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An Optimal Model for Crowd Evacuation with Swarm Intelligence Considering Panic Propagation

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Abstract. *In emergency evacuation scenarios, traditional evacuation path planning methods often ignore the effect of panic on crowd behaviour, which may lead to the failure to achieve optimal evacuation results in practical applications. In order to solve this problem, this study proposes a swarm intelligence crowd evacuation model considering panic propagation based on an improved water wave optimisation algorithm. Firstly, the propagation of panic in the evacuation process and the influence on individual behaviours are quantified through behavioural character analysis and emotional infection models. Then, the traditional water wave optimisation algorithm is improved by combining chaos theory and longitudinal crossover strategy, which enhances the algorithm's global search capability and local search accuracy. In addition, a wavelength update optimisation mechanism based on panic is introduced, which enables the algorithm to adaptively adjust the search strategy to cope with the uncertainty caused by panic. The experimental parameters, scenarios and processes are described in detail in the experimental design section, which verifies the effectiveness of the improved algorithm in terms of evacuation time, path security and algorithm convergence performance. The experimental results show that the proposed model and algorithm have significant advantages in evacuation efficiency and safety compared with existing methods. The results of this study not only improve the scientific and practicality of evacuation path planning, but also provide new technical means for emergency evacuation management and public safety fields.*
Keywords: Emergency evacuation; Panic; Swarm intelligence algorithm; Water wave optimisation; Chaos theory; Vertical crossover strategy

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1. **Introduction.** Crowd evacuation modelling is an important branch in the field of safety science and operations research, which focuses on how to efficiently and rapidly guide a large number of people to evacuate from a hazardous area during an emergency

[1, 2, 3]. With the acceleration of urbanisation, the need for emergency evacuation is increasing due to high buildings and dense population. For example, in emergencies such as fires, earthquakes, and terrorist attacks, timely and effective evacuation can significantly reduce casualties and property losses [4, 5]. Therefore, the study of crowd evacuation models is of great theoretical and practical significance for improving public safety, optimising emergency plans and guiding actual evacuation operations.

Currently, the research on crowd evacuation modelling has achieved rich results and developed a variety of models and algorithms, such as the social force model [6, 7], the metacellular automata model [8], and the fluid dynamics model [9, 10]. These models simulate crowd movement and evacuation behaviours from different perspectives, taking into account a variety of influencing factors such as individual behaviours, environmental characteristics, psychological factors, and so on. However, there are still some limitations in the existing models, such as the computational efficiency and accuracy when dealing with large-scale crowds, complex environments and dynamically changing situations. In addition, the influence of psychological factors, such as panic, on evacuation behaviour has not been fully studied. Therefore, how to combine modern computing technology, artificial intelligence and psychological research results to improve the practicality and prediction accuracy of the models is a hot topic and a challenge for the current research.

The research objective of this paper is to develop and validate an improved swarm intelligence optimisation algorithm for solving the optimal path planning problem of crowd evacuation considering panic propagation. By introducing a quantitative index of panic and chaos theory, this paper aims to strengthen global search efficiency and local search accuracy of the swarm intelligence optimisation algorithm to more effectively simulate the dynamic behaviour of crowds in emergency evacuation situations. In addition, this paper aims to experimentally validate the effectiveness of the algorithm in terms of evacuation time, path safety and algorithm convergence performance, and to compare it with existing methods to demonstrate its superiority in dealing with complex evacuation scenarios. Ultimately, this research aims to provide a new optimisation tool for emergency evacuation management to improve evacuation efficiency and safety.

1.1. **Related work.** In crowd evacuation modelling, researchers have simulated and analysed crowd behaviour and evacuation paths during emergencies to improve public safety and reduce casualties during disaster events. These models typically consider macro- and micro-behaviours of crowds [11], including panic, herd behaviour, and interaction forces between individuals. For example, the Social Force Model (SFM) is a well-known microscopic model that predicts the evacuation behaviour of crowds by simulating the social interaction forces among individuals.

Intelligent optimisation algorithms, on the other hand, are key techniques for solving complex optimisation problems, and they usually mimic biological evolution or physical phenomena in nature, such as genetic algorithms and Particle Swarm Optimization (PSO) algorithms. The algorithms maintain a strategic equilibrium between broad-ranging search initiatives and targeted exploitation tactics to secure the best possible or acceptable outcomes. Yang et al. [12] proposed an evacuation model based on metacellular automata, which takes into account the crowd density and individual behaviour. The study verified the effectiveness of the model through simulation experiments, but there are some limitations in the evacuation efficiency of high-density crowds. Jahangiri et al. [13] optimised the evacuation paths by a simulated annealing algorithm, which outperformed the conventional method in terms of global search capability. However, the simulated annealing algorithm may need to rely on experience in determining the initial temperature and cooling rate, which may affect the stability and reliability of the algorithm.

Shimura and Yamamoto [14] proposed an evacuation path optimisation model based on a multi-objective genetic (GA) algorithm, which takes into account both evacuation time and safety. Although the model strikes a balance in multi-objective optimisation, there is still room for improvement in terms of the computational complexity of the algorithm and its efficiency in practical applications. Liu et al. [15] developed an evacuation path optimisation method based on the ant colony algorithm, which determines the evacuation routes by simulating the paths of ants searching for food. The algorithm performs well in solving static evacuation problems, but its adaptability in dynamically changing environments needs to be improved. Asadi and Karami [16] optimised the evacuation paths by the PSO algorithm, which is able to find the near-optimal solution quickly. However, the PSO algorithm may encounter the problem of local optimality when dealing with multiple obstacles and complex terrain. Yang et al. [17] proposed a fuzzy evacuation model using fuzzy logic to deal with uncertainty and ambiguity in the evacuation process. The model performs well in dealing with uncertainty information, but further efficiency improvement is needed in real-time data processing and model parameter adjustment. Xiao and Li [18] investigated the propagation of panic during evacuation and proposed an evacuation model based on emotional contagion. The model provides a new perspective in understanding the impact of panic on evacuation behaviour, but it is still a challenge to accurately quantify panic in practical applications.

1.2. **Motivation and contribution.** Analysing the above studies, it can be found that in emergency evacuation situations, traditional evacuation path planning methods often neglect the influence of panic on crowd behaviour, which may lead to the failure to achieve optimal evacuation results in practical applications. Therefore, under the condition of considering the propagation of panic, this study proposes an optimal path planning for crowd evacuation based on improved group intelligence algorithm.

1. For the first time, a new evacuation model that takes into account the propagation of panic emotions is proposed by combining the quantitative analysis of panic emotions with a swarm intelligence optimisation algorithm. By means of behavioural character analysis and emotion infection model, this paper quantifies the impact of panic emotion on individual evacuation behaviour and incorporates it into the optimization process of evacuation paths. The model is able to more realistically simulate the dynamic behaviour of crowds in emergency situations, especially the behavioural changes under the influence of panic emotions, thus improving the accuracy and practicality of evacuation path planning.
2. The traditional Water Wave Optimization (WWO) algorithm [19, 20] is innovatively improved by introducing chaos theory and longitudinal crossover strategy, which significantly improves the global search capability and local search accuracy. The improved WWO algorithm enhances the diversity of the population through chaotic initialisation and chaotic local search, and increases the exploration ability of the population by using the vertical crossover strategy, so as to avoid falling into local optimal solutions more effectively. In addition, this paper proposes a wavelength update optimisation mechanism based on panic, which enables the WWO algorithm to adaptively adjust the search strategy to cope with the uncertainty and dynamic changes caused by panic.

2. Analysis of relevant principles.

2.1. **Key issues in emergency crowd evacuation.** The core responsibility of emergency evacuation is to safely transfer people from potentially dangerous areas to safe areas within a limited time. Although this problem seems simple, it is similar to the Traveling

Salesman Problem (TSP), but in practical solution, there are more variables and conditions to be considered. From the perspective of evacuation operation, the solution should at least include the evaluation of personnel status, the determination of safe areas and the planning of evacuation routes.

The core objective of emergency crowd evacuation is to safely evacuate as many people as possible in the shortest possible time. The efficiency of evacuation depends on a number of factors, including the planning of evacuation paths, the number and layout of exits, and the size and behavioral characteristics of the crowd. Safety, on the other hand, involves avoiding accidents such as pushing, shoving and trampling during evacuation, which requires that evacuation paths should not only be short, but also be able to adapt to the dynamics of the crowd to ensure that all people can be evacuated in an orderly manner.

In an emergency, the psychological behavior of the crowd has a significant impact on the evacuation process. Panic may lead individuals to make irrational decisions, such as blindly following others or rushing to the nearest exit, which may cause congestion or even a stampede. Therefore, understanding and modeling the psychological responses and behavioral patterns of crowds under stress is essential for developing effective evacuation strategies.

Emergency evacuations usually occur in dynamic and uncertain environments, such as smoke from fires, structural damage to buildings, or the uncertainty of terrorist attacks. These factors increase the complexity of evacuation and require evacuation models to be able to adapt to changes in the environment and quickly re-plan evacuation paths. At the same time, evacuation strategies need to be flexible enough to cope with changing situations and unforeseen events.

In summary, the key issues in emergency crowd evacuation are how to efficiently and safely guide a large number of people to rapidly evacuate in complex and dynamic environments, taking into account the influence of psychological behavior and environmental uncertainty. Solving these problems requires interdisciplinary research efforts combining knowledge from the fields of operations research, psychology, computer simulation and intelligent optimization algorithms.

2.2. **Swarm Intelligence Algorithm.** Swarm Intelligence (SI) algorithms are computational models that simulate group behaviours in nature, which include, but are not limited to, fish swimming in schools, birds flying in flocks and ants foraging for food. The core idea of these algorithms is to achieve self-organisation and optimisation of complex systems through simple inter-individual interactions and local information exchange. In crowd evacuation models, swarm intelligence algorithms are used to simulate and optimise evacuation paths for fast and orderly evacuation [21, 22].

Group intelligence algorithms typically include multiple individuals (or agents), each representing a potential solution in the search space. Individuals gradually approximate the optimal solution through positional updates in an iterative process. The position update usually follows the following mathematical expression:

$$\mathbf{v}_i^{t+1} = \mathbf{v}_i^t + \mathbf{u}_i^t \tag{1}$$

$$\mathbf{x}_i^{t+1} = \mathbf{x}_i^t + \mathbf{v}_i^{t+1} \tag{2}$$

where $\mathbf{v}_i^t$ denotes the velocity of individual i at time step t, $\mathbf{x}_i^t$ denotes the position of the individual, and $\mathbf{u}_i^t$ is the velocity update term determined by the experience and information of the individual and the group.

Each individual in the SI algorithm is an independent computational unit that searches for optimal solutions in the solution space in parallel. Individuals coordinate their behaviours by exchanging information locally without global information. SI algorithms are capable of adapting to changes in the environment and generating complex collective behaviours through interactions between individuals. The sharing of knowledge among individuals is the basis of the group intelligence algorithm. The communication mechanism can be direct, as in PSO, where individuals adjust their flight direction according to the global optimal solution, or indirect, as in Ant Colony Optimization (ACO), where ants communicate indirectly by releasing pheromones on their paths. In the swarm intelligence crowd evacuation optimal model that considers the propagation of panic, we can take panic as an influencing factor of individual behaviour. The effect of panic on crowd evacuation behaviour is simulated by adjusting the information exchange mechanism and iterative update strategy among individuals.

3. Modelling of crowd evacuation taking into account emotional impact.

3.1. Behavioural profiling of evacuees.

During an emergency evacuation of a crowd, the behavioural tendencies and psychological state of the evacuees may change at the physical and chemical levels, and the whole process is complex. People waiting for evacuation will show different behaviours under the influence of psychological factors. For example, during an emergency evacuation, ordinary individuals can be affected by panicked individuals, infecting them with panic and causing changes in the speed and direction of the panicked individuals. This will produce some non-adaptive changes in group behaviour. Some ordinary individuals who are unfamiliar with the environment will be contaminated with panic and herd effect will occur. This means that people's emotions are easily influenced by the panic of others.

In the process of crowd evacuation, psychological factors play an important role in simulating the dynamics of evacuating individuals. The psychological factors affecting the simulation session include a variety of factors, which cover the movement of evacuees as well as the psychological interventions between evacuees. The occurrence of crowd evacuation and its typical psychological and behavioural characteristics are directly influenced by these psychological factors. Studies conducted around the behavioural performance characteristics of emergency evacuation crowds can be broadly classified into the following types, as shown in Figure 1, including the basic attributes of the individual, the behavioural characteristics of the individual, and the behavioural characteristics of the group. Behavioural characteristics of individuals are microscopic, and behavioural characteristics of groups are macroscopic. The basic attributes of an individual are certain characteristics shared by individuals, such as personnel quality, educational background, and physical function. Individuals' behavioural performance changes due to internal physical qualities and the external environment, which consequently play a role in the evacuation of people. In this context, it is important to study the characteristics of people in emergency situations. Some common human behavioural characteristics are described below.

The behavioural characterisation of evacuating crowds is crucial in group intelligence crowd evacuation models that consider the propagation of panic. This section explores the dynamics of crowd behaviour during an emergency and describes these behavioural characteristics using mathematical expressions.

3.1.1. *Individual Behaviour Model.*

Individual behaviour can be described by the Social Force Model, which assumes that individuals are subjected to multiple forces during

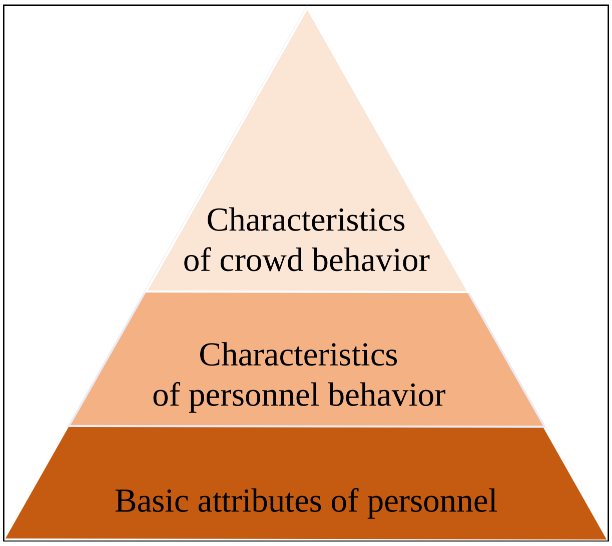

Figure 1. Characteristics of human behaviour

evacuation. The following is the basic mathematical expression for the Social Force Model.

$$m_i \frac{d^2\mathbf{x}_i}{dt^2} = \sum_{j \neq i} F_{ij} + F_{\text{target}_i} + F_{\text{obstacles}_i} \tag{3}$$

where m_i is the mass of individual i, $\mathbf{x}_i$ is the position of the individual, F_{ij} is the interaction force between individual i and j, F_{target_i} is the force pointing towards the safe exit, and $F_{\text{obstacles}_i}$ is the force between the individual and the obstacle.

3.1.2. *Effects of panic on behaviour.* Panic can enhance an individual's willingness to move towards the exit, which can be achieved by adjusting F_{target_i}:

$$F_{\text{target}_i} = k_p \cdot \left(1 - e^{-\beta \cdot E_i}\right) \cdot \mathbf{r}_{\text{target}_i} \tag{4}$$

where k_p is the panic factor, E_i is the panic sentiment of individual i, β is the sensitivity of panic to behavioural influences, and $\mathbf{r}_{\text{target}_i}$ is the unit vector pointing to the nearest safe exit.

Panic E_i can be given by the following recursive relation.

$$E_i^{t+1} = E_i^t + \alpha \cdot \left(E_{\text{avg}}^t - E_i^t\right) + \gamma \cdot I_{\text{panic}}(t) \tag{5}$$

where E_i^{t+1} is the panic emotion of individual i at time step $t+1$, E_i^t is the panic emotion at the current time step, E_{avg}^t is the average panic emotion of the group at the current time step, α is the rate of emotion propagation, $I_{\text{panic}}(t)$ is the effect of the external panic source at time t, and γ is the coefficient of influence of external panic source on individual panic emotion.

3.1.3. *Macroscopic description of group behaviour.* Group behaviour can be described by the continuity and momentum conservation equations:

$$\frac{\partial n(\mathbf{x},t)}{\partial t} + \nabla \cdot (n(\mathbf{x},t)\mathbf{v}(\mathbf{x},t)) = 0 \tag{6}$$

$$\frac{\partial n(\mathbf{x},t)\mathbf{v}(\mathbf{x},t)}{\partial t} + \nabla \cdot [n(\mathbf{x},t)\mathbf{v}(\mathbf{x},t)\mathbf{v}(\mathbf{x},t)] = -\nabla p(\mathbf{x},t) + \nabla \cdot \sigma\left(\nabla \mathbf{v}(\mathbf{x},t)\right) + \mathbf{F}_{\text{ext}}(\mathbf{x},t) \tag{7}$$

where $n(\mathbf{x},t)$ is the density of the crowd at location $\mathbf{x}$ and time t, $\mathbf{v}(\mathbf{x},t)$ is the average velocity of the crowd, $p(\mathbf{x},t)$ is the pressure, σ is the coefficient of viscosity, $\mathbf{F}_{\text{ext}}(\mathbf{x},t)$ is the external force (e.g., from panic).

A key challenge in mathematical modelling is to accurately describe the spread of panic and how it affects the behaviour of individuals and groups. Panic can lead to irrational and unpredictable behaviour, which requires models that can capture these complex dynamics.

3.2. **Emotional contagion model.** Crowd emotional contagion is the psychosocial behaviour of a group that is influenced by its own perceptions and cognitions. This behavioural activity has a direct impact on the behavioural performance and cognition of other members of the group, and also affects the behaviour and cognition of other individuals in the group through the contagion of other people's emotions. There are differences in the emotional contagion caused by individuals with different personalities to others. Therefore, modelling the problem of crowd evacuation taking into account emotional factors belongs to a very valuable topic, including individual differentiation and personalisation.

The propagation of panic can be described by inter-individual interactions in which the emotional state of each individual can be considered as a dynamic variable. The rate of change of emotional state can be represented by the following differential equation.

$$\frac{dE_i}{dt} = -\lambda E_i + \sum_{j=1}^{N} a_{ij} B_j \left(E_j - E_i\right) \tag{8}$$

where E_i denotes the panic level of individual i, λ is the natural decay rate of individual panic, N is the total number of people in the group, a_{ij} denotes the intensity of contact between individual i and j, and B_j is the behavioural influencing factor of individual j, which reflects the influence of individual j on the propagation of panic in i.

An individual's sensitivity to panic can be described by a threshold model that defines the critical value at which an individual feels panic:

$$T_i = T_0 + \sum_{j=1}^{N} a_{ij} G_j \tag{9}$$

where T_i is the panic threshold of individual i, T_0 is the base threshold, and G_j is the panic influence of individual j, which reflects the effect of individual j on the panic threshold of i.

The dynamic evolution of panic can be described by the following recursive relationship.

$$E_i^{t+1} = f\left(E_i^t, \mathbf{G}_i^t\right) \tag{10}$$

where E_i^{t+1} is the panic level of individual i at time step $t+1$, E_i^t is the panic level at the current time step, $\mathbf{G}_i^t$ is the set of all the factors affecting individual i's panic, and f is a non-linear function which can be defined according to the specific propagation mechanism.

Panic affects not only an individual's psychological state, but also their evacuation behaviour. Evacuation behaviour can be related to the level of panic by:

$$v_i^{t+1} = v_i^t + \alpha\left(E_i^t\right) \cdot \left(v_{\text{target}} - v_i^t\right) \tag{11}$$

where v_i^{t+1} is the evacuation speed of individual i at time step $t+1$, v_i^t is the speed at the current time step, $\alpha\left(E_i^t\right)$ is an adjustment coefficient that depends on the level of panic, and v_{target} is the speed of evacuation towards the safety exit. The desired evacuation speed.

4. **Optimal path planning for crowd evacuation based on improved water wave optimisation algorithm.**

4.1. **Traditional water wave optimisation algorithms.** Crowd evacuation optimal path planning is a relatively complex nonlinear planning problem, and it is difficult to solve the problem with traditional mathematical planning methods. Compared with other swarm intelligence methods, the water wave optimisation algorithm has the advantages of fast convergence speed, high accuracy, few parameters, simple implementation and small computation. The results of the benchmark test function set show that the water wave optimisation algorithm is superior to PSO and ACO in terms of overall optimisation performance. WWO is a group intelligence optimisation algorithm that simulates the propagation and interaction of water waves on the water surface [23, 24]. It seeks the most efficient outcome through the imitation of dissemination processes, refraction and wave breaking phenomena of water waves.

In the WWO algorithm, each potential solution is treated as a water wave object with position $\mathbf{x}$, wavelength (λ) and wave height (h). The wavelength (λ) of a water wave is updated as follows.

$$\lambda_i^{t+1} = \lambda_i^t \cdot e^{-\alpha \cdot \left(f\left(\mathbf{x}_i^t\right) - f\left(\mathbf{x}_{\text{best}}^t\right)\right)} \tag{12}$$

where α is the decay rate, $f\left(\mathbf{x}_i^t\right)$ is the fitness of the ith water wave at time step t, and $f\left(\mathbf{x}_{\text{best}}^t\right)$ is the fitness of the globally optimal water wave.

The wave height (h) is updated as follows.

$$h_i^{t+1} = h_i^t - \delta h \tag{13}$$

where δh is the wave height decay value, ensuring that the wave height decreases as the iteration progresses.

The propagation mechanism of water waves can be modelled by position updating, the position updating rule for each water wave object is as follows.

(1) Location update:

$$\mathbf{x}_i^{t+1} = \mathbf{x}_i^t + \lambda_i^t \cdot (\text{rand}() - 0.5) \tag{14}$$

where rand() is a random function that generates random numbers in the interval $[0, 1]$.

(2) Energy Accumulation and Wavelength Adjustment.

$$\lambda_i^t = \lambda_{\max} - \beta \cdot \left(f\left(\mathbf{x}_i^t\right) - f\left(\mathbf{x}_{\min}^t\right)\right) \tag{15}$$

where $\lambda_{\max}$ is the initial maximum wavelength, β is the wavelength adjustment factor, and $f\left(\mathbf{x}_{\min}^t\right)$ is the minimum fitness value.

In the search space, water waves can encounter different media, leading to refraction phenomena. At the same time, water waves may encounter obstacles during propagation, leading to broken wave phenomena. These phenomena can be modelled by [25].

(1) Refraction:

$$\mathbf{x}_i^{t+1} = \mathbf{X}_i^t + \Delta\mathbf{x}_i^t \tag{16}$$

where $\Delta\mathbf{x}_i^t$ is the change in water wave position due to refraction.

(2) Broken waves. When the wave height of a water wave drops to zero or encounters an obstacle, it breaks up and generates a new water wave object, whose position and wavelength are adjusted to the surrounding environment.

In the sequel, we will introduce how the traditional WWO algorithm can be improved to adapt to the crowd evacuation optimal path planning problem considering panic propagation. By introducing chaos theory and longitudinal crossover strategies, we expect to elevate the global search capability and local search precision of the WWO algorithm.

4.2. **Improved WWO algorithm.** In order to enhance the search performance of the WWO algorithm even further, this paper improves the traditional WWO algorithm by alternately introducing chaotic local search and vertical crossover strategy. Chaotic local search is performed on the optimal individuals so that there is a chance to jump out of the optimum in the local range. And the vertical crossover operation is performed on the more optimal individuals in order to have a chance to avoid entrapment in a local maximum in the global scope. The two are used alternately under certain conditions to ensure the diversity of individuals in the water wave population, and at the same time avoid the algorithm trapped in a local maximum resulting in poor accuracy of the search for the optimum.

4.2.1. *Chaotic initialisation and chaotic local search.* The initial population distribution directly affects the algorithm's optimality searching effect, the general initialisation population adopts random initialisation, but when the individuals in the population are in the vicinity of the optimal solution, the WWO algorithm can converge rapidly and obtain higher accuracy. When the distance between the individuals in the random initial population and the optimal solution is farther away, the convergence of the algorithm becomes slower and the accuracy of the optimisation search becomes lower. Due to the randomness and regularity of the chaotic operation, it makes it global and non-repeatable within a certain range, thus it can solve the less-than-optimal distributions that may occur during the random initialisation. In this paper, the Tent mapping method [26, 27] is used to initialise the population in order to improve the diversity of the population.

$$x_{t+1} = \begin{cases} 2x_t, & 0 \le x_t \le 0.5 \\ 2(1 - x_t), & 0.5 < x_t \le 1 \end{cases} \tag{17}$$

Chaotic local search is performed by chaotic perturbation in the neighbourhood of the optimal solution in order to jump out of the local optimal solution. Assuming that $\mathbf{x}$ is the current optimal solution, chaotic local search can be achieved by the following steps:

$$\mathbf{x}'_i = \mathbf{x}_i + \Delta\mathbf{x} \tag{18}$$

$$\Delta\mathbf{x} = \gamma \cdot (\mathrm{rand}() - 0.5) \tag{19}$$

where γ is a parameter controlling the intensity of the chaotic perturbation.

4.2.2. *Vertical crossover strategy.* The vertical crossover strategy increases the diversity of the population by exchanging information between different dimensions and helps to jump out of the local optimum. Longitudinal crossover is achieved by crossing between two different dimensions of an individual. Two different dimensions i and j are chosen. Perform crossover on the values of individual $\mathbf{x}$ on dimensions i and j to generate a new individual $\mathbf{x}'$.

The longitudinal crossover strategy is triggered with a certain probability during the iterations of the algorithm. In each iteration, with a certain probability p_c, it is decided whether to perform a longitudinal crossover or not. If a longitudinal crossover is performed, two dimensions i and j are randomly selected for crossover. The crossed individuals $\mathbf{x}'$ will participate in the subsequent fitness assessment.

The probability of a vertical crossover strategy p_c can be determined by.

$$p_c = \min\left(1, p_{c0} \cdot e^{(t_{\max} - t)/T}\right) \tag{20}$$

where p_{c0} is the initial crossover probability, t is the current number of iterations, $t_{\max}$ is the maximum number of iterations, and T is a parameter controlling the change in crossover probability.

Through chaotic initialisation and chaotic local search, the improved WWO algorithm is able to quickly spread to all regions of the solution space in the initial stage. And in the later stages of the WWO algorithm, through the vertical crossover strategy, it is able to perform a more detailed search in the local region, thus improving the probability of finding the global optimal solution. The introduction of these strategies makes the improved WWO algorithm more suitable for complex optimisation problems, such as the optimal path planning problem for crowd evacuation considering panic propagation.

4.2.3. *Optimisation of wavelength update based on panic.* In the improved WWO algorithm, the wavelength update is not only affected by the water wave adaptation, but also the effect of panic on evacuation behaviour should be considered. Panic emotion may lead to drastic changes in individual behaviour, which requires the WWO algorithm to be able to respond quickly and adjust the search strategy.

First, we need to quantify the impact of panic on individual behaviour.

$$P_i^t = P_0 + \beta \cdot \left(D_i^t - D_{\text{avg}}^t\right) \tag{21}$$

where P_i^t is the panic value of individual i at time step t, P_0 is the base panic level, β is the sensitivity coefficient of panic, D_i^t is the distance of individual i from the source of the danger, and D_{avg}^t is the average of the distances of all the individuals from the source of the danger at time step t.

In the improved WWO algorithm, the update of wavelength not only relies on the individual's adaptation, but also needs to consider the effect of panic. The update rule for wavelength can be expressed as follows.

$$\lambda_i^{t+1} = \lambda_i^t \cdot e^{-\alpha\left(f\left(\mathbf{x}_i^t\right)-f\left(\mathbf{x}_{\text{best}}^t\right)\right)} \cdot \gamma \cdot P_i^t \tag{22}$$

where λ_i^{t+1} is the wavelength of individual i at time step $t+1$, α is the attenuation rate associated with adaptation, and γ is the attenuation rate of the effect of panic.

The introduction of panic makes the wavelength update more dynamic and able to adapt quickly to environmental changes. In order to prevent excessive localised searches due to too small a wavelength or ineffective searches due to too large a wavelength, the wavelengths need to be appropriately bounded by upper and lower bounds of.

$$\lambda_{\min} \leq \lambda_i^{t+1} \leq \lambda_{\max} \tag{23}$$

where $\lambda_{\min}$ and $\lambda_{\max}$ are the minimum and maximum values of the wavelength, respectively.

Panic changes dynamically over time and as evacuation progresses. The dynamic adjustment of panic can be realised by the following recursive relationship.

$$P_i^{t+1} = \rho \cdot P_i^t + (1-\rho) \cdot P_0 + \beta \cdot \left(D_i^t - D_{\text{avg}}^{t+1}\right) \tag{24}$$

where ρ is the decay coefficient of panic and P_i^{t+1} is the panic value of individual i at time step $t+1$.

4.3. **Practical application example.** With the above mathematical expression, we are able to construct a wavelength update mechanism that takes panic into account, which enables the improved water wave optimisation algorithm to better simulate the dynamics of an emergency evacuation situation, and thus find a more efficient evacuation path. Next, we will show how to apply this mechanism to a real-world evacuation path optimisation problem. Suppose we are dealing with an evacuation path optimisation problem for a multi-storey building. We can use the following steps to apply the above mechanism to a real problem:

Step 1: Create a network model of the building, including all floors, stairs, exits and corridors.

Step 2: Simulate the evacuation process using the water wave algorithm, where each water wave represents a potential evacuation path.

Step 3: Update the panic level in real time by monitoring the density of people during evacuation and the development of the emergency situation.

Step 4: Dynamically adjust the wavelength of the water waves according to the level of panic and the adaptation of the evacuation path to better simulate the effect of panic on evacuation behaviour.

Step 5: The optimisation algorithm runs and iterates until the optimal evacuation path is found.

Step 6: Conduct an evacuation drill in an actual building to validate and adjust the model.

In this way, the improved water wave optimisation algorithm can be effectively applied to the evacuation path optimisation problem considering panic to provide a faster and safer evacuation solution.

5. **Experiments and analysis of results.**

5.1. **Description of the experimental setting.**

The experiment aims to evaluate the effectiveness and efficiency of the Improved WWO algorithm in dealing with the crowd evacuation problem considering panic. In order to verify the performance of the IWO algorithm for emergency crowd evacuation, Matlab 2019b is used for example simulation. A detailed comparative study of the performance of the PSO algorithm [28], the WWO algorithm [29], and the improved WWO algorithm in terms of path planning capability, convergence trend of the algorithms, and the time required for evacuation in emergency evacuation scenarios has been carried out through simulation experiments with the aim of evaluating the three algorithms in terms of the path planning efficiency, the stability and the convergence rate of the process of reaching the optimal solution, as well as the time required for the completion of the evacuation. The purpose of this study is to evaluate the different performance of the three algorithms in terms of path planning efficiency, stability and convergence rate in reaching the optimal solution, and the time required to complete evacuation.

In this paper, the experimental scene is set as a rectangular place with a length of 60m, a width of 40m, and an exit width of 3m, which can be effectively modelled for the place of crowd evacuation, as shown in Figure 2. The distribution of individuals in the place has strong randomness, and with the change of time, the location and speed of individuals will change.

The initial value settings of the main parameters of the improved WWO algorithm are shown in Table 2.

5.2. **Path optimisation performance comparison.**

Firstly, the path of all personnel evacuation is simulated, and the distance moved by all personnel to reach the evacuation point is calculated, and the three algorithms are simulated separately, and the results are shown in Table 3.

The distances moved by 100 people evacuated to the safe site are summed up to obtain that the differences in the distances moved by the three algorithms are small. The total distance moved by the PSO algorithm is 79.417 m, while the total distance moved by the WWO algorithm is 76.773 m. Compared with the other two algorithms, the improved WWO algorithm has a better performance of path optimisation, and the total

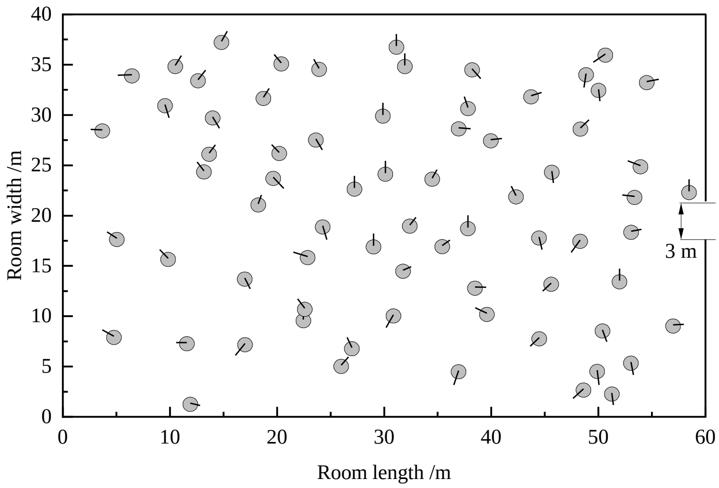

Figure 2. Evacuation scenarios

Table 1. Initial value settings of the main parameters of the experiment

Parameter name	**Descriptions**	**Numerical value**
Population Size	Number of individuals (water waves) in the water wave algorithm	30
Iterations	Number of iterations for the algorithm to run	200
Panic Sensitivity	Sensitivity coefficients for the impact of panic on wavelength updates	1
Chaos Strength	Strength of chaotic perturbations	0.1
Local Search Range	Scope of chaotic local search	0.2
Crossover Probability	Probability of implementing a vertical crossover strategy	0.05
Min/Max Wave Length	Minimum and maximum values of wavelength	(0.5, 1.5)
Decline Rate	Wavelength attenuation	1.002

distance moved is only 73.524 m, which is significantly smaller than that of the other two algorithms. algorithms.

Table 2. Path optimisation performance of three algorithms

Algorithms	**Total distance travelled/m**
PSO	79.417
WWO	76.773
Improved WWO	73.524

5.3. **Convergence performance comparison.** In order to verify the convergence performance algorithm, the distance travelled is simulated with the number of iterations, and the results are shown in Figure 3. The analysis results show that the improved WWO algorithm performs the best as far as convergence efficiency is concerned, successfully finding the optimal evacuation path with a length of 73.524 m through a process of 52 iterations. This finding confirms the efficiency and reliability of the improved algorithm in solving such optimization problems, while the WWO algorithm reaches convergence in 108 iterations and the PSO algorithm reaches convergence in 142 iterations. From the convergence process, it can also be seen that the PSO algorithm and WWO algorithm obtain the local optimal solution in 4 and 2 times respectively, while the improved WWO algorithm in this paper has no local optimal solution, which indicates that it has a clear advantage in convergence performance.

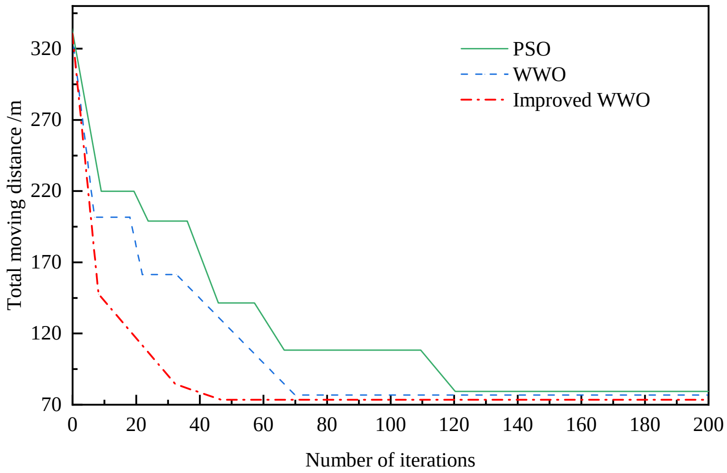

Figure 3. Convergence performance comparison

5.4. **Comparison of evacuation time performance.** In order to fully verify the evacuation time performance, the consumption time of the three algorithms in obtaining the optimal path is simulated separately, and each algorithm performs 10 simulations, and the simulation results are shown in Figure 4. Analyzing ten simulations of the evacuation process through the PSO method reveals an average completion time of approximately 3200 seconds, while the simulation time of 10 evacuation runs of the WWO algorithm is about 2600s, and the simulation of 10 evacuation runs of the improved WWO algorithm time average is around 1900s. And from the point of view of the stability of the running time, the time fluctuation of the improved WWO algorithm during 10 simulations is small, while the other two algorithms have large fluctuations in the running time, so this paper's algorithm has an obvious advantage in the evacuation time performance.

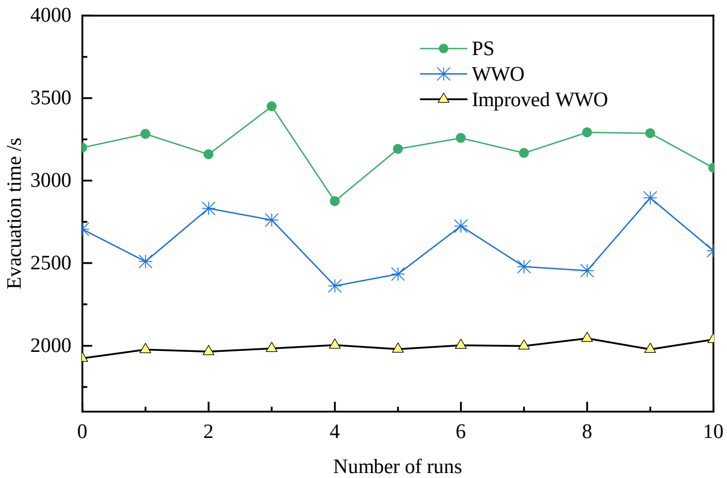

Figure 4. Comparison of evacuation time

6. **Conclusion.** In this study, a swarm intelligence optimisation model incorporating the effect of panic emotion was proposed for the path optimisation problem in emergency evacuation situations, and an improved water wave optimisation algorithm was developed. Through behavioural characterisation, a quantitative model of panic emotion was established, which is capable of assessing the impact of panic emotion on individual evacuation behaviour. This innovation makes the evacuation model closer to the actual emergency situation and improves the realism and effectiveness of evacuation simulation. The proposed improved water wave optimisation algorithm enhances the global and local search capabilities of the algorithm through chaos theory and vertical crossover strategy. In addition, the wavelength update mechanism based on panic makes the algorithm adaptive to the dynamic changes in emergency situations. The effectiveness of the improved water wave optimisation algorithm in terms of evacuation time, path security and algorithm convergence performance is verified. The experimental results show that the algorithm is able to find a better evacuation path under the consideration of panic emotion. Future research can explore more complex evacuation scenarios, such as multi-floor building evacuation and large-scale crowd evacuation.

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