenomenon, we define average travel distance ($\bar{d}$)

and average speed ($\bar{v}$) as follows

$$\bar{d} = \frac{1}{N}\sum_{i=0}^{N} d_i \ \ \& \ \ \bar{v} = \frac{1}{N}\sum_{i=0}^{N}\frac{1}{T_i}\sum_{j=1}^{T_i} v_i^j. \tag{6}$$

Here, d_i is the real travel distance of pedestrian i walking from its initial position to the destination. T_i is the number of simulation time steps of i spent from the initial position to the destination. v_i^j is the average speed of i in the period of time step $j-1$ to time step j. Figure 14 shows the the relationship between $\bar{d}$ and β, as well as $\bar{v}$ and β. As can be found from this Figure 14(a), with the increase of β, the averaged travel distance keeps increase while the averaged speed firstly increases and then decrease. This is because pedestrians take avoiding congestion into account when $\beta > 0$, the route changing behaviors resulted in a longer average distance. For the reason that there was less pedestrians on the new route, the pedestrian speed increased. That means increasing β is essentially sacrificing distance in exchange for faster movement speed. Taking both route length and congestion level into account makes the evacuation time decrease, as shown in Figure 14(b). It should be noted that when $\beta < 0.5$, the decision-making process was still more affected by the route length, the travel distance increasing rate cannot be fast. However, when $\beta > 0.6$, the influence of route length become smaller, detour phenomena can be observed, as a consequence, the travel distance increased significantly. Meanwhile, $\bar{v}$ shows a slight reduction, this was because the frequently detours resulted in more conflicts and collisions with other pedestrians, thereby lowering the movement speed of the whole crowd. This counter flow situation makes the evacuation time increase again, as shown in Figure 14(b). For the situation when β is between 0.4 and 0.6, the evacuation can be completed within a time around the shortest evacuation time.

5. Model application: Fail safety of emergency exits

In Sections 4.1 and 4.2, under the condition that all exits are available, we found the number of people escaped from EN1 is large, while the number of people escaped from EN4 is very small. If the ones escaped from EN4 changed their destination to EN3, the

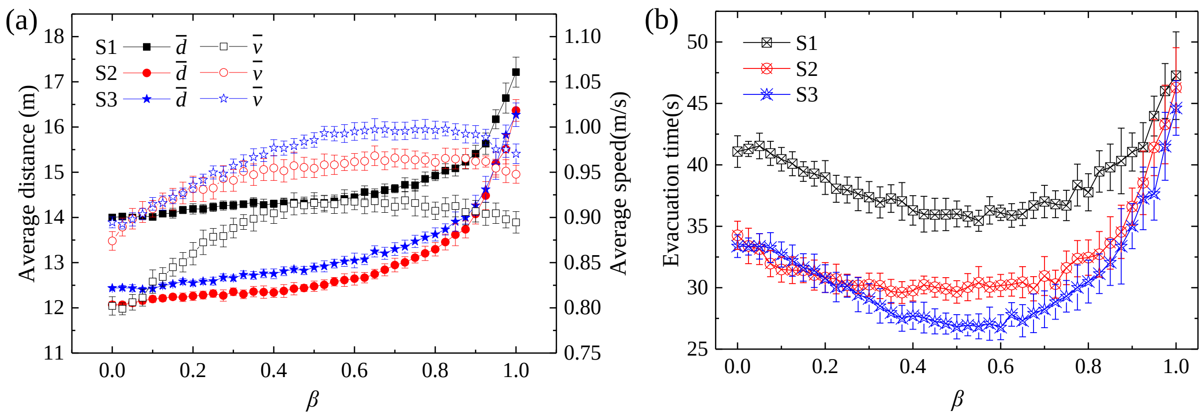


Figure 14: The influence of β on evacuation efficiency indexes in the three scenarios. (a) the variation of $\bar{d}$ and $\bar{v}$; (b) the variation of evacuation time.

evacuation time would not increase. Assuming that a fire blocks EN4, the evacuation would only be slightly affected, however, if EN1 was blocked, the evacuation efficiency would be quite different. Does this indicate that EN1 has a greater impact on the evacuation than EN4? We simulated pedestrian evacuation in the virtual building using the parameter combination ($\mu = 0$ and $\beta = 0.45$) to investigate the effect of blocked node on evacuation time and discuss the contribution of each node to the evacuation. We assume that pedestrian got the information of which exits had been blocked from the broadcast when they started to evacuate. Results can be found in Table 2.

First, effects of blocking BN4 and BN5 will be discussed. BN4 and BN5 are critical nodes in the graph because when BN4 is blocked, neither EN1 nor EN2 can be used anymore, and neither can LC. However, it can be found from Table 2 that when BN4 or BN5 was blocked in S1, the evacuation time only increased about 1.5 s. This is very short when compared with the results in S2 and S3. This can be explained by the fact that the the widths of BN3 and CC are wide enough to allow a high enough flow from BN3. Thus, the average speed of people in CC will not be affect by the blocking of BN4 and BN5. In fact, as shown in Figure 15(a), when BN4 was blocked, the increased 1.43 s was mainly contributed by the little longer travel distance in CC when all pedestrians chose LC, while when BN5 was blocked, the increased 1.56 s was mainly contributed by the little longer queuing time near EN1 as marked by black dash ellipse in Figure 15(b). However, in S2, blocking BN4 made some of the people on the right side of TR escape from BN2. This behavior was expected: reaching CC as soon as possible is much better than queuing at the left side. As shown in Figure 15(c), the two pedestrians evacuated from BN1 and BN2 merged near BN1, and the merging flow rate was determined by the width of CC. Therefore, BN4 became the new bottleneck in this case, which directly affected the evacuation time. It can be inferred that the flow rate of BN4 is definitely lower than the sum of the flow rates of BN1 and BN2 under no fire conditions. For this reason, the evacuation finished 5.23 m later. Due to the width of EN3 is 2 m which is twice the width of EN1, the evacuation efficiency in LC is higher than RC if BN4 and BN5 had the same pedestrian arrival rate. This is the reason why the time increases extra 1 s when BN5 was blocked.

Cases	S1	S2	S3	Average Difference
Normal	0	0	0	0
BN4 blocked	1.43	**5.23**	**4.48**	3.71
BN5 blocked	1.56	**6.32**	**6.32**	4.73
EN1 blocked	-0.19	-0.04	-0.35	-0.58
EN2 blocked	**4.15**	1.7	**5.8**	3.88
EN3 blocked	-0.01	**3.97**	1.23	1.73
EN4 blocked	0.03	-0.08	-0.25	-0.3

Table 2: Evacuation time differences (in seconds) compared to normal condition.

We examine the situation of blocking other exit nodes. It can be found in Table 2 that blocking EN1 barely affects the evacuation process. The reason behind this phenomenon is that since the pedestrians in CC cannot perceive the congestion degree of each exit, they only concern the number of people on both sides of CC. Even if EN1 is blocked in S1, most people still chose to escape to RC. However, since the evacuation distance to EN2 is not very long, and its width is 2 m, which was larger than the width of CC, failure of EN1 had

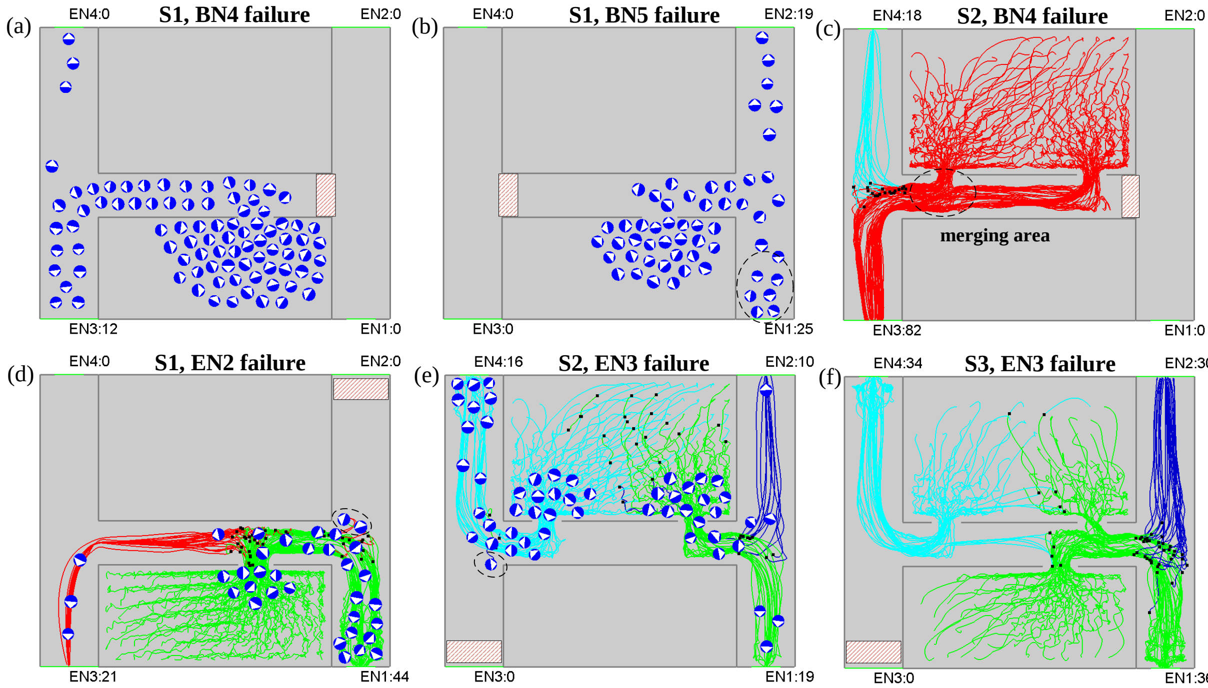


Figure 15: Simulation snapshots in different cases. (a) congestion only formed in BR but not in CC or EN3. (b) few pedestrians accumulated near EN1; (c) the trajectories of pedestrians show that pedestrian flows merged in the area marked by black dash ellipse; (d) three pedestrians in the black ellipse would like to go to EN3 after they found the congestion near EN1; (e) the phenomenon similar to RC of (d) occurred at LC; (f) few pedestrians accumulated near EN1 like (b).

barely impact on evacuation, and no jam formed on the route. For similar reason, EN1 has almost no influence in S2 and S3.

When EN2 was blocked, the situation was more complicated, the evacuation time increased by 4.15 s and 5.8 s in S1 and S3, respectively. Here, many pedestrians still chose to go to RC, which induced a congestion near EN1, hence the evacuation time grow about 4.15 s. Additionally in this case, we found that the two pedestrians marked out in Figure 15(d) decided to change to LC after they had arrived in RC and found the queue of BN1. Later, they were blocked by the counter flow, which had not get the congestion information. A few seconds later, they gave up the change and went to EN1. Other pedestrians, that just reach RC became the new pedestrians waiting to switch to LC. The situation in S3 is similar. While in S2, the number of people evacuated by BN1 and BN2 was roughly the same. Since the evacuation width of LC was much larger than RC when EN2 was blocked, the time the last pedestrian evacuating from EN1 determines the overall evacuation time. The width of BN1 was equal to EN1, theoretically, people flowed from BN1 will not cause congestion near EN1. But we found that a small number of pedestrians accumulated near BN1, which also caused a 1.7 s increase in the evacuation time.

For EN4, as shown in Sections 4.1 and 4.2, an exit with a further distance and smaller width, was rarely chosen by pedestrians during evacuation. Therefore, there is almost no change in the evacuation process when EN4 was blocked.

The blocking of EN3 mainly affects the evacuation time in S2 and S3. In S1, the width of EN4 is sufficient for a few pedestrians avoiding congestion. In S2, about 50 people who chosen LC can only escape from EN4, which resulted in the longest average distance and little congestion near EN2, the evacuation time increases about 3.97 s. Besides, we also found the waiting pedestrian marked out in Figure 15(e) in this case. In S3, it can be found in Figure 15(f), fewer people changed to the LC from the right side of TR and BN3 compared with the normal pedestrian evacuation, the increased few people chosen RC delayed the evacuation about 1.23 s.

To quantify node importance, the increased evacuation time caused by the blocking of the node has been employed. The longer the increased time is, the more important the node is. Considering the different initial distribution of pedestrians will result in the different node importance, results of S1, S2, and S3 are averaged. Therefore, the node importance from great to small is BN5, EN2, BN4, EN3, EN1. EN4 and EN1 have approximately the same importance. From this importance list it can be found that the nearest exit EN1 for most pedestrians was not the most important node for evacuation, and its node importance is almost the same as EN4 which was the farthest exit: whether it is available or blocked, it has no obvious effect on evacuation time. We can find according to Table 2 that when EN3 or EN4 was blocked, evacuation efficiency was barely affected. However, when EN3 and EN4 were blocked at the same time, i.e., BN5 was blocked, the evacuation became difficult. Taking into account crowd safety, the most important thing is to take measures to ensure CC will not be blocked.

6. Conclusions

Taking into account boundedly rational decision-making during the evacuation, a novel evacuation route choice model has been proposed in the present study. In the model, parameters including *Congestion Sensitivity* and *Conservative Level* were adopted to quantify the influence of travel distance and route congestion information on pedestrian's route choice behavior. Based on a dynamic configuration and individual location based graph, route estimation and switching rules were set to reflect bounded rationality. Comparing the simulation results with an on-site pedestrian experiment, the model was validated. Results also indicate that free walking time is slightly important than queuing time for participators in the experiment scenario.

The effects of the *Congestion Sensitivity* and the *Conservative Level* on route choice behavior and evacuation time are discussed. We found that low *Conservative Level* could generally result in a shorter evacuation time, and with the increase of the *Conservative Level*, evacuees tend not to change their current routes. Consequently, congestion occur on the narrow shortest route, leading to a significant increase in the evacuation time. For *Congestion Sensitivity*, when ignoring queuing time, pedestrians' mean travel distance to exits is the shortest, but their speed is lower due to the caused congestion. Increasing *Congestion Sensitivity* could cause a longer distance in favor of an increased average speed. When *Congestion Sensitivity* is greater than a threshold, detour behavior which was triggered because repeated choices between two doors or exits appeared, results illustrated that long-distance and frequent detours greatly decrease crowd evacuation efficiency.

At last, we discussed the node importance by performing simulations with the proposed model. Simulation results show that the nearest exit is not necessary the most important exit in an evacuation process. Intersections linked to multiple exits or available routes are critical, since their malfunction may cause congestion on other routes or exits. The width of the exit is another key factor that affects the evacuation. Wide exits are more important than narrower exits, even if they are relatively more distant. However, the effect of doors or exits should be further determined by analyzing the boundedly rational route choice behavior during the evacuation process. Other factors that may influence pedestrian's route choice decision, such as pressure, the number of doors on future route, level of safety (e.g. fire), are not considered in the actual model. In addition, a more robust validation by means of route choice experiments in complex scenarios is needed to further gain more insights in the evacuation process and the decision making of the pedestrians.

Acknowledgment

The work presented in this paper is supported by the National Natural Science Foundation of China (No. 71871189), the Science and Technology Development Funds of Sichuan Province (No. 2020YFS0291), the National Key Research and Development Program of China (No. 2017YFC0804900) and the China Scholarship Council (Grant No. 202007000111).

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