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Article

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Posted Date: September 1st, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-10560804/v1>

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Additional Declarations: No competing interests reported.

A Cell Transmission Model for Pedestrian Evacuation Simulation Considering Panic and Guidance

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Abstract. Pedestrian evacuation behavior in fire scenarios is influenced by various factors. To investigate the impacts of these factors on the evacuation process, this study develops a pedestrian evacuation simulation model based on the Cell Transmission Model (CTM) under fire conditions. By incorporating both a fire potential field and a static potential field, the model simulates the evacuation dynamics in fire scenarios. Different fire ignition points and levels of pedestrian panic are configured to explore their effects on evacuation time and evacuation paths. Furthermore, a signage guidance model is introduced by constructing a guidance potential field to examine the mechanism by which signage affects evacuation behavior. Experimental results show that the proximity of the fire source and the intensity of pedestrian panic significantly influence evacuation efficiency. Signage guidance significantly reduces evacuation time. This study lays a theoretical foundation for optimizing evacuation strategies and supports architectural planning and emergency drills.

Keywords: Cell Transmission Model; Fire scenarios; Panic Factor; Signage Guidance.

1. Introduction

With the acceleration of urbanization, the phenomenon of population aggregation in buildings has become increasingly prominent, and the occurrence of sudden incidents such as fires may lead to serious casualties. Traditional evacuation studies have mostly relied on physical experiments and behavioral simulations. However, due to the unpredictability of real fire environments, the development of effective evacuation simulation models has become a critical research topic. Cao et al. [1] quantified the psychological stress levels of evacuees under fire conditions based on the social force model. Jun Zhang et al. [2] developed a hybrid-posture fire evacuation model using the social force model, which can reproduce observed pedestrian detour and fire avoidance behaviors during experiments, enabling pre-planned evacuation paths that avoid high-temperature areas according to the fire source status. Their study found that when individuals evacuate using crawling, squatting, or bending postures, the evacuation time increases with higher crowd density and fire temperature. Zhang et al. [3] proposed using escalators in shopping malls as additional evacuation routes and analyzed the effects of different fire shutter states on evacuation efficiency through simulation. Feng et al. [4] proposes a hybrid approach integrating BIM, Fire Dynamics Simulator (FDS), and a multi-objective optimization algorithm for metro station fire simulation and evacuation optimization, and validation shows that this method effectively improves multiple indicators such as evacuation time, density, and cost. Wen et al. [5] quantified the computational rules of friction and repulsive forces, proposed a new cellular automata model, and, using Helbing's molecular model, focused on investigating the relationship between building structural features—such as exit width—and evacuation time.

With the continuous advancement of research on evacuation in fire scenarios, the impact of guidance on evacuation efficiency has attracted increasing scholarly attention. Current studies on evacuation guidance generally fall into two categories.

One line of research focuses on investigating the underlying mechanisms and quantifying relevant models to examine the impact of the number and spatial deployment of guidance personnel on crowd evacuation performance. For example, Ma et al. [7] based on an extended social force model, systematically analyzed the impact of guidance personnel on group

evacuation performance. Their earlier studies indicated that the number of guides has a significant influence on evacuation efficiency— even a small number of guides can effectively direct large crowds, notably improving evacuation performance even under extremely low visibility conditions. In follow-up research [8], they further revealed a “dual effect” of guidance: guidance is effective when the local density of neighboring evacuees within the visual range is moderate, but may negatively affect evacuation by increasing egress time when the density is either too low or too high. Lei et al. [9] constructed an optimization model for the spatial deployment of guidance personnel and evacuation route planning. They simulated emergency evacuation scenarios in urban rail transit transfer stations, highlighting the role of guides under incident conditions. Liu et al.[10], integrating Gaussian Mixture Models and fuzzy logic theory, proposed a guided crowd evacuation dynamics model based on a cellular automata framework. They investigated the effects of guide quantity, movement speed, and exit width on evacuation dynamics. The results showed that while guidance personnel can improve evacuation performance to some extent, more is not necessarily better. Additionally, expanding the exit width within a certain range can enhance exit throughput and significantly reduce total evacuation time.

Another line of research exploring the impact of different guidance strategies on evacuation performance based on established models. Guanning Wang et al. [11] conducted simulation analyses to evaluate the effect of a wall-following guidance strategy, where evacuation assistants guide pedestrians along walls, on the evacuation process. Wang et al. [12] investigated the influence of a zonal guidance strategy—implemented by multiple rescuers—on the evacuation of panicked pedestrians. Jian Tang et al. [13] focusing on large-scale building environments, examined three guidance strategies adopted by evacuation personnel: equal-area zonal guidance, shortest-path guidance, and a hybrid strategy combining zoning with shortest-path routing. Their study analyzed how each strategy affects total pedestrian evacuation time. Liu et al. [14]based the social force model to simulate rescue behavior during the evacuation process. The findings revealed that such behavior facilitates the formation of "rescue channels," which in turn enhances overall evacuation efficiency. Nie et al. [15] developed a “macro-guidance–micro- avoidance” model based on an improved NSGA-II

algorithm coupled with cellular automata for simulating emergency evacuation in nuclear power plants. By incorporating radiation diffusion, pedestrian characteristics, and psychological factors, the model significantly improves the accuracy of exit selection and evacuation time prediction.

Currently, pedestrian evacuation models are primarily categorized into macroscopic and microscopic models. Macroscopic models focus on the overall movement dynamics of crowds without capturing individual-level behaviors, making them insufficient for accurately representing the interaction between microscopic pedestrian behavior and macroscopic flow phenomena in complex environments. In contrast, microscopic models can realistically simulate individual pedestrian behaviors, but their simulation outcomes are often constrained by algorithmic complexity, making it challenging to analyze evacuation patterns under the influence of multiple interacting factors. To address these limitations, Guo et al. [16] proposed a novel Cell Transmission Model based on potential field theory and cellular automata. This model integrates the advantages of both macroscopic and microscopic approaches while overcoming some of the limitations of traditional methods, thereby offering a more accurate representation of the pedestrian evacuation process. Due to its computational efficiency and adaptability, CTM has gradually become a widely adopted tool in pedestrian evacuation simulations. Li et al. [17] developed an extended CTM that incorporates features such as risk-averse behavior, panic psychology, and pedestrian inertia, thereby enhancing the realism of evacuation simulations. Their findings suggest that appropriate pedestrian flow distribution and signage placement can significantly improve evacuation performance. Sun et al. [18], using an improved CTM that accounts for psychological factors and safe interpersonal distances, demonstrated that placing appropriately designed obstacles near exits can alleviate congestion and enhance overall evacuation efficiency. Sun et al. [19] proposed a CTM capable of modeling inbound pedestrian flows by introducing static field-driven forces and transition probabilities, effectively simulating pedestrian clustering and flow evolution processes. The simulation results demonstrate that the model accurately characterizes the distribution trends of pedestrians and the variations in outflow proportions under different parameter conditions, providing a reference for optimizing the layout of entry areas and improving

traffic efficiency. Li et al. [20] based on the Cell Transmission Model, a pedestrian “yielding behavior” parameter is introduced to simulate the boarding and alighting process under bidirectional pedestrian flow at bottlenecks. Simulation results show that a properly set yielding parameter can alleviate congestion and reduce transfer time. Moreover, the study reveals that the “alight first, board later” rule is not always optimal, and captures pedestrian self-organization phenomena such as overflow outside the vehicle and queuing at door areas. Guo [21] proposed a dynamic pedestrian flow allocation model based on spatial potential field and proportional exchange mechanism, effectively simulating the large-scale evacuation process in a multi-exit environment. The model can identify local congestion and optimize path selection, and is applicable to the design of guiding sign systems and dynamic evacuation management. Zhang et al. [22] proposed an evacuation guidance optimization model based on the coupling of the simplified cellular transport model and the directed root forest (DRF), which significantly improved the computational efficiency of the dynamic guidance strategy in large-scale buildings. The numerical results show that this model performs excellently in shortening the evacuation time, balancing the load of each exit and improving the response speed of the evacuation plan, and has the potential for generating real-time guidance strategies

Although existing studies have investigated pedestrian evacuation behavior under fire scenarios using various modeling frameworks, applications of the Cell Transmission Model in this context remain relatively limited—particularly in integrating fire characteristics with guidance strategies. This study develops a pedestrian evacuation model under fire conditions based on CTM by incorporating a fire potential field and a static potential field to better characterize pedestrian behavior changes during emergencies. Numerical simulations are conducted to analyze the dynamics of pedestrian responses in fire scenarios. Furthermore, a signage-based guidance model is introduced by establishing a guidance potential field to simulate the influence of wayfinding cues. The model evaluates the impact of such guidance strategies on evacuation performance, providing insights into the effectiveness of signage deployment under fire-induced evacuation conditions.

2. Evacuation modeling considering panic factor

2.1. Model description

The Cell Transmission Model represents a discrete-time, discrete-space simulation methodology, widely employed in pedestrian evacuation and traffic flow analyses. In this study, we utilize an extended CTM to simulate pedestrian evacuation dynamics within a fire scenario. The core principle of the model involves discretizing space into a grid of cells, and simulating pedestrian movement through the interaction between these cells. The evacuation environment is discretized into hexagonal cells, each with a side length of 1 meter, resulting in a cell area of $3\sqrt{3}/2 m^2$. Each cell can accommodate multiple evacuees or remain unoccupied. At each discrete time step, pedestrians can either remain stationary or move based on the potential difference between cells. The population density within the evacuation environment is denoted as ρ . Upon fire ignition, the visual field of pedestrians is compromised, inducing a state of panic. Consequently, individuals tend to rapidly move away from the fire source, seeking evacuation exits. The presence of guidance signage can mitigate panic, facilitating a more efficient and directed evacuation towards safe exits.

2.2. Model construction and key mechanisms

Spatial discretization. In this model, the entire building space is discretized into regular hexagonal grid cells. Compared to traditional square grids, the hexagonal structure offers superior directional equilibrium and spatial continuity, enabling a more realistic representation of pedestrian movement in all directions. Each cell represents a minimal occupiable unit within the space, with a capacity set at 16 persons, indicating the maximum number of pedestrians that can be accommodated simultaneously. During each discrete time step, pedestrians can choose to move to one of the six surrounding adjacent cells. The direction of movement is determined by the potential energy difference and the diversion ratio of the current cell. The maximum flow between each pair of adjacent cells is limited to $Q = 10$, simulating the constraints on passage capacity due to spatial narrowness and localized congestion. Fig.1 illustrates the connection between the center of a hexagonal

cell and its six neighboring cells, along with the feasible movement directions.

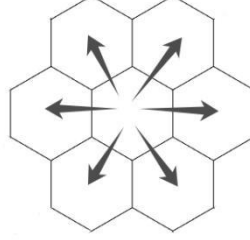


Fig. 1. Hexagonal cell structure and pedestrian movement directions.

Cellular potential. Pedestrian movement decisions are driven by cellular potential energy, which characterizes each cell's attractiveness to pedestrians and serves as a crucial basis for guiding their movement direction. The cellular potential energy within a spatially discretized room is referred to as the potential field. During movement, pedestrians must adhere to the rule of moving from high-potential-energy cells to low-potential-energy cells. In this model, the potential field comprises three components: the static potential field, the fire potential field, and the guidance potential field.

(1) Static Potential Field: The static cell potential quantifies the shortest distance from a cell to the target exit, escalating with the cell's separation from the exit. The computation of the static cell potential proceeds as follows:

Step 1: Let $k = 1$, for all non-exit cells, set $\overline{p}_i^e = 0$, for all exit cells, let $\overline{p}_j^e = 1$.

Step 2: For all cells i satisfying $\overline{p}_i^e = k$, check all neighboring cells j : if the neighboring cell j is connected to cell i and satisfies $\overline{p}_i^e = 0$, then assign $\overline{p}_j^e = k + 1$.

Step 3: Check all cells i , If $\overline{p}_i^e > 0$, proceed to Step 4; otherwise, set

$k = k + 1$ and return to Step 2.

Step 4: Let $k = 2$, For all cells i satisfying $\overline{p_i^e} = 1$, set $p_i^e = 1$.

Step 5: For all cells i satisfying $\overline{p_i^e} = k$, check all neighboring cells j ,
set $V_i^e = \{j \mid \text{It is connected to the cell and } \overline{p_j^e} = k - 1\}$, If the number of
elements in V_i^e is 1,

then $p_i^e = p_j^e + 1$; if the number of elements in V_i^e is greater than 1, then

$$p_i^e = \sum_{j \in V_i^e} \frac{p_j^e}{|V_i^e|} + \theta, \quad \theta \in (0,1], \text{ for this study let } \theta = 0.9.$$

Step 6: For all cells i , terminate if $k = \max(\overline{p_i^e})$; otherwise, set
 $k = k + 1$ and proceed to step 5.

Based on the computational methodology for the static potential field, the spatial distribution within the room remains invariant. p_i^e is solely contingent upon the distance of pedestrians from the building's designated egress points. Regions within the building's spatial domain that are in closer proximity to the exits exhibit a diminished static potential field, thereby facilitating pedestrian movement towards these areas.

(2) Fire potential field: The calculation method for the fire potential field is essentially similar to that of the static potential field. However, considering that pedestrians tend to move away from fire sources, the fire potential field is constructed following a descending gradient principle. Since both the static and fire potential fields influence pedestrian movement, the potential value at the fire's origin is set to the maximum value $\max(\overline{p_i^e})$ of the static potential field. This ensures that pedestrians will tend to avoid the fire source during the evacuation process. Let p_i^f represent the fire potential value of cell i

relative to the fire location. Based on the above description, the computation of the fire potential field proceeds as follows:

Step 1: Set $k = \max(p_i^e)$, for all non-fire source cells, set $\overline{p_i^f} = 0$, for all fire source cells, set $\overline{p_j^e} = 1$.

Step 2: For all cells i satisfying $\overline{p_i^f} = k$, check all neighboring cells j : if the neighboring cell j is connected to cell i and satisfies $\overline{p_i^f} = 0$, then assign $\overline{p_j^f} = k - 1$.

Step 3: Check all cells i , If $\overline{p_i^f} > 0$, proceed to Step 4; otherwise, set $k = k - 1$ and return to Step 2.

Step 4: Let $k = \max(p_i^e) - 1$, For all cells i satisfying $\overline{p_i^f} = k$, set $p_i^f = k$.

Step 5: For all cells i satisfying $\overline{p_i^f} = k$, check all neighboring cells j , set $V_i^f = \{j \mid \text{It is connected to the cell and } \overline{p_j^f} = k - 1\}$, If the number of elements in V_i^f is 1, then $p_i^f = p_j^f - 1$; if the number of elements in V_i^f is greater than 1,

then $p_i^e = \sum_{j \in V_i^e} \frac{p_j^e}{|V_i^e|} - \theta$, $\theta \in (0,1]$, for this study let $\theta = 0.9$.

Step 6: For all cells i , terminate if $k = \min(\overline{p_i^f})$; otherwise, set $k = k - 1$ and proceed to step 5.

According to the above calculation procedure of the fire potential field, once the location of the fire source is determined, The distribution of the fire potential field in the built environment does not change with the time step. The closer a location is to the fire source, the higher its fire potential value,

and the stronger the pedestrians' tendency to avoid that area.

(3) Guidance potential field: The guiding potential energy field reflects the guiding effect of guiding signs on the evacuation behavior of pedestrians. Guiding signs have a certain appeal to pedestrians. The closer pedestrians are to the guiding signs, the lower the guiding potential energy value at their location, making the area more attractive to pedestrians and prompting them to move towards the safety exit. The calculation of the guiding potential energy field is based on the following principle: Each guiding sign is regarded as a "secondary target", and the role of the guiding potential energy is to make pedestrians move in the direction of the guiding sign and then indirectly guide them to the safety exit. In this paper, the same expansion algorithm as the static potential energy field is adopted. Starting from the guiding sign as the initial point, potential energy values are gradually assigned to the surrounding cells. The potential energy values increase as the distance from the guiding sign increases. It is worth noting that if there are multiple guiding signs in the scene, the minimum potential energy field generated by all guiding points is taken as the superimposed field to ensure that each pedestrian is affected by the nearest guiding sign. The potential value of the guidance potential field is denoted by p_i^g .

Evacuation model considering panic factor and parameter settings. Pedestrians are highly sensitive to both the location of fire sources and the location of exits. The closer a pedestrian is to the fire source, the higher their level of panic; conversely, the farther a pedestrian is from the fire source and the closer they are to a safe exit, the lower their panic level. Panic levels also evolve dynamically over time. The following equation describes the temporal evolution of panic levels:

$$K_i(t) = D \times \frac{1 - \exp(-\alpha l_e)}{1 + \exp(\alpha l_f)} \times \exp(-t\beta) \quad (1)$$

Where $K_i(t)$ denotes the panic level of a pedestrian. The parameter D (global panic levels) regulates the overall fluctuation range of panic levels among pedestrians and is defined within the range $[0, 10]$. Parameters l_e, l_f

represent the distances between a pedestrian and the nearest exit, and between the pedestrian and the fire source, respectively. α is a tuning coefficient that balances the influence of the fire source and the exits on pedestrian decision-making, ensuring both have comparable magnitudes of impact. t represents the simulation time step, while β is the time sensitivity coefficient, governing the dynamic evolution of panic. In this model, the parameters are set as follows: $D = 9$, $\alpha = 0.05$, and $\beta = 0.03$.

The panic level directly influences the weighting factors of the static potential field and the fire potential field. The adjustment mechanism is defined as follows:

$$K_i^e(t) = \exp(-\alpha K_i(t)), \quad K_i^f(t) = 1 - K_i^e(t) \quad (2)$$

Where $K_i^e(t)$ represents the weighting factor of the static potential field, and

$K_i^f(t)$ represents the weighting factor of the fire potential field. The parameter α is the sensitivity coefficient of panic emotion, which is set to 0.5 in this model. At each time step, the sensitivity coefficients of the static and fire potential fields dynamically change according to the variation in panic level. When the panic level increases, $K_i^e(t)$ decreases, indicating that pedestrians have more difficulty making rational decisions and thus exhibit reduced evacuation performance. Conversely, $K_i^f(t)$ increases, implying that panicked pedestrians are more inclined to prioritize avoiding hazardous areas during evacuation.

(1) Panic pedestrian movement model without signage guidance: By coupling the static potential field and the fire potential field, the combined potential field influencing pedestrian movement is expressed as:

$$p_i(t) = K_i^e(t)p_i^e + K_i^f(t)p_i^f, \quad K_i^e(t) + K_i^f(t) = 1 \quad (3)$$

Where $K_i^e(t)$ denotes the weight influence factor of the static potential field,

and $K_i^f(t)$ denotes the weight influence factor of the fire potential field, both

ranging within the interval (0,1]. Since both fields jointly influence pedestrian movement, their respective weight factors are constrained to sum to 1.

(2) Panic pedestrian movement model with signage guidance: In the model, the guidance signage becomes effective at 6 seconds after the fire outbreak. After the introduction of the guidance signage, the movement of panicked pedestrians is influenced by the static potential field, the fire potential field, and the guidance potential field. Accordingly, the combined potential influencing pedestrian movement is given as:

$$p_i(t) = \overline{K}_i^e(t)p_i^e + \overline{K}_i^f(t)p_i^f + \overline{K}_i^g(t)p_i^g, \quad \overline{K}_i^e(t) + \overline{K}_i^f(t) + \overline{K}_i^g(t) = 1 \quad (4)$$

where $\overline{K}_i^e(t)$, $\overline{K}_i^f(t)$, and $\overline{K}_i^g(t)$ represent the weighting factors of the static potential field, the fire potential field, and the guidance potential field after guidance is introduced, respectively. All three weighting factors take values in the range (0,1] and are subject to the constraint that their sum equals 1. Due to the influence of the guidance potential field, these weighting factors are adjusted after guidance is applied. The updated weighting factors are calculated as follows:

$$\overline{K}_i^e(t) = \exp(-a\overline{K}_i(t)), \quad \overline{K}_i^f(t) = [1 - \overline{K}_i^e(t)] \cdot (1 - \gamma), \quad \text{and} \quad \overline{K}_i^g(t) = [1 - \overline{K}_i^e(t)] \cdot \gamma \quad (5)$$

where $\overline{K}_i(t)$ denotes the panic level of pedestrians after receiving guidance.

Under the influence of the guidance signage, the panic level of pedestrians is reduced accordingly. γ is the guidance influence coefficient, representing the extent to which guidance affects pedestrian decision-making. The value of γ ranges within (0,1], and in the model, γ is set to 0.6.

2.3. Movement rules

In the model, pedestrian movement follows the basic principle of "moving from higher potential to lower potential." At each time step, pedestrians determine the outflow proportions in each of the six neighboring directions based on the potential differences between the current cell and its adjacent cells, and then redistribute accordingly. However, actual pedestrian flow is not solely determined by individual intention; it is also constrained by cell capacity, the available space in neighboring cells, and boundary flow

capacity. Therefore, the model distinguishes between the theoretical outflow (i.e., the potential number of pedestrians transferring based on the calculated outflow proportions) and the actual outflow (i.e., the realizable number of pedestrians transferring under spatial and capacity constraints). By integrating theoretical behavior with realistic constraints, the model more accurately captures the dynamic evolution of the evacuation process.

Calculation of outflow proportions. Let Ω represent all cells in the walking space, and let R_i denote a downstream cell of cell i . Let $n_i(t)$ be the number of pedestrians in cell i at time t , and let $\varphi_{ij}(t)$ denote the proportion of pedestrians in cell i who intend to move to the downstream cell j during that time step. At each time step, the number of pedestrians in each cell is updated in parallel based on these outflow proportions. The outflow proportion $\varphi_{ij}(t)$ from cell i to cell j at time t is proportional to the potential difference $p_i(t) - p_j(t)$ between the two cells:

$$\varphi_{ij}(t) = \frac{p_i(t) - p_j(t)}{\sum_{k \in R_i} (p_i(t) - p_k(t))}, \quad \forall i \in \Omega, j \in R_i, t = 0, 1, 2, \dots \quad (6)$$

Calculation of theoretical outflow. Let $w_{ij}(t)$ denote the theoretical number of pedestrians that can move from cell i to its adjacent downstream cell j during that time step. The theoretical outflow is calculated as follows:

$$w_{ij}(t) = \min [\varphi_{ij}(t)R_i(t), Q_{ij}] \quad (7)$$

$R_i(t)$ represents the total theoretical number of pedestrians flowing from cell i to the downstream cells, while Q_{ij} denotes the maximum flow capacity along the shared edge between cell i and cell j .

Calculation of actual outflow. Although the upstream cell can supply a certain number of pedestrians to the corresponding downstream cell, not all of these pedestrians can successfully move into the downstream cell. The actual outflow must also take into account the receiving capacity of the

downstream cell, that is to say, its remaining available capacity. Consequently, at time step, the number of pedestrians successfully flowing from cell i to a downstream cell j is proportional to the theoretical outflow from cell i towards j and the remaining capacity of the target downstream cell, the actual outflow volume is expressed as:

$$y_{ij}(t) = \min \left(w_{ij}(t), \frac{N_j(t) - n_j(t)}{\sum_{k \in S_j} w_{kj}(t)} w_{ij}(t) \right) \quad (8)$$

Where S_j denotes the upstream cell of cell j , $N_j(t) - n_j(t)$ denotes the residual capacity of cell j .

Pedestrian count update. Based on the above, the number of pedestrians in cell i at time $t+1$ is determined by three components: the number of pedestrians in cell i at time t , the actual number of pedestrians flowing into cell i from its adjacent upstream cells, and the actual number of pedestrians flowing out from cell i to its adjacent downstream cells. The population of cell i at time $t+1$ is then determined as

$$n_i(t+1) = n_i(t) + \sum_{k \in S_i} y_{ki}(t) - \sum_{j \in R_i} y_{ji}(t) \quad (9)$$

With the above components, the cell transmission model for fire scenarios has been fully formulated, offering a theoretical basis for analyzing pedestrian evacuation behavior under fire conditions.

3. Simulation experiment

Taking a specific studio as an example, the simulation scenario is shown in Fig.2. The entire room is divided into $11 \times 19 + 10 \times 20$ cells, with each cell having a specified edge length $l = 1\text{m}$. Two exits are located on the north wall, each with a width of $\sqrt{3}\text{m}$. The maximum capacity of each cell is $N=16$, and the maximum flow capacity along the shared edge between two adjacent cells is $Q=10$. Each time step is 1.2 seconds, which means the movement speed of the pedestrian is $v=1.44\text{ m/s}$. Initially, pedestrians are uniformly distributed throughout the scenario.

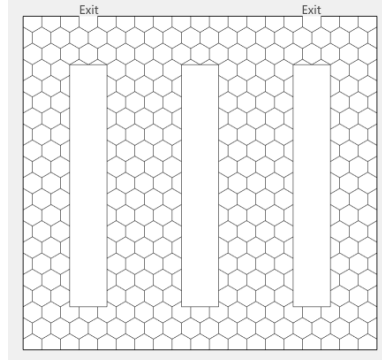


Fig. 2. Simulation scenario

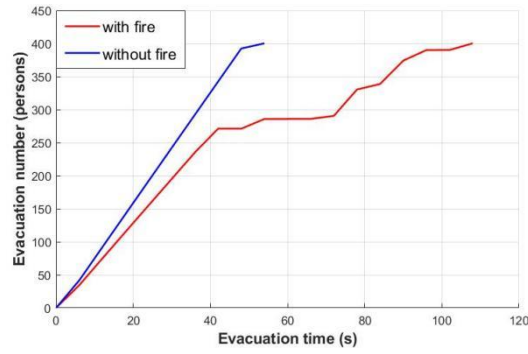


Fig. 3. Comparison of pedestrian evacuation under fire and non-fire scenarios

3.1. Effects of fire on pedestrian evacuation dynamics

The initial pedestrian distribution and the location of the fire source are shown in Fig.2. The fire source is placed at the center of the scenario, with two exits located at the top of the scene. Pedestrians are uniformly distributed across the space, with an initial density of 0.5 persons/m². At the initial evacuation moment, the positions of different individuals vary, and their spatial distances from safety exits and fire sources are not the same. Moreover, panic emotions are greatly influenced by environmental factors, so there are significant differences in the initial panic values among individuals. Fig. 4 shows the spatial distribution of panic emotion levels of individuals within each cell at the initial moment. The values are calculated by Eq (1), providing key support for the subsequent calculation of potential energy weight factors

and the modeling of evacuation behaviors based on emotional states.

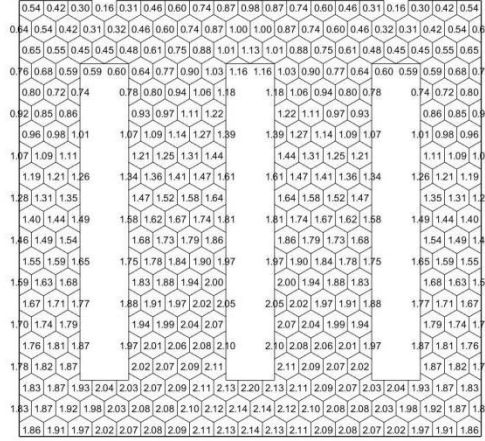


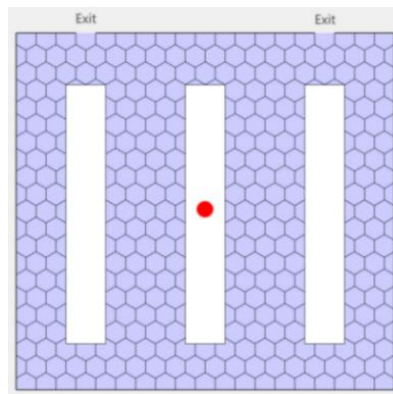
Fig. 4. Distribution map of initial panic values of different cells

Since pedestrians unaffected by fire follow an evacuation strategy based solely on the location of the exits, while those under fire influence adopt strategies that also aim to avoid the fire source, the evacuation time under fire conditions is expected to be longer than that under non-fire conditions.

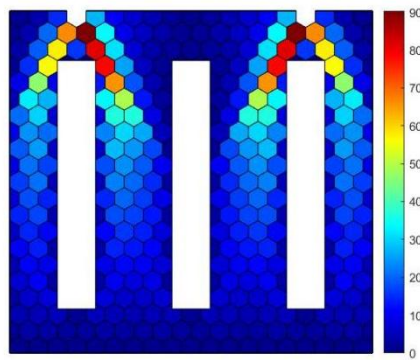
Fig.3 illustrates the change in the number of evacuated pedestrians over time under different conditions, the evacuation speed in the "no fire" scenario (blue line) is significantly faster than in the "fire" scenario (red line). During the initial stage, both scenarios exhibit similar evacuation rates. However, in the following stages, the number of evacuees in the no-fire condition increases rapidly, while the evacuation rate in the fire scenario gradually slows down and fluctuates in the later phase. These results indicate that fire significantly impairs evacuation efficiency, potentially causing congestion or changes in pedestrian behavior, thereby slowing the overall evacuation process.

The number of steps taken by pedestrians across each cell can effectively reflect their movement patterns. To further explore how rescue guidance affects pedestrian evacuation routes under fire conditions, we generated heatmaps showing the number of steps each cell was traversed by pedestrians. Fig.5 (b), (c), and (d) present the heatmaps under three different scenarios. By comparison, it can be observed that when a fire occurs, pedestrians tend to

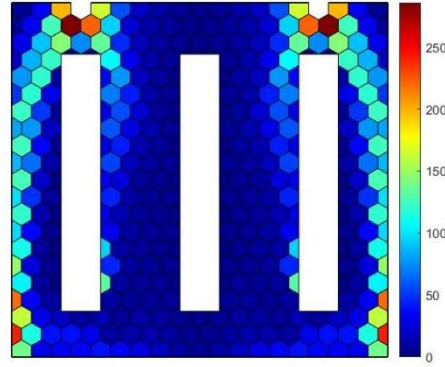
avoid hazardous areas, which affects evacuation efficiency. After the introduction of guiding signs, pedestrians experience a reduction in panic, gain a clearer understanding of exit locations, and adjust their movement trajectories to reach the exits more quickly. Nevertheless, the fire remains present during the evacuation, so pedestrians are still subject to a certain degree of fire-induced influence while moving.



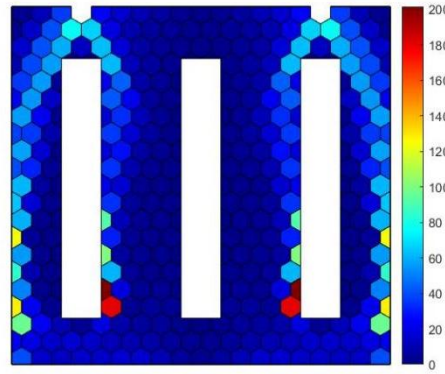
(a)



(b)



(c)



(d)

Fig. 5. Heatmaps of the number of steps a pedestrian takes across each cell: (a) Initial pedestrian distribution and fire source location; (b) Pedestrian traversal heatmap under the no-fire scenario; (c) Pedestrian traversal heatmap under the fire scenario; (d) Pedestrian traversal heatmap with signage guidance under fire conditions.

3.2. Impact of fire source location on pedestrian evacuation efficiency

Sudden events are characterized by significant randomness and unpredictability. Fire, as a typical public safety emergency, presents a high level of uncertainty regarding both its occurrence time and spatial location within a room. To investigate the specific impact of fire source location on pedestrian evacuation efficiency, four typical fire source location scenarios were designed (as shown in Fig.6), with the fire sources placed at different

distances from the safety exits, labeled as locations A, B, C, and D. By comparing and analyzing the evacuation process and the final evacuation completion time in each scenario, the influence of fire source location distribution on evacuation efficiency is assessed.

In the simulation, the initial pedestrian density is set to 1 person/m² to reflect the common pedestrian flow state in buildings with medium density. Fig.7 shows the total time required for pedestrians to complete evacuation under different fire source location settings. The results indicate that when the fire source is located near the center of the room or far from the exit, the evacuation time is relatively shorter. However, when the fire source is positioned near the main exit (such as locations C or D), the evacuation time is significantly extended.

This result suggests that the fire source location directly affects both evacuation paths and psychological decision-making. When the fire occurs near the exit area, certain passageways experience congestion, reducing the effective evacuation capacity of the exits. Additionally, due to the high-risk environment near the exit, pedestrians are hesitant to approach or are forced to change their original paths, leading to increased congestion and reduced overall system efficiency. Furthermore, fire sources located near exits are more likely to trigger panic responses among pedestrians, causing them to choose longer, detouring escape routes, further extending the evacuation time.

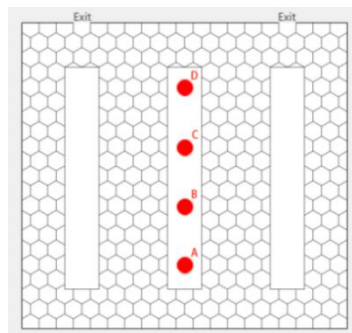


Fig. 6. Four fire source location settings

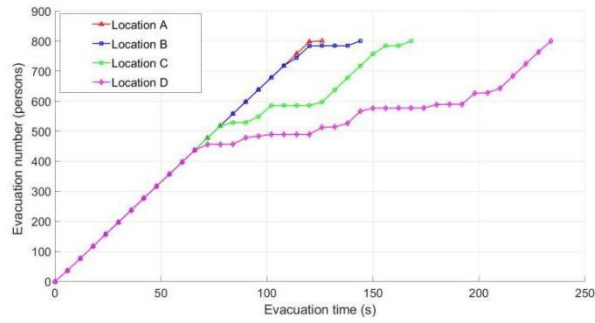
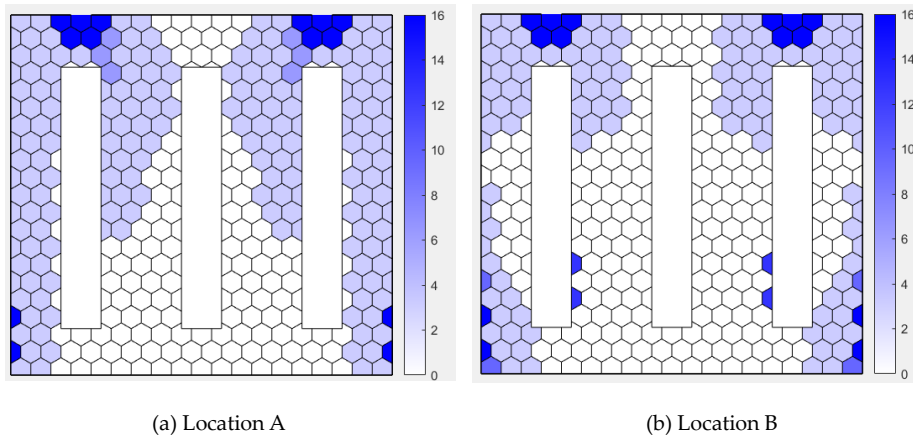


Fig. 7. Evacuation line chart for different fire source locations

To further explore the specific impact of fire source location on local congestion and pedestrian stagnation during the evacuation process, this study analyzes the distribution of pedestrians within the room at 15 seconds after the fire occurs, under different fire source arrangements. This time point corresponds to a stage where the fire has significantly influenced the pedestrian evacuation paths, effectively reflecting the impact of fire source location on evacuation path blockage, pedestrian clustering, and the distribution of trapped areas.



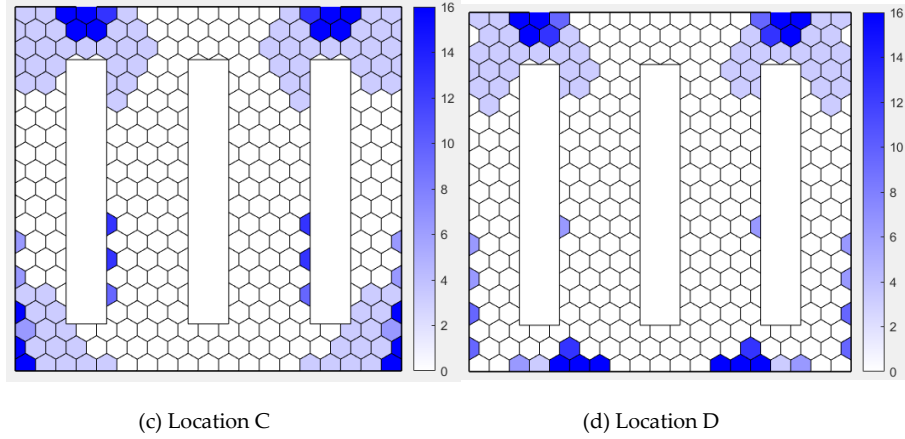


Fig. 8. Pedestrian distribution in the room at 15 seconds after fire occurrence for different fire source locations

Fig.8 shows the pedestrian distribution in the room at 15 seconds after the fire occurrence for different fire source locations. The results indicate that when the fire source is located near the exit, the evacuation paths of pedestrians are significantly obstructed, leading to clustering effects in the corners and along the walls of the room. This phenomenon suggests that a fire source near the exit not only exacerbates congestion in local areas but may also cause pedestrians to become stationary or seek refuge in place when the passability is limited, thus reducing overall evacuation efficiency. In contrast, when the fire source is positioned farther from the exit, the extent of path restriction is lower, allowing pedestrians to converge toward the exit more quickly. The clustering areas are relatively dispersed, and the proportion of stranded pedestrians significantly decreases. This comparison further validates the significant impact of the fire source location on evacuation order and efficiency.

In summary, the closer the fire source is to the safety exit, the greater its interference with evacuation paths and the stronger its impact on the spread of panic, thus significantly reducing evacuation efficiency. Therefore, in practical building safety design and emergency response planning, special attention should be given to fire prevention and early response mechanisms in areas near major evacuation routes and exit zones.

3.3. Impact of signage guidance on evacuation efficiency

In real evacuation scenarios, factors such as complex building layouts, reduced visibility (e.g., smoke obstructions), and high crowd density often make it difficult for pedestrians to make optimal escape decisions in a timely manner. This can lead to blind path choices, congestion in local areas, and severely impact overall evacuation efficiency. Therefore, setting up appropriate signage guidance becomes one of the key measures to improve emergency evacuation efficiency.

To explore the impact of guide signs placement on the evacuation process, this study introduces a "Guide Potential Field" mechanism based on guide weights. In the model, guide signs influence pedestrians' potential energy judgment in the evacuation scenario by providing clear directional information, guiding them toward better paths. Especially in areas with high levels of panic, this can effectively suppress irrational movement behaviors and improve the overall organization and coherence of the evacuation process. The placement of guide signs is shown in Fig.9.

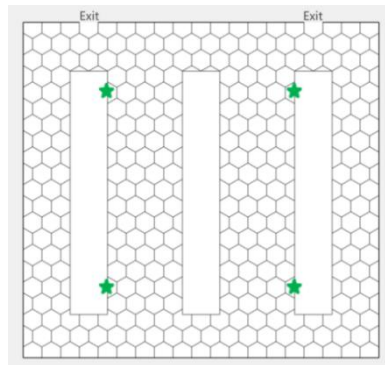


Fig. 9. Guide signs placement diagram

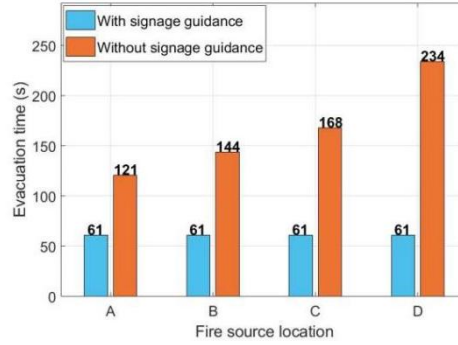


Fig. 10. Comparison of evacuation times for different fire source locations

This study sets up two comparative experimental scenarios: without guide signs and with guide signs. Under the same initial crowd density (0.5 person/m²), fire source location, and model parameters, comparative simulation experiments were conducted. The simulation results are shown in Fig.10. Under the condition of having guide signs, the overall evacuation time was significantly shortened. Without guide signs, some pedestrians, stimulated by the fire, became panicked, resulting in irrational behaviors such as blindly following others and clustering in corners. This led to disordered evacuation paths, congested passages, and decreased efficiency. However, after the introduction of guide signs, pedestrians were able to quickly obtain evacuation direction information, improving decision-making efficiency, alleviating emotional fluctuations, and accelerating the evacuation process. Additionally, guide signs enhanced pedestrians' awareness of the environment, making their evacuation behavior more rational and effectively preventing local confusion caused by information asymmetry.

To further explore the applicability and effectiveness of guide signs in the pedestrian evacuation process, this study set multiple initial pedestrian density levels (0.5 person/m², 1 person/m², and 1.5 person/m²) based on the introduction of guide signs, and analyzed the changes in evacuation efficiency under guide intervention. The fire source was located in the center of the scene, as shown in Fig.4 (a). Fig.11 shows the evacuation times with and without guide signs under different pedestrian density levels. The experimental results indicate that guide signs can effectively improve overall

evacuation efficiency. Particularly in low and medium-density scenarios, guide signs optimized path selection and dispersed crowd flow, significantly reducing the risk of local congestion and improving evacuation orderliness and coherence. Although under high-density conditions, the guiding effect was limited by spatial bottlenecks and the inertia of crowd behavior, and the efficiency improvement was relatively small, it still helped to alleviate chaotic conditions and delayed the deterioration of evacuation efficiency. This indicates that guide signs, as a low-cost and highly adaptable intervention, show good application potential in complex density scenarios and are one of the important strategies for improving evacuation efficiency. Therefore, in practical applications, guide strategies should be dynamically adjusted based on density distribution characteristics to achieve more precise and efficient intervention guidance.

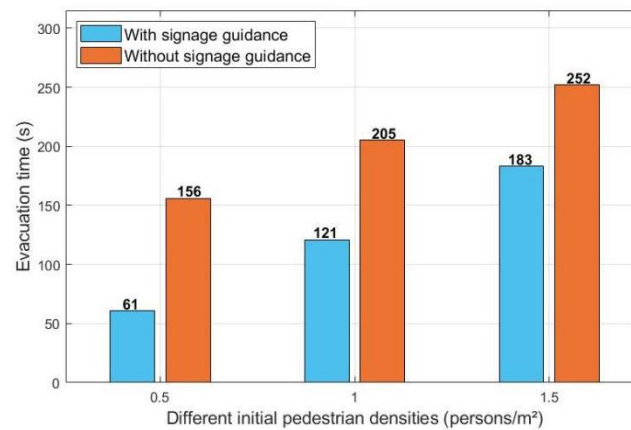


Fig. 11. Comparison of evacuation times at different pedestrian densities

4. Conclusion

This study develops a pedestrian evacuation model for fire scenarios based on an extended Cell Transmission Model, incorporating a fire potential field, a static potential field, and a guidance potential field to account for panic behavior and signage effects. Through numerical simulations, we examine the

impacts of fire presence, fire source location, and guidance signage on evacuation performance. The simulation results indicate the following:

(1) Fire conditions lead to longer evacuation times compared to non-fire scenarios. The presence of fire induces heightened panic, which tends to increase irrational movement and local clustering, thereby reducing overall evacuation efficiency.

(2) The location of the fire source plays a critical role in evacuation efficiency. When the fire is positioned near the main exits, evacuation paths are more severely obstructed, and pedestrian flow becomes more congested, resulting in longer completion times. Conversely, fire sources farther from exits cause relatively less disruption. However, the magnitude of this effect is contingent on the specific spatial layout and pedestrian density, and should not be generalized without further validation.

(3) The introduction of signage guidance, modeled via a guidance potential field, shows a positive effect on evacuation efficiency in our simulations. With guidance, pedestrians exhibit more directed movement, reduced clustering, and shorter evacuation times across different density levels. The improvement is more pronounced at low and medium densities, while under high-density conditions, the benefit is constrained by spatial bottlenecks and the inertia of crowd movement.

While these results demonstrate the potential utility of the proposed model, several limitations must be acknowledged. First, the model assumes a fixed fire growth pattern and does not consider dynamic changes in fire intensity, smoke spread, or visibility degradation over time, which may substantially alter pedestrian behavior in reality. Second, the panic formulation is phenomenological and relies on several empirical parameters that are calibrated based on literature rather than direct experimental data from real fire evacuations; their generalizability across different populations and building geometries remains untested. Third, the simulation scenarios are limited to a single room with two exits and a moderate number of pedestrians; the model has not been validated against empirical data from large-scale, multi-compartment buildings or real-world fire drills. Finally, the model does not account for interactions such as herding, leader-follower dynamics, or physical contact forces, which may be critical under high-density panic conditions.

Therefore, the conclusions drawn from this study should be interpreted as indicative rather than predictive. The model provides a useful framework for exploring qualitative trends and generating hypotheses, but direct quantitative application to real-world evacuation planning requires further calibration, validation, and integration with more detailed fire dynamics and human behavior models. Future work should focus on empirical validation, sensitivity analysis of key parameters, and extension to multi-source fires and dynamic guidance strategies.

Funding

This research was funded by the General Program of the Inner Mongolia Autonomous Region Natural Science Foundation, grant number 2024MS07002 and the Key Research and Achievement Transformation Program Projects of Inner Mongolia Autonomous Region, grant number 2025YFHH0215.

Disclosure of Interests

The authors have no competing interests to declare that are relevant to the content of this article.

Author contributions

Na Li: Writing – review & editing, Methodology. **PengChang Li:** analysis and interpretation of results. **XiaoChuan Zhao:** Writing – original draft.

Data availability

All data generated or analysed during this study are included in this published article.

Additional information

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