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Research article

The study on mechanical model considering optimal self-adaption in the bottleneck area☆

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ABSTRACT

It aims to solve the problem that the evacuation state of pedestrians depicted by the traditional social force model in a crowded multiexit scenario has a relatively large difference with the actual state, especially the 'optimal path' considered by the self-driving force is the problem of shortest path, and the multiexit evacuation mode depicted by the 'herd behavior' is the local optimum problem. Through in-depth analysis of actual evacuation data of pedestrians and causes of problem, a new crowd evacuation optimization model is established in order to effectively improve the simulation accuracy of crowd evacuation in a multi-exit environment. The model obtains the direction of motion of pedestrians using a field model, fully considers the factors such as exit distance, distribution of pedestrians and regional crowding degree, makes a global optimization for the self-driving force in the social force model using a centralized and distributed network model, and makes a local optimization for it using an elephant herding algorithm, so as to establish a new evacuation optimization method for optimal self-adaption in the bottleneck area. The performance status is compared between the improved social force model and the new model by experiments, and the key factors that affect the new model are analyzed in an in-depth manner. The results show that the new model can optimize the optimal path choice at the early stage of evacuation and improve the evacuation efficiency of pedestrians at the late stage, so as to ensure relatively even distribution of pedestrians at each exit, and also make the simulated evacuation process be more real; and the improvement in overall evacuation efficiency is greater when the number of pedestrians to be evacuated is larger. Therefore, the new model provides a method to solve the phenomenon of disorder in overall pedestrian evacuation due to excessive crowd density during the process of multi-exit evacuation.

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1. Introduction

In recent years, stampede accidents have occurred frequently, especially the stampede in Seoul, South Korea, that caused heavy casualties and property losses, and therefore the study of pedestrians and evacuation dynamics has become the focus of scholars at home and abroad, and the study of crowd evacuation plays an important role in ensuring the controllability of the stampede and reducing the accident casualty [1]· During evacuation, the motion dynamics of human in a crowded building environment is affected by the interaction between individuals and the physical environment, especially when the geometric space for motion is restricted and people are relatively more. In the case of multiexit scenario and relatively high density, the planned optimal path is affected by the degree of crowding of the current area and evacuation space, the positions of different exits, and the distribution of people at different exits, which has an important influence on the overall evacuation time and evacuation efficiency. Therefore, for effective crowd evacuation, it becomes particularly important to discuss the changes in the relationship among evacuation time, evacuation efficiency, and optimal path in a multiexit environment by considering the crowding degree and exit utilization rate in the bottleneck area.

At present, a simulation model is established for studying the characteristics of crowd behavior. It effectively depicts the interaction among individuals, which mainly includes a continuous model and a discrete model. The continuous model is typically represented by social force model(SFM) [2–8] and the discrete model is typically represented by the cellular automata model(CAM) and lattice gas model(LGM) [9–17]. While Helbing et al. [18] early studied the formation mechanism of phenomena such as "fast is slow" and "arching" as well as changes in crowd behavior characteristics in the pedestrian evacuation process using the social force model. Li Shiwei et al. [19,20], combined with difference of crowd in the direction visible range selection of the crowd, improved the cellular automaton model based on the blurred visible range of the walking direction and the density of exit pedestrians, to avoid influencing the weights of factors related to transfer probability. Zhang Lei et al. [21,22] depicted the action effects of the crowding force on individual pedestrians, and the absorption and resistance effects of the crowding force in the transfer process using the effect of the crowding force, the resultant force parameter, the absorption coefficient and the anti-casualty coefficient, to improve the evacuation model of cellular automatons. Li Qiaoru et al. [23] considered the situation in which pedestrians are not familiar with the evacuation environment, namely pedestrians can't specify the exit position, and compared the choice of path and evacuation strategy of pedestrians when the evacuation information is complete and not complete by dividing the evacuation space into different areas and using the improved "social force model". Huo Feizhou et al. [24] introduced the concepts of pedestrian crowding, support, and friction with reference to the social force model, designed an extended cellular automaton model to study the behaviors of pedestrian stampede, explored the phenomena of stampede in the pedestrian evacuation process in public places, and discussed the effects of pedestrian density, pedestrian distribution way, exit setting, exit obstacles, etc. on the evacuation results. Chen Zehao et al. [25,26] studied the pedestrian evacuation dynamics in a single exit square room and found that individual interests mightcould positively or negatively affect evacuation dynamics, depending on whether it can promote the formation of collective cooperation or not, and also discussed the effects of placing obstacles before exit and diversified spatial competition responses of pedestrians on evacuation dynamics. Nicolas Andries Tio et al. [27] successfully reproduced an evacuation drill using the improved social force model and developed a new library to simulate the dynamics of pedestrian flow, where competitive behavior is a key factor for the "the faster, the slower" effect as lack of competitive behavior can inhibit the effect of 'the faster, the slower'. Zi Shahoseini et al. [28] studied the role of spatial constraint layout and the influence of the motion velocity level on the evacuation performance of pedestrian facilities, especially for the dense crowd. Under specific geometric constraints, it has a lgreater possibility to form a jam (that is, a longer queue or a longer time interval between two consecutive pedestrians passing through). By inspection of trajectory model, it shows that this may be attributed to the degree to which two streams have to mix with each other, so as to be able to merge and share space. Some layouts, especially symmetrical ones, allow two streams to remain separate after entering the shared space, and other settings generate a more obvious mixture of motion trails so that the two streams can penetrate through the shared area. Sun Yutong et al. [29] established a density navigation field model based on an equal potential field and proposed a density navigation algorithm to guide target selection during the crowd movement process by calculating the density factor and the distance factor. By combining the density evacuation algorithm with the social force model, the crowd evacuation simulation was made using a two-layer mechanism to effectively improve the crowd evacuation efficiency. Tvarogovska et al. [30] used a hybrid finite volume-finite element method to solve the problem and conducted error analysis on solver, gradient algorithm and second-order model to obtain the first-order convergence, demonstrating that Hughes' model cannot reproduce the complex crowd dynamics, such as stop-and-go waves and jam at bottleneck. Miyagawa et al. [31] developed a multi-grid cellular automaton model to study the effects of sidling and the starting evacuation process, showing that turning behavior makes the escape time shorter and moderate turning velocity is the best choice for evacuation. Lv Wei et al. [32] established a mesoscopic cellular automaton model for personnel evacuation that is applied to a large-scale personnel evacuation scenario according to the motion characteristics of pedestrian flow, which can analyze the macroscopic evacuation situation within the scenario and observe the state changes of individual cells. Zhang Dezhen et al. [33] established a pedestrian multi-exit selection model based on the social force model considering the distance between pedestrian and exit, pedestrian density near exit, and width of exit, to carry out a simulation analysis for the effects of pedestrian density near exit and width of exit. Yue Furong et al. [34] established a microscopic meta-automata cellular automaton simulation model that considers the motion behaviors of pedestrians on escalator, and simulated the isolation situation under different pedestrian motion velocities, queuing ways and different escalator velocities, and studied the actual traffic capability of escalator under different pedestrian motion ways. A. M L et al. [35] found that evacuation staff motion speed of the evacuation personnel plays a crucial role in balancing egress time and safety. Thus, it is expected that by instructing the evacuation staff to move at a predefined speed, it can achieve the desired balance between evacuation time, probability of accident, and comfort. Li Kun et al. [36] found that appropriate layout of two obstacles not only helps to remove the bottleneck near the exits, but also controls the pedestrian speed to achieve the best global evacuation efficiency. But when obstacles are placed asymmetrically, an inappropriate offset parameter may seriously hinder the evolution of evacuation dynamics. However, the 'optimal path' planned by the field value of the traditional social force model is just the shortest path, which doesn't consider factors such as exit distance, number of exits and degree of regional crowding. In the situation of mass pedestrian flow evacuation, it will cause congestion or uneven distribution of people at each exit and other problems if 'herd behavior' appears or pedestrians evacuate toward the same exit, thus reducing evacuation efficiency and resulting in the existence of hidden safety hazards.

In conclusion, there are few related studies in the existing literature in multiexit areas that only consider the factors of path congestion and then improve the traditional model to optimize its evacuation index. However, there are many factors affecting pedestrian movement in multiexit environment, and it is easy to fall into the optimal layout when considering a single factor. Therefore, the field model can be used as a basis for choosing the direction of people's self-driving force. In the process of evacuation, considering the distance and number of exits, the distribution of people in the exit area and the local congestion, the field model can be modified in real time by using the distributed network model and the image group algorithm, so that people can choose the optimal path, and finally the global effective optimal evacuation scheme can be realized and the evacuation index can be improved.

2. Improved social force model

The social force model is characterized by microscopicity, continuity, etc., which is widely applied in pedestrian flow. The social force model is mainly composed of three forces, among them, F_q is the driving forced suffered by pedestrian; F_w is the acting force between pedestrian and obstacle; and F_p is the acting force among pedestrians. The specific expression of the social force model is as follows:

$$\overrightarrow{F} = \overrightarrow{F_q} + \overrightarrow{F_w} + \overrightarrow{F_p} \tag{1}$$

The improved social force model divides the repelling forces among pedestrians into the following three situations: outside the influence range; within the influence range and non-intersecting; intersecting and not more than the maximum extrusion degree. For the repelling forces among pedestrians outside the influence range, it can be ignored; and for the repelling forces among pedestrians that are within the influence range and nonintersecting, the formula is expressed as follows:

$$\overrightarrow{F_p} = A \cdot \frac{e^R - d}{B} \cdot \overrightarrow{n_t} \tag{2}$$

For the repelling forces that are intersecting and not more than the maximum extrusion degree, the formula is expressed as below:

$$\overrightarrow{F_p} = A \cdot \frac{e^R - d}{B} \cdot \overrightarrow{n_t} + Kg \cdot [R - d] \cdot \overrightarrow{n_t} + kg \cdot [R - d] \cdot \overrightarrow{v_t} \cdot t \tag{3}$$

Where, $\overrightarrow{v_t}$ is relative velocity in the tangential direction; t is vector in the tangential direction; Kg is coefficient of human body flexibility; kg is coefficient of sliding friction; R is sum of two pedestrian radii; d is centroid distance between two pedestrians; A is intensity of social force among pedestrians; B is coefficient of pedestrian action range; and $\overrightarrow{n_t}$ is vector of direction that a pedestrian points to other pedestrians.

The repelling forces between pedestrians and obstacles are similar with that among pedestrians, which can be divided into the following three cases; among them, the optimization formula for the repelling forces that are within the influence range and nonintersecting is as follows:

$$\overrightarrow{F_w} = A \cdot \frac{e^{R_w} - d_w}{B} \cdot \overrightarrow{n_w} \tag{4}$$

The formula for the repelling forces that are within the influence range and non-intersecting is as follows:

$$\overrightarrow{F_w} = A \cdot \frac{e^{R_w} - d_w}{B} \cdot \overrightarrow{n_w} + Kg \cdot [R_w - d_w] \cdot \overrightarrow{n_w} + kg \cdot [R_w - d_w] \cdot \overrightarrow{v_w} \cdot t \tag{5}$$

Where, R_w is radius of a pedestrian (radius of the nearest mass point on an obstacle can be ignored); d_w is distance between a pedestrian and the nearest mass point on an obstacle; v_w is relative velocity in the tangential direction; and $\overrightarrow{n_w}$ is vector of direction that the nearest mass point on an obstacle points to a pedestrian.

The calculation formula of self-driving force F_q is as shown in Eq. (6), where F_q (magnitude of self-driving force) and $\overrightarrow{E_q}$ (expected velocity direction) are the key points for optimization of the traditional social force model.

$$\overrightarrow{F_q(t)} = m_a \frac{\left(v_0(t)\overrightarrow{E_q(t)} - v_a(t)\overrightarrow{E_a(t)}\right)}{\tau} = \frac{1}{\tau}\left(F_q(t)\overrightarrow{E_q(t)} - F_a(t)\overrightarrow{E_a(t)}\right) \tag{6}$$

Where, τ is response time of individual (s); v_0 is magnitude of expected velocity; $v_a(t)$ is actual velocity magnitude of pedestrian a; $\overrightarrow{E_q(t)}$ is expected velocity direction of pedestrian; $\overrightarrow{E_a}(t)$ is actual velocity direction of pedestrian; m_a is mass of pedestrian a; $F_a(t)$ is magnitude of resultant force suffered by pedestrian, which is determined by Eqs. (2)–(6); and $\overrightarrow{E_a}$ (t) is direction of resultant force suffered by the pedestrian. During the simulation experiment and analysis, we refer to Helbing's research results to give the various

Table 1
Parameter values.

Parameter	Value
Adaptation time τ/s	0.5
Action intensity of social force among pedestrians A/kN	1.5
Coefficient of action range among pedestrians B/m	0.8
Coefficient of human body flexibility $k/N/m$	1.5×10^5
Coefficient of human friction $K/N/m$	6×10^5
Person mass m/kg	80
Person radius r/m	0.3

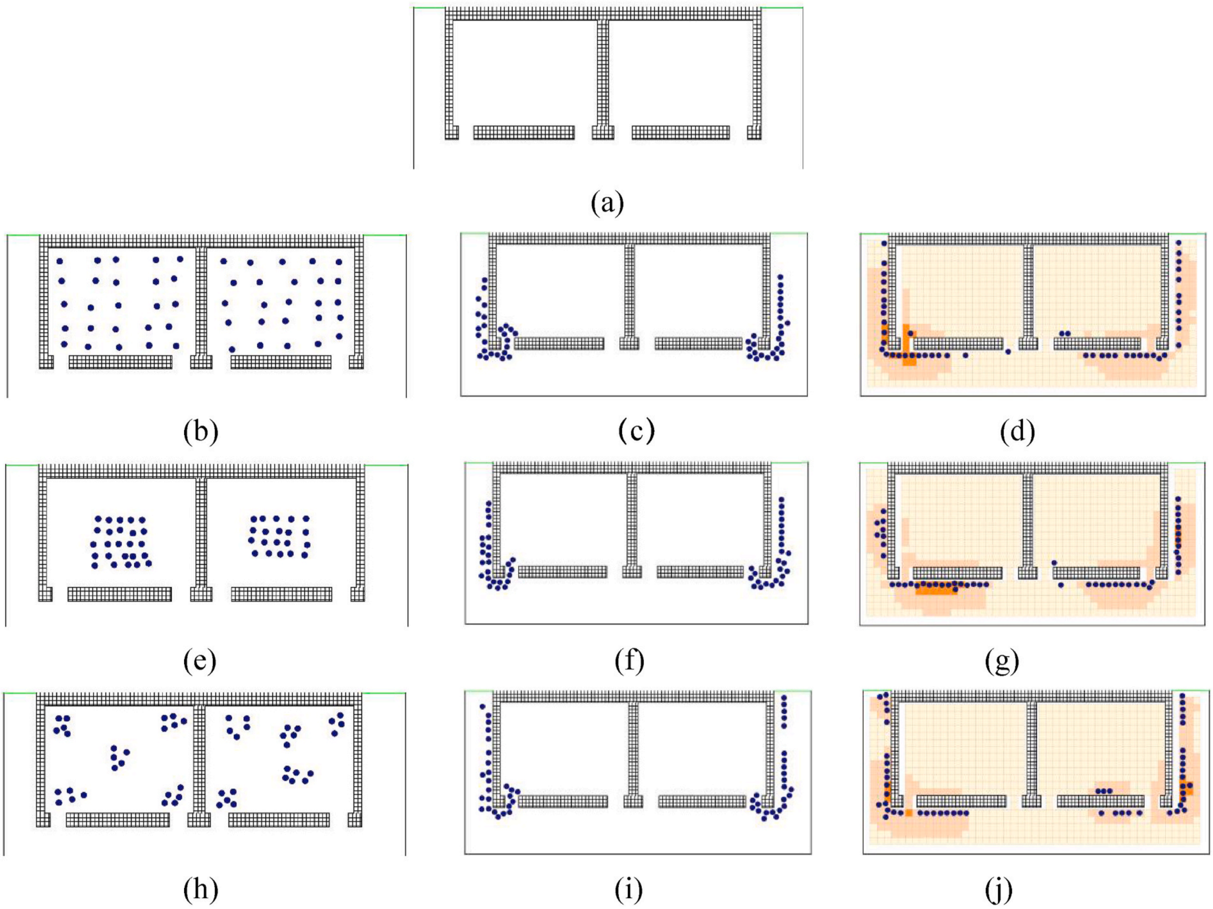


Fig. 1. The influence of internal factors of different groups on the evacuation model
Illustration:(a) The original scene, (b)Scatter scene, (c)Improved social force model (t = 10s), (d) Distributed network model (t = 10s), (e) Focus situation scene, (f)Improvement social force model (t = 10s), (g) Distributed network model (t = 10s), (h) Small group scene, (i)Improved social force model (t = 10s), (j) Distributed network model (t = 10s), (k)Improved social force model in different evacuation scenarios, (l) Distributed network model in different evacuation scenarios.

parameters required for this improved SFM [36], specific values of parameters in equation. (2-6) are as shown in Table 1.

However, the 'optimal path' planned by the field value of the traditional social force model is just the shortest path, which does not fully consider factors such as exit distance, number of exits, and degree of regional crowding, and may cause jam or uneven distribution of people at each exit in the case of evacuation of the mass pedestrian flow or when pedestrians evacuate towards the same exit, thus reducing the evacuation efficiency and resulting in the existence of hidden safety hazards.

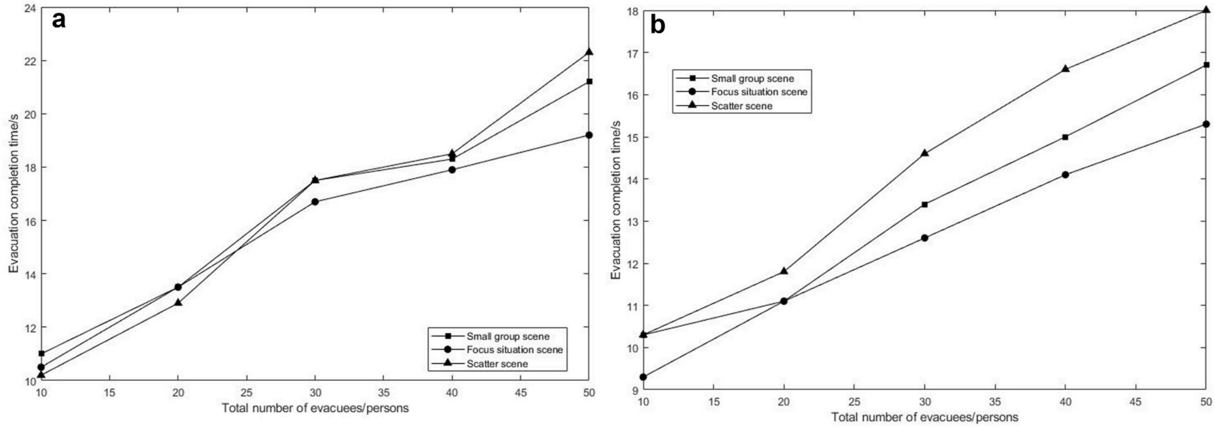


Fig. 2. Relationship between the total number of evacuees and the evacuation completion time under three conditions
(a) Evacuation under the condition of improving the social force model
(b) Evacuation in the case of a distributed network model.

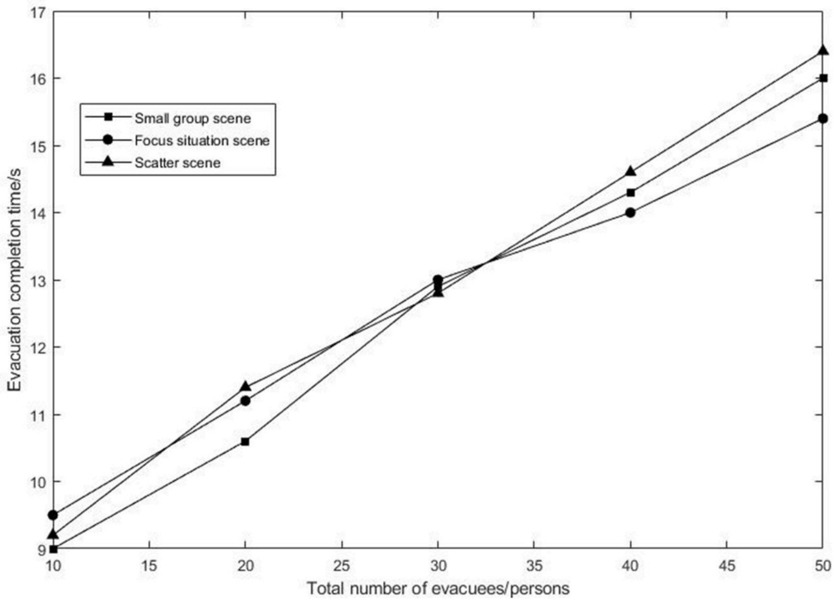


Fig. 3. The relationship between evacuation numbers and evacuation completion times after local optimization.

3. Optimization model

3.1. Centralized and distributed network model

For the pedestrian flow model in the multi-exit situation, $\overrightarrow{E_q}$ in the traditional social force model is optimized considering factors such as exit distance, number of exits, and degree of regional crowding and by virtue of the idea of a centralized and distributed network model [37], namely the path choice of pedestrian is optimized. Given that pedestrians may cause mass congestion in the bottleneck area in the process of evacuation, and in order to ensure the authenticity of simulated evacuation and the reliability of data, the initial situation mentioned in this paper is as shown in Fig. 1a: the scenario is 20 m long and 18 m wide, the exit is 0.9 m wide, and with 50 evacuees. Evacuation is completed when pedestrians exit the staircase. Obstacles are provided in the classroom to improve algorithm efficiency. To study the limitations of local optimization of the centralized and distributed network model, evacuation will be simulated under three different situations, namely the distributed situation as shown in Fig. 1b, the centralized situation as shown in Fig. 1e, and the small group situation as shown in Fig. 1h–as well as the evacuation situation of pedestrians at t = 10s.

Compared to the traditional social force model, during evacuation, social force and field value cannot solve problems such as

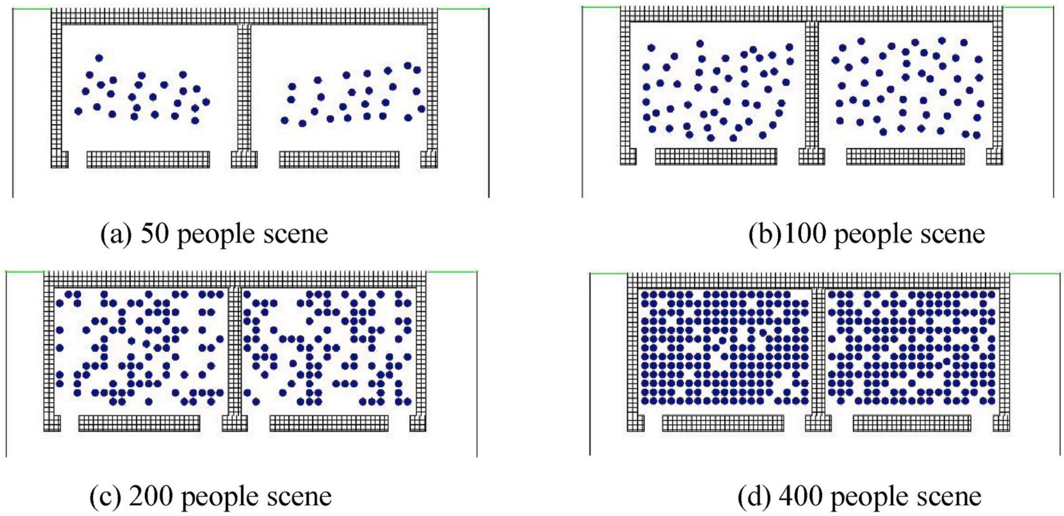


Fig. 4. Distribution of pedestrians for different initialisations
Illustration: Fig. 3 (a)-Fig. 3 (d) shows the evacuation of 50,100,200, and 400 persons respectively; Fig. (e)-Fig. (h) shows the time relationship between the number of evacuees (50,100,200,400) and the evacuation.

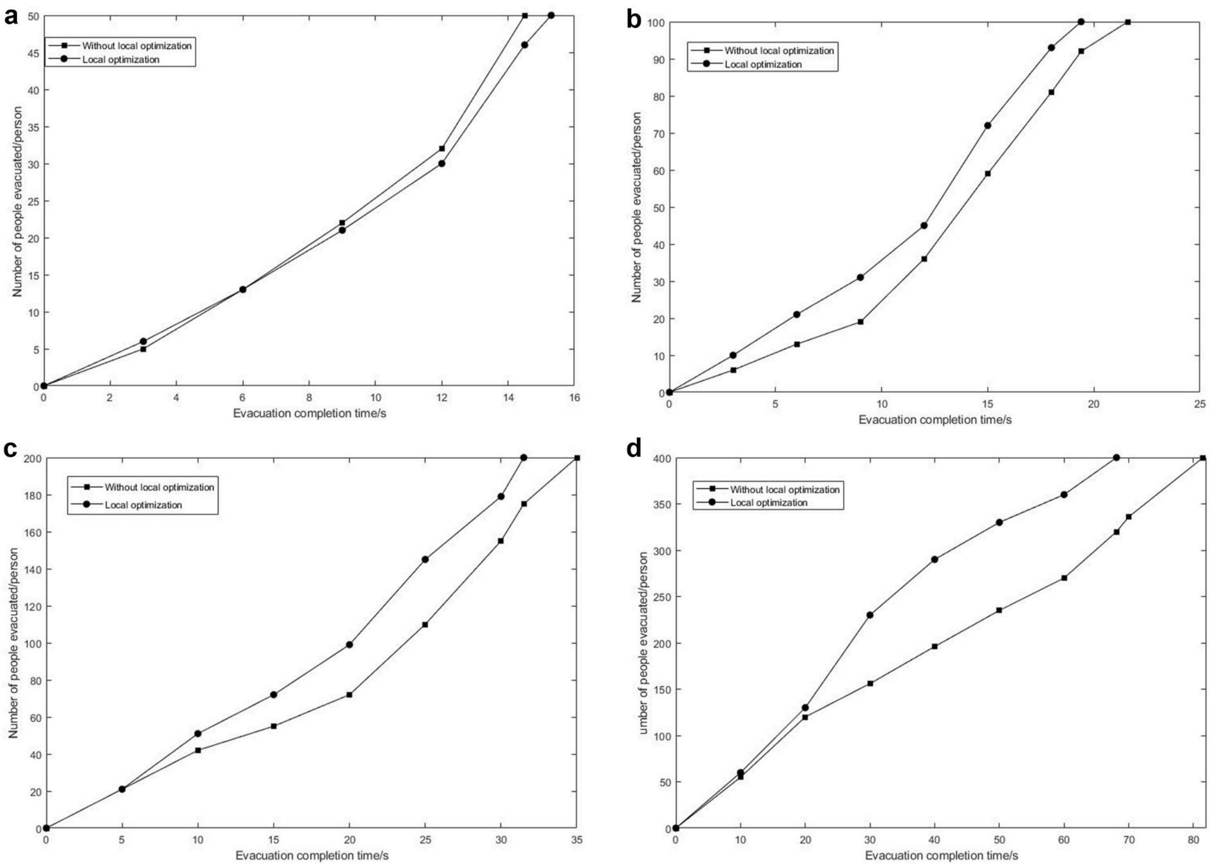


Fig. 5. Local optimization simulation.

pedestrians selecting the optimal exit in the multi-exit situation. However, the centralized and distributed network model can carry out a global optimization to optimize the path choice of each pedestrian and let each pedestrian select the relatively optimal exit for evacuation, which can improve the evacuation efficiency and meanwhile make simulated evacuation more real. But for the crowd that

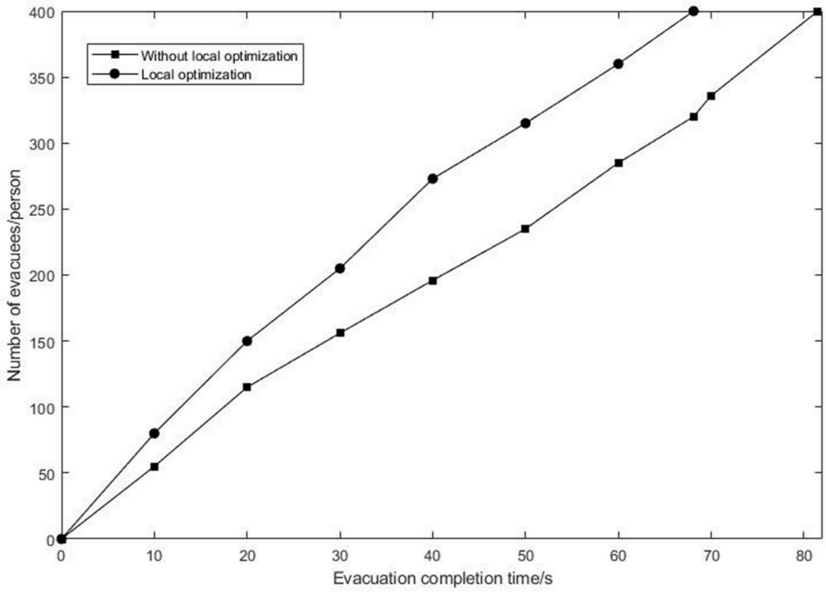


Fig. 6. Relationship between evacuation time and number of people evacuated.

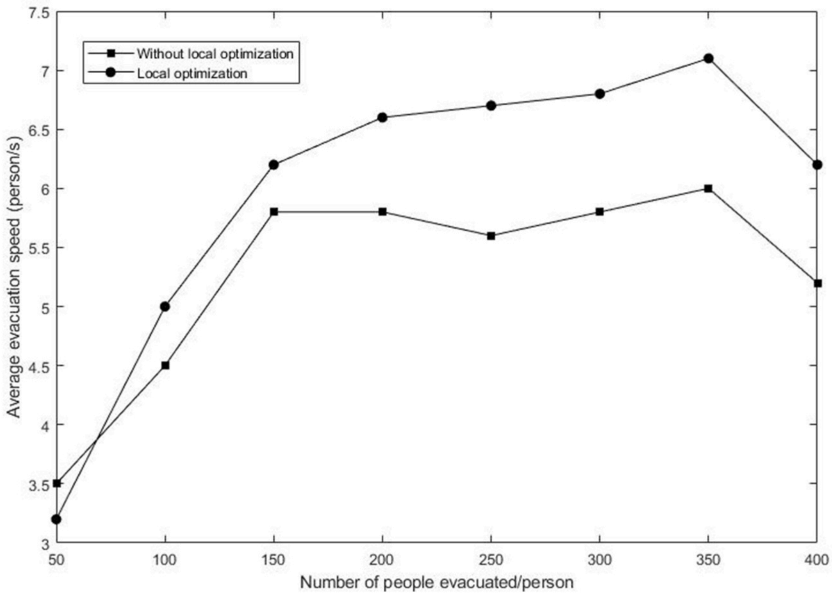


Fig. 7. Relationship between the number of people evacuated and the average evacuation speed.

select the same exit, the centralized and distributed network model can't fully consider the internal influence of each 'group'.

The results of the evacuation simulation are shown in Fig. 2a and b. The overall evacuation time under the improved social force model is larger than that under the situation of the centralized and distributed network model. However, in the case of an improved social force model, location situation and the degree of pedestrian centralized and distributed degree of pedestrians almost have no influence on evacuation completion time. While in the case of centralized and distributed network model, location situation and the degree of pedestrian centralized and distributed have a significant influence on evacuation completion time, and the time of all pedestrians to complete evacuation will be reduced if pedestrians are too disperse. However, since there is no obstacle in the classroom, the time for these 50 pedestrians to complete evacuation should tend to be identical no matter whether the pedestrians are centralized or not. This is the limitation of the centralized and distributed network model in local optimization. Therefore, it requires the introduction of a local optimization algorithm to compensate for the shortcomings of local optimization of the centralized and distributed network model.

3.2. Elephant herding algorithm

Through research, it is found that there is a considerable degree of connection between the centralized and distributed network model and elephant herding algorithm [38]. The centralized and distributed network model has a very good overall optimization capability, but it is easy to fall into a locally optimal solution or have weak local optimization capabilities, while the elephant herding algorithm has a better local optimization capability and can also improve the efficiency of simulated crowd evacuation.

Evacuation simulation is made again for the distributed situation in Fig. 1b, the centralized situation in Fig. 1c, and the small group situation in Fig. 1d by local optimization of elephant herding algorithm. The results are shown in Fig. 3, under local optimization of the elephant herding algorithm, the evacuation completion times of these 50 pedestrians have basically tended to be identical no matter the pedestrians are centralized or not.

Local optimization of the elephant herding algorithm can improve the efficiency of simulated evacuation. The initial situation is shown in Fig. 1a. In Fig. 4, four different crowd situations of 50 persons, 100 persons, 200 persons, and 400 persons are distributed at various positions, thus to analyze the time used by evacuation with or without local optimization. The difference in evacuation time is 1s in Fig. 5a and b, 5s in Figs. 5c and 14s in Fig. 5d.

Further analysis of the relationship between evacuation time and the number of people evacuated (as shown in Fig. 6), and the relationship between the number of people evacuated and the average evacuation speed (as shown in Fig. 7), with and without local optimization. When the number of people evacuated is small, local optimization will significantly reduce the overall evacuation efficiency and may even have a negative increase. When the number of pedestrians to be evacuated isgreater, local optimization will improve the overall evacuation efficiency.

3.3. New model building

Given that the elephant herding algorithm and the centralized and distributed network model have a very high degree of fit and both are related algorithms to study the evacuation of mass, the centralized and distributed network model can be used to judge globally, thus to plan the optimal path for each pedestrian, while the elephant herding algorithm is to optimize locally, thus to affect the whole situation. Therefore, the idea of building a new model is as follows: the crowd to be evacuated is divided into multiple small populations by the centralized and distributed network model, and the elephant herding algorithm is introduced to optimize the local exploration capacity of small populations. That is to say, the elephant herding algorithm is designed to optimize the local exploration capability of pedestrians based on the centralized and distributed network model, which can compensate for the lack of local optimization when the centralized and distributed network model is used for crowd evacuation, namely optimizing F_q in the traditional social force model.

Based on the improved social force model, a new model is built using a centralized and distributed network model and the elephant herding algorithm. Assuming that the crowding degree field value at the position of pedestrian is V_{now}, crowding degree field value of the nearest bottleneck area (exit) is V_{aim} and the current pedestrian's distance from the bottleneck area is *dis* (pixels per unit). The clustering value of the current pedestrians selecting the bottleneck area for evacuation is expressed by Eq. (7).

$$C=\begin{cases}\dfrac{|V_{now}-V_{aim}|}{dis}\cdot\left(\beta^{dis}+1\right),|V_{now}-V_{aim}|\geq\alpha\\ \dfrac{a}{dis}\cdot\left(\beta^{dis}+1\right),|V_{now}-V_{aim}|<\alpha\end{cases}\tag{7}$$

where α is a weighted value, the larger the value of α is, the more sensitive the pedestrian is to distance; and the smaller the value of α is, the more sensitive the pedestrian is to the degree of crowding. β is a discrete value of pedestrian evacuation, *t* he larger the value of β is, the more centralized the pedestrians are in the process of evacuation; and the smaller the value of β is, the more distributed the pedestrians are in the evacuation process.

After obtaining the current clustering value of pedestrians C , the probability that the pedestrians select the current bottleneck area for evacuation is $C\cdot 100\%$. Meanwhile, the current cluster value will be affected by the last clustering value C, the current distance $D_{(i,j,k)}$ and the last distance $D_{(i,j,k-1)}$, of which specific formula is as follows:

$$Pte(C_{this},n,m,k)=\max\left(\sum_{i=1}^{n}\sum_{j=1}^{m}\left(C_{(i,j,k-1)}\cdot\beta^{\left(D_{(i,j,k)}-D_{(i,j,k-1)}\right)}\right)\right)\tag{8}$$

Where, *i* represents the current pedestrian, of which the value range is 1,2,3 … n; *j* represents the *j*th exit in the scene, of which the value range is is 1,2,3 … m; *k* is a time node, of which the value range is determined by evacuation time; $C_{(i,j,k-1)}$ is a clustering value of current pedestrian *i* for exit *j* at the time node *k-i*; and $D_{(i,j,k)}$ is the distance of current pedestrian *i* for exit *j* at the time node *k*. $Pte(C_{this}, i,j,k)$ itself has the attribute values (x_{aim},y_{aim}) , representing actual position of the *j*th exit, and *Pte* is actual position where *n* pedestrians successfully select the *j*th exit among *m* exits at the time node *k*, and C_{this} is current clustering value saved, which is ready for the next calculation.

According to the calculated value of *Pte,* the expected direction of speed of the pedestrians for the next evacuation can be calculated as follows:

$$\overrightarrow{E_q} = \left(Pte.x_{aim} - x_p, Pte.y_{aim} - y_p\right) \tag{9}$$

Where, (x_p, y_p) represents actual position of the pedestrian.

The local exploration capacity of pedestrians is optimized using the elephant herding algorithm based on the centralized and distributed network model. The method is described as follows:

First, all pedestrians are divided into different groups using the centralized and distributed network model. The grouping basis is the bottleneck area passed by the optimal evacuation path of pedestrians calculated by the centralized and distributed network model, and the pedestrians that are aiming at the same bottleneck area are a group.

Next, after the grouping is complete, a group is calculated using the elephant herding algorithm. Assuming that the number of individuals of a group is n, the position of patriarch of the group X_{best} is calculated according to Eq. (10).

$$X_{best} = \varepsilon \cdot \sum_{j=1}^{n} \frac{X_d}{n_j} \tag{10}$$

Where, ε is influence range control parameter of the elephant herding algorithm, which takes 0.6 in this paper.

Next, for nonpatriarch individuals, their motion is affected by the position of patriarch. The iterative Z-type variable scale factor shall be calculated using Formula (11) before separately performing the calculation for each individual.

$$Z = Z\left(Z\, min_{max} \cdot k \cdot \left(\frac{t}{T}\right)^2\right)_{min} \tag{11}$$

Where, T is iteration time; k is current iteration times, and each k corresponds to that time.

Next, local exploration optimization is made for each non-patriotic individual, and next position X_{new} of each non-patriarch individual is expressed by Eq. (12).

$$X_{new} = X_{old} + Z \cdot (X_{best} - X_{old}) \cdot \gamma \tag{12}$$

Where, X_{old} is current position of pedestrian; γ is two-dimension parameter, which takes 0.5 in the paper.

Finally, after calculating the next position X_{new} of pedestrians, it can be obtained that the pedestrians are under the influence of an elephant herding algorithm at the moment. After optimization, it can be expressed by Eq. (13).

$$F_q^{'} = \varepsilon \cdot \frac{X_{new} - X_{old}}{X_{best} - X_{old}} \cdot F_q \tag{13}$$

Therefore, the self-driving force calculated by the new model can be expressed as Eq. (14).

$$\overrightarrow{F_q} = \frac{1}{\tau}\left(\left(Pte.x_{aim} - x_p, Pte.y_{aim} - y_p\right) \cdot \left(1 + \varepsilon \cdot \frac{X_{new} - X_p}{X_{best} - X_p}\right) F_q - F_a \overrightarrow{E_a}\right) + \overrightarrow{F_w} + \overrightarrow{F_p} \tag{14}$$

Where, $(Pte.x_{aim}, Pte.y_{aim})$ are the coordinates of target exit calculated by clustering value C; X_{new}, X_p and X_{best} are respectively next position of pedestrian under the influence of the elephant herding algorithm, current position of pedestrian, and the position of population patriarch; $F_a \overrightarrow{E_a}$ is magnitude of resultant force suffered, which is closely related to $\overrightarrow{F_w}$ and $\overrightarrow{F_p}$. The specific implementation steps of the new model are as follows:

Step 1. Initialize the scenario and first calculate the field value of the whole scenario;

Step 2. Calculate all bottleneck points in the scenario according to the field value;

Step 3. Start the simulated evacuation:

Step 3.1. Calculate the crowding degree matrix in the current scenario;

Step 3.2. Perform a global optimization for pedestrian i, and obtain the current clustering value C according to Eqs. (7) and (8), calculate the optimal path of the pedestrian and calculate the optimized $\overrightarrow{E_q}$ by Eq. (9);

Step 3.3. Classify the pedestrians whose optimal paths pass through the same bottleneck point as the same population, and calculate the position of patriarch of the population;

Step 3.4. Perform a local optimization for pedestrian i, calculate the action force of patriarch for pedestrian, and calculate the optimized force according to Eq. (13);

Step 3.5. Calculate the next coordinates of the position of the pedestrian according to Eq. (14) after obtaining the optimized $\overrightarrow{E_q}$ and $F_q^{'}$. If the pedestrian reaches the exit, skip to Step 4; and if not, repeat Step 3;

Step 4. The pedestrian completes the evacuation.

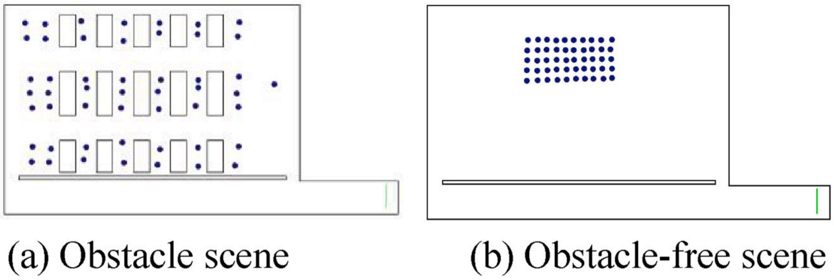


Fig. 8. Initializing scene layout and personnel distribution status with or without obstacles.

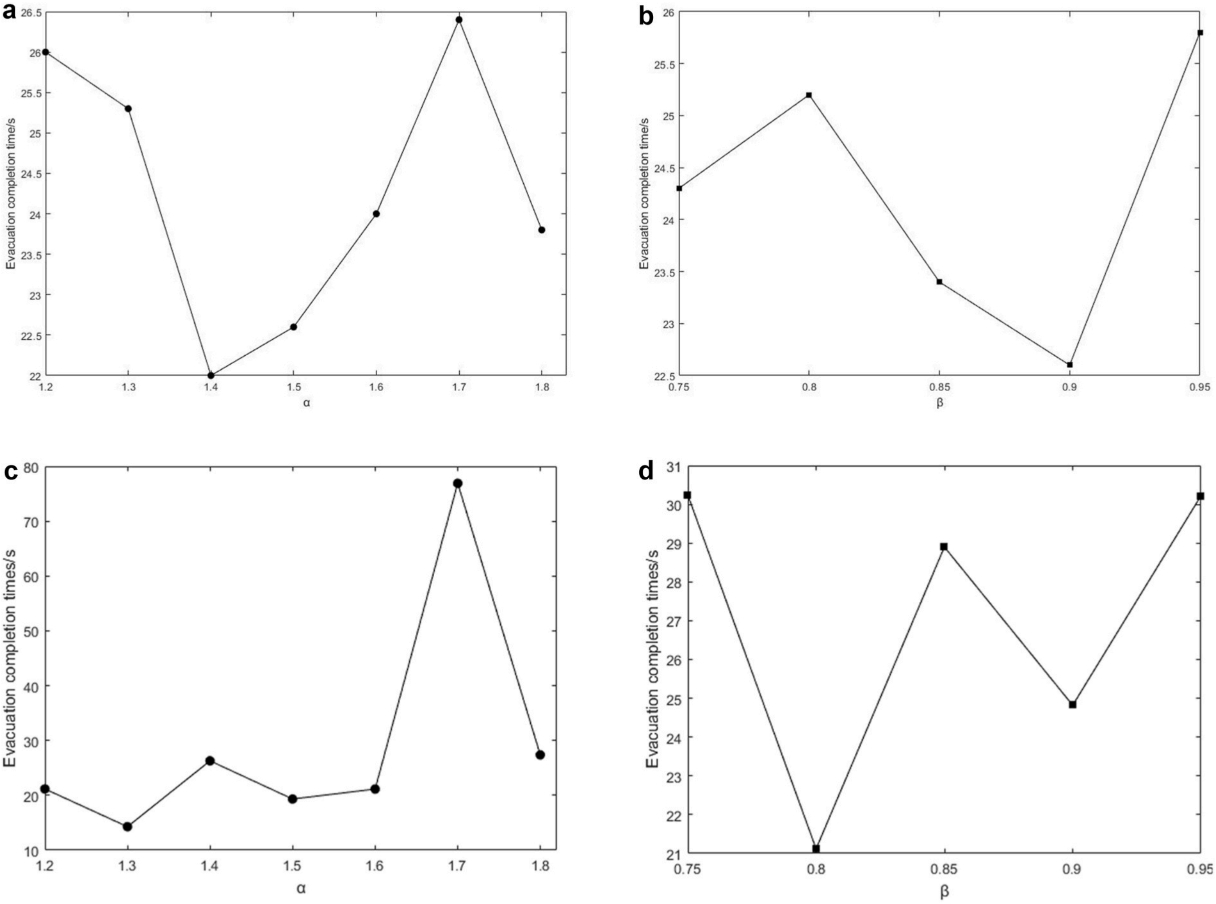
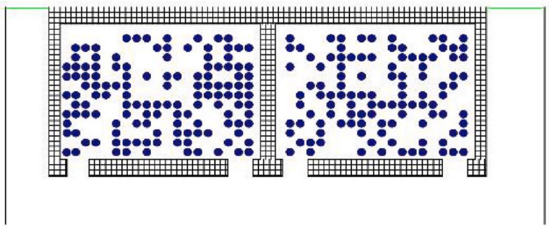


Fig. 9. The optimal values of the weights and the discrete values.

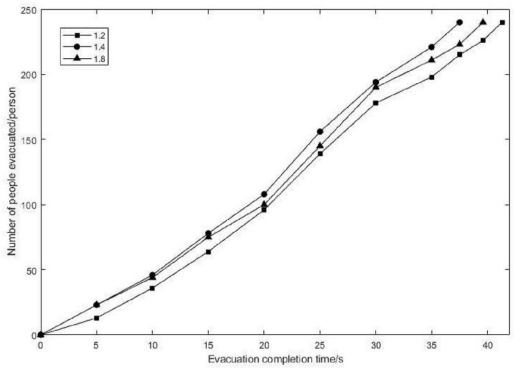
4. Model simulation and analysis

4.1. Model parameter Verification

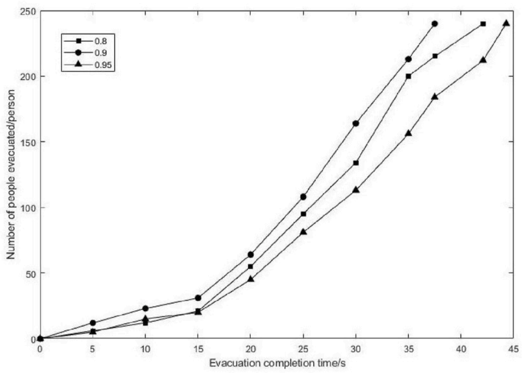
Given that pedestrians may all experience mass congestion in the bottleneck area during the evacuation process, in order to ensure the authenticity of simulated evacuation and the reliability of data, the initial situation mentioned in this paper is as shown in Fig. 8: the scenario is 18 m long and 13 m wide, with 50 persons to be evacuated. The simulated evacuation is carried out respectively, by changing the value of α while number of pedestrians and the position of the pedestrian are kept unchanged. The results are as shown in Fig. 9a : when $\alpha = 1.4$, the time for all pedestrians to complete the evacuation is the shortest and the simulated evacuation effects are more real. Furthermore, simulated evacuation is carried out respectively by changing the value of β while other parameters are kept unchanged, as shown in Fig. 9b, $\beta = 0.9$ is the optimal value. However, the experiments are carried out in an environment without obstacles (as shown in Fig. 8b). The experimental results in Fig. 9c and d shows that the optimal value of α is 1.3 and β is 0.8 in the scene



(a) 240 people initial scene

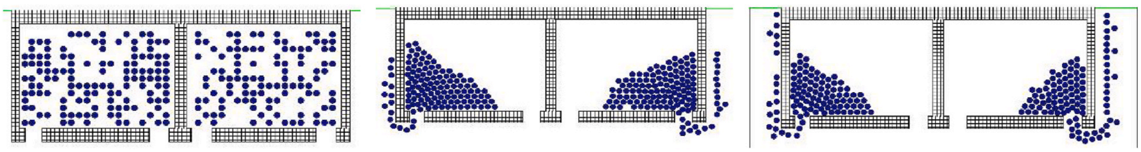


(b) The size selection of the weight value



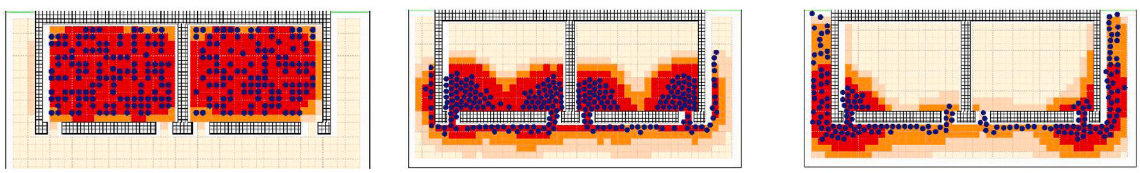
(c) The size selection of the discrete values

Fig. 10. The influence of the optimized weight and discrete value on the evacuation.



(a)0s (b)10s (c)30s

Fig. 11. Improved social force model simulation.



(a)0s (b)10s (c)30s

Fig. 12. New model simulation.

without obstacles. Therefore, considering that the actual indoor environment generally contains obstacles, the experimental results with obstacles are adopted here as the specific values of the weight value α and the discrete value β.

It is further verified whether different weighted value α and discrete value β in the clustering value C have some effects. The initial case is shown in Fig. 10a, the scenario is 18 m long and 13 m, which is provided with 240 pedestrians. Simulated evacuation is carried out, respectively, by changing the value of α while the number of pedestrians and pedestrian position are kept unchanged, as shown in Fig. 10b, the time for all pedestrians to complete evacuation is the shortest when $\alpha = 1.4$. As shown in Fig. 10c, when simulated evacuation is carried out, respectively, by changing the value of β while other parameters are kept unchanged, $\beta = 0.9$ is the optimal value.

The experiments show that the elephant herding algorithm and the centralized and centralized and distributed network model both

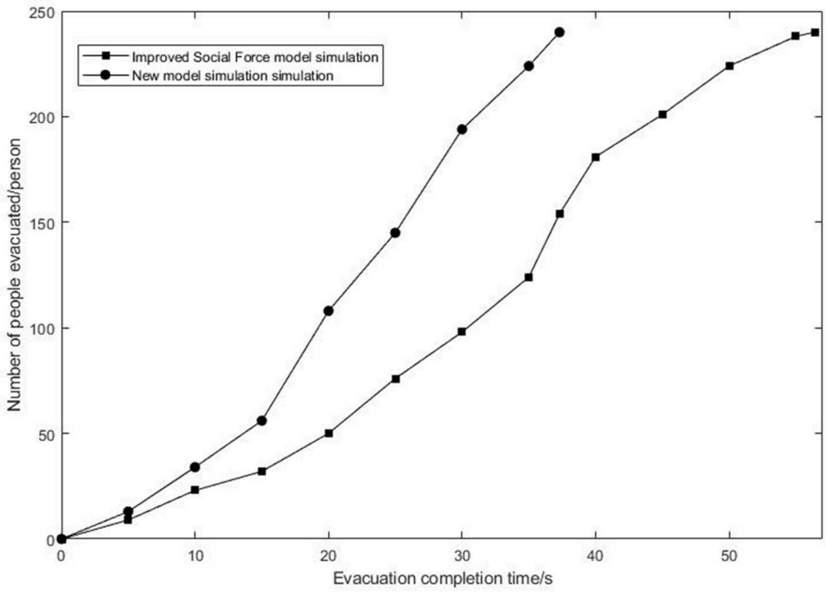


Fig. 13. Comparison of evacuation time.

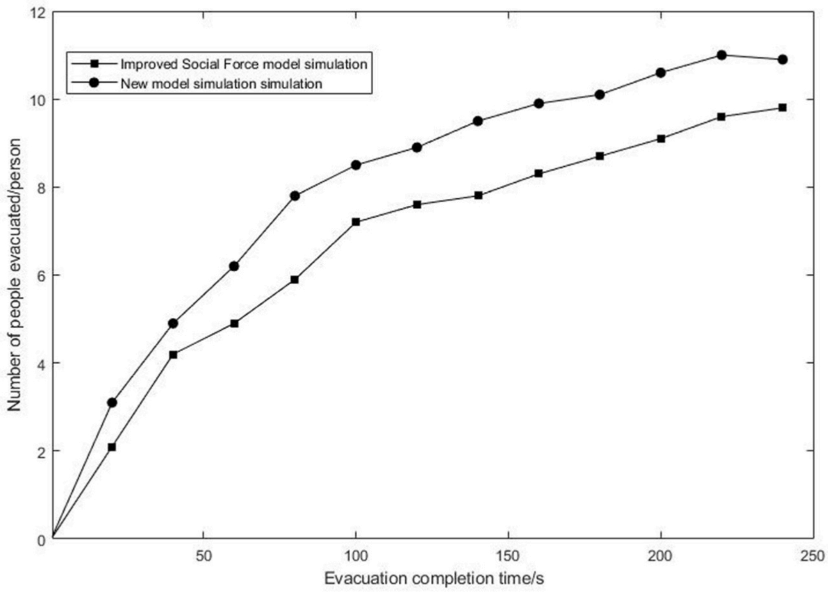


Fig. 14. Comparison of evacuation rates.

have very high degree of fit, and keep consistency in parameter selection and also have identical influences and effects.

4.2. Model performance Verification

According to the new model and data processing method, and based on Parameter Table 1 and model parameter weighted value α and discrete value β, simulation experiment analysis is carried out. The improved social force model simulation is as shown in Fig. 11. The scenario is 20 m long and 18 m wide, with 240 persons to be evacuated, the time for all pedestrians to complete evacuation is 55s when global optimization is not used (in the improved social model); After using global optimization (in the new model), as shown in Fig. 12, the time for all pedestrians to complete evacuation is 37s. At t = 10s and t = 30s, the new model has a more even distribution of pedestrians at each exit, with a higher exit utilization rate and evacuation efficiency, with a difference of 20s in the overall evacuation completion time. Therefore, the new model considers the degree of crowding to optimize the path selection in the early stage and to

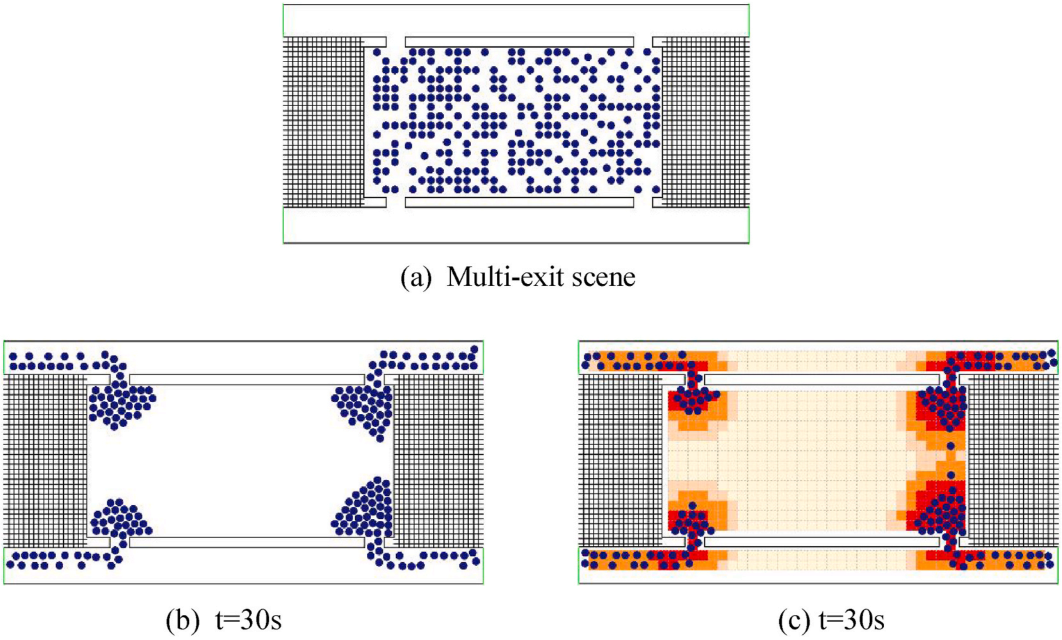


Fig. 15. Multi-exit scenario to simulate evacuation.

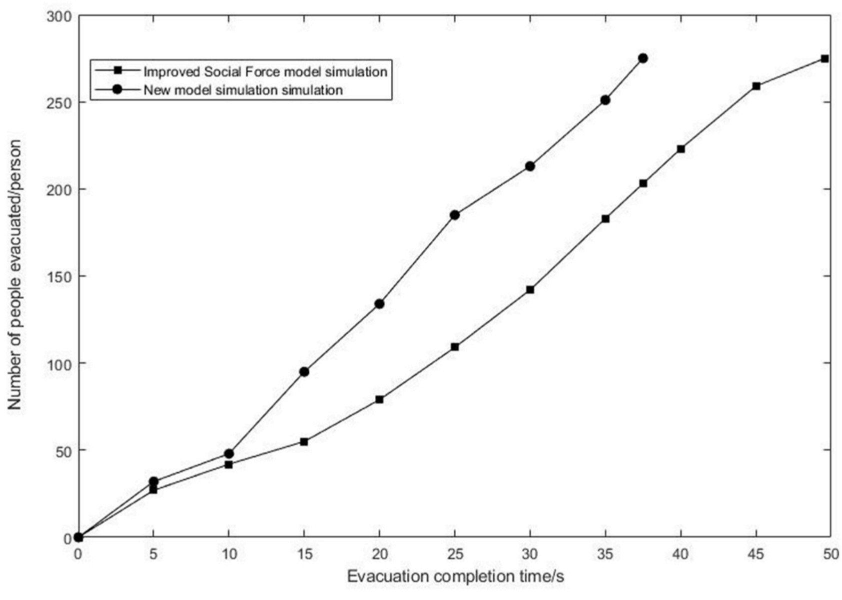


Fig. 16. Comparison of evacuation time.

improve the efficiency of evacuation in the late stage.

By comparing the changes in evacuation time and number of evacuees between the two models, it can be seen from Figs. 13 and 14 that, relative to evacuation simulated by the improved social force model, the new model has a significant improvement in simulated evacuation efficiency and exit choice. The simulated evacuation effects after optimization are more real. And as the density of crowd increases, the average evacuation speed tends to increase rapidly at first and then slowly decrease.

The effects of the new model on simulated evacuation in the case of multiple exits are further studied. As shown in Fig. 15, the scenario is 18 m long and 15 m wide, where 270 persons are arranged under the initial situation. Simulated evacuation is made, respectively, using the improved social force model and the new model. When the evacuation time is t = 30s, as shown in Fig. 15b and c, namely simulated evacuation situations of the improved social force model and the new model, the evacuation efficiency of the latter is superior to that of the former, with a relatively mean distribution of pedestrians at each exit. Changes in evacuation time and the

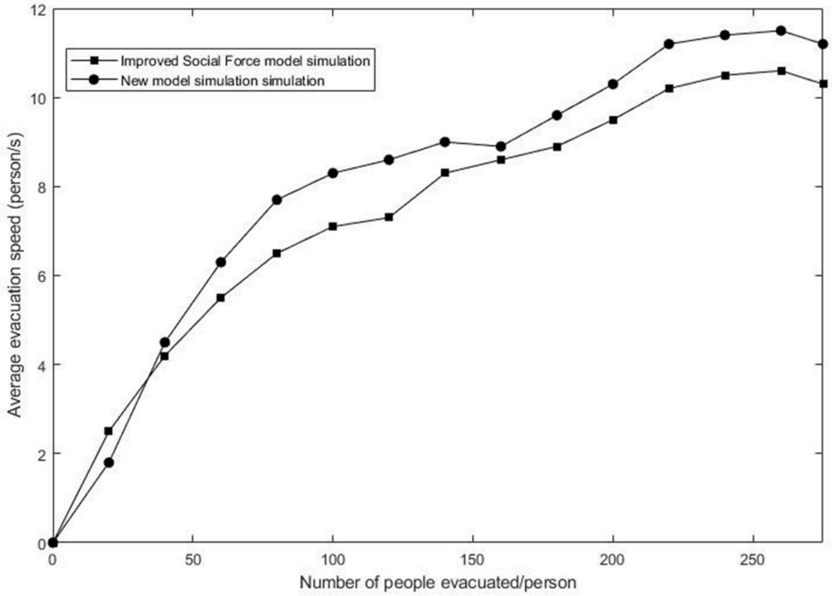


Fig. 17. Comparison of evacuation rates.

number of evacuees are simulated. As shown in Figs. 16 and 17, the new model has very obvious overall optimization for simulated evacuation under the multiexit situation.

5. Conclusions

In order to solve the problem that there is a relatively large difference between the evacuation state of pedestrians depicted by the traditional social force model in the crowded multi-exit scenario and the actual state, this paper fully considers the factors such as exit distance, number of exit, distribution situation of pedestrians at each exit and regional congestion, makes a global optimization for the self-driving force in the social force model using a centralized and distributed network model, and makes a local optimization for it using an elephant herding algorithm, so as to establish a new evacuation optimization method for optimal self-adaption in the bottleneck area. The experiments show that the model can realize an effective crowd evacuation in a complex environment and realize a crowd evacuation simulation in a multi-exit environment. The main experimental conclusions are as follows.

1) In the new model, the weight value and the discrete value will affect the evacuation efficiency of pedestrians. Through multiple simulated evacuation experiments, the model has the highest evacuation efficiency when weight value and discrete value are 1.4 and 0.9 respectively.
2) Relative to the improved social force model, the new model considers the global congestion and the distance between the pedestrian and the exit, and optimizes the expected direction of velocity in the social force model to prevent pedestrians from crashing at the same exit. In terms of evacuation efficiency and authenticity of evacuation simulation, the new model has better performance and is applied to the complex scenario with multiple exits and mass pedestrians.
3) The new model is to optimize the self-driving force in the social force model. Local optimization has a greater improvement in overall evacuation efficiency when the number of pedestrians to be evacuated is larger.
4) Based to multiple simulated evacuation experiments, the new model is superior to the improved social force model and only considers the situation of a centralized and distributed network model in terms of improving evacuation efficiency.

Availability of data and materials

The data that support the conclusions of this study are available from the first author Y.L., upon reasonable request.

CRediT authorship contribution statement

Longcheng Yang: Resources, Project administration, Conceptualization. **Huajun Wang:** Project administration. **Jun Hu:** Project administration, Methodology, Conceptualization. **Hongyu Pan:** Supervision, Investigation, Data curation. **Juan Wei:** Software, Resources. **Lei You:** Software, Data curation. **Hao Zhang:** Software, Resources. **Junxi Wang:** Writing – original draft, Software, Resources, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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