ingegneria sismica
International Journal of Earthquake Engineering
Anno XLIII - Num. 2 - 2026

An Evacuation Path Optimization Model Combining Digital Twins and Intelligent Improvement Algorithms for Complex Building Fire Environments

Yuwen Chen[1,*]

[1] Xiamen University, Xiamen, Fujian, 361102, China

SUMMARY: *Aiming at evacuation path optimization in complex building fire environments, this study proposes a dynamic evacuation path optimization model that integrates digital twin and intelligent optimization algorithm. By constructing a digital twin of the building fire scene, the fire environment in the building is monitored and analyzed in real time. Combined with the improved particle swarm algorithm, the difficulty and distance of each evacuation section are dynamically calculated by obtaining the parameters of multiple influencing factors in the building. Using the updating ratio factor, the poorer paths are eliminated, and the accuracy of the planned paths is judged, and the optimal evacuation path is obtained by iterative updating. The results show that: the improved algorithm in this paper, with 16 iterations, obtains the shortest evacuation distance of 36.51 m. The algorithm solves the evacuation time after the fire spreads for 120, 240, and 360 s to be 25.67, 52.09, and 88.46 s, respectively. In the evacuation of medium-scale road networks, the optimal path of the improved particle swarm algorithm includes 15 nodes and 14 road sections, and the evacuation time is shorter than that of the comparison method. The method saves 18.2~24.4m of evacuation distance in the simulated 10-medium fire scenarios. The evacuation efficiency of this paper's method in fire simulation is good, and it takes 326.2s to evacuate 2865 people. In conclusion, the method proposed in this paper can be used as a technical framework for intelligent emergency evacuation system.*

KEYWORDS: *Digital twin; improved particle swarm algorithm; fire evacuation; path optimization*

1 Introduction

With the acceleration of urbanization, high-rise buildings have been able to rise rapidly in cities [1]. However, the problem of evacuation in case of fire in high-rise buildings, especially in complex building environments, has become an important factor limiting their safety [2, 3]. In the event of fire, the speed and efficiency of evacuation are critical to minimize casualties [4, 5]. Therefore, how to optimize the evacuation path of complex building fire environments has become a pressing issue in the field of building safety at present.

The current status of evacuation paths for complex building fire environments involves several aspects, including building structure, human behavior, and equipment and facilities [6, 7]. In terms of building structure, considering the complexity of high-rise buildings, the setup of evacuation paths must take into account both design specifications and actual operation to ensure that people can be evacuated quickly and in an orderly manner in an emergency [8-10].

*23220211151621@stu.xmu.edu.cn
https://doi.org/10.65102/is20261041

Published: 30 April, 2026

However, in the actual fire evacuation process, the uncertainty of human behavior makes the designed paths may face challenges, such as congestion and blockage [11, 12]. At the same time, the special characteristics of people evacuation in fire conditions are not fully considered in the building design, resulting in some paths being difficult to meet the actual needs in emergency situations [13, 14]. Panic and irregular behavior of personnel in fire conditions may lead to confusion and congestion of evacuation paths, increasing the safety risk [15]. In addition, some existing high-rise buildings have insufficient standardization of evacuation path markings and emergency equipment, which affects evacuation efficiency [16-18]. The problems partly stem from the fact that the special needs in fire situations are not sufficiently considered in building design and planning, and in order to cope with these problems, the combination of digital twins and intelligent optimization algorithms gives us insights.

In this paper, we construct a digital twin-driven evacuation framework for fire environments, including three parts: physical space, twin space, and digital twin applications, to realize applications such as building fire safety monitoring, risk analysis, and emergency response. Meanwhile, the particle swarm algorithm is improved by introducing the optimization strategy of the algorithm with real-time adjustment of parameters such as fire index, channel difficulty and step length. When the planned path meets the set requirements, it is the optimal evacuation path. The intelligent improvement algorithm is combined with the digital twin framework to simulate the evacuation of people in a complex building fire environment, and the evacuation distance and time are used to verify the evacuation effect of the proposed method.

2 Digital twin-driven fire environment evacuation program

2.1 Five-dimensional model of digital twin technology

Digital twin technology [19, 20] is a technology that combines physical entities and digital information. It takes physical entities as the basis and creates corresponding digital models in virtual space to realize mutual mapping and interaction between physical entities and digital models. This technology has been applied in many fields, such as smart city, smart factory, intelligent manufacturing, etc. Digital twin technology enables the simulation, optimization, monitoring and maintenance of physical entities to improve the efficiency and reliability of physical systems.

Systems in which physical and computer systems are connected and work together through a network are referred to as "cyber-physical systems" or "Internet of Things (IoT)". Among them, "intelligent physical systems" are called "intelligent Internet of Things (IIoT)" by fusing technologies such as sensors and networks to achieve self-control and optimization. This convergence of the physical and digital worlds is also known as a "cyber-physical system" or "Cyber-Physical System (CPS)" system. The CPS system is designed to improve the autonomy, adaptability, real-time and security of the system. CPS systems can be applied in various fields, such as manufacturing, transportation, medical, energy, etc.

Digital twin is a CPS system that converts physical entities into virtual models through simulation, prediction and optimization. The core of digital twin technology is to convert physical objects into digital models and to realize the reproduction of physical phenomena in the digital world through the interaction between digital models and physical reality.

In order to better meet the needs of different domains, digital twin constitutes a new five-dimensional model by adding two dimensions (twin data and services) to the three-dimensional model. The digital twin five-dimensional model can be represented by the following equation:

$$M_{DT} = (PE, VE, Ss, DD, CN) \tag{1}$$

where PE stands for the entities in the physical scenario and VE stands for the models in the virtual scenario. Ss is used to encapsulate all the functionalities such as algorithms, data and results in the service while DD is the fusion of physical and informational data and CN is used to connect the components.

2.2 Digital Twin Based Evacuation Framework for Fire Environments

The essence of the digital twin lies in the establishment of a mapping relationship between the physical entity and the digital model, and to ensure that the communication between the two can be effectively realized, to solve the security management of complex buildings often rely on manpower and limited monitoring equipment, it is difficult to achieve comprehensive coverage of building security and real-time monitoring. The building security based on digital twin refers to the use of digital technology and data models for modeling and simulation of building safety to improve the building safety management and emergency response capabilities of the method and to achieve real-time synchronization and interaction between the physical and virtual. In this paper, we propose a digital twin framework for building fire evacuation as shown in Fig. 1. The modeling framework consists of three parts: physical space, twin space, and digital twin application.

The physical space covers all the physical entities in the building, such as roads, green belts, etc., as well as all kinds of sensor-aware devices, such as cameras and smoke alarms. Together, these physical entities and devices constitute the security infrastructure of the building. Second, the twin space is the key to the digital twin model of building security. It is mainly composed of twin data and BIM model. The twin data collects all kinds of security information in the building in real time through intelligent sensing devices, such as people flow, traffic flow, environmental quality, etc., to provide a data base for subsequent model construction and data analysis. The BIM model, on the other hand, provides a three-dimensional visualization management platform for safety management through digital modeling of the building. The connection between the physical space and the twin space is realized through intelligent sensing and virtual-reality mapping. Intelligent sensing devices are able to sense the safety information in the building in real time and transmit it to the twin space through the network. Virtual-reality mapping refers to the mapping of physical objects in the physical space to the twin space, establishing a correspondence between the two. Finally, the twin space implements twin applications through a data-driven model. These applications include, but are not limited to, security monitoring, risk analysis, emergency response, etc. Through the deep mining and analysis of twin data, potential safety hazards can be discovered in time, providing strong support for building safety management. The digital twin-based building security model brings a new perspective and method for building safety management. By constructing the mapping relationship between the physical space and the twin space, it realizes real-time monitoring and analysis of the building security environment, and improves the efficiency of security management and the speed of emergency response.

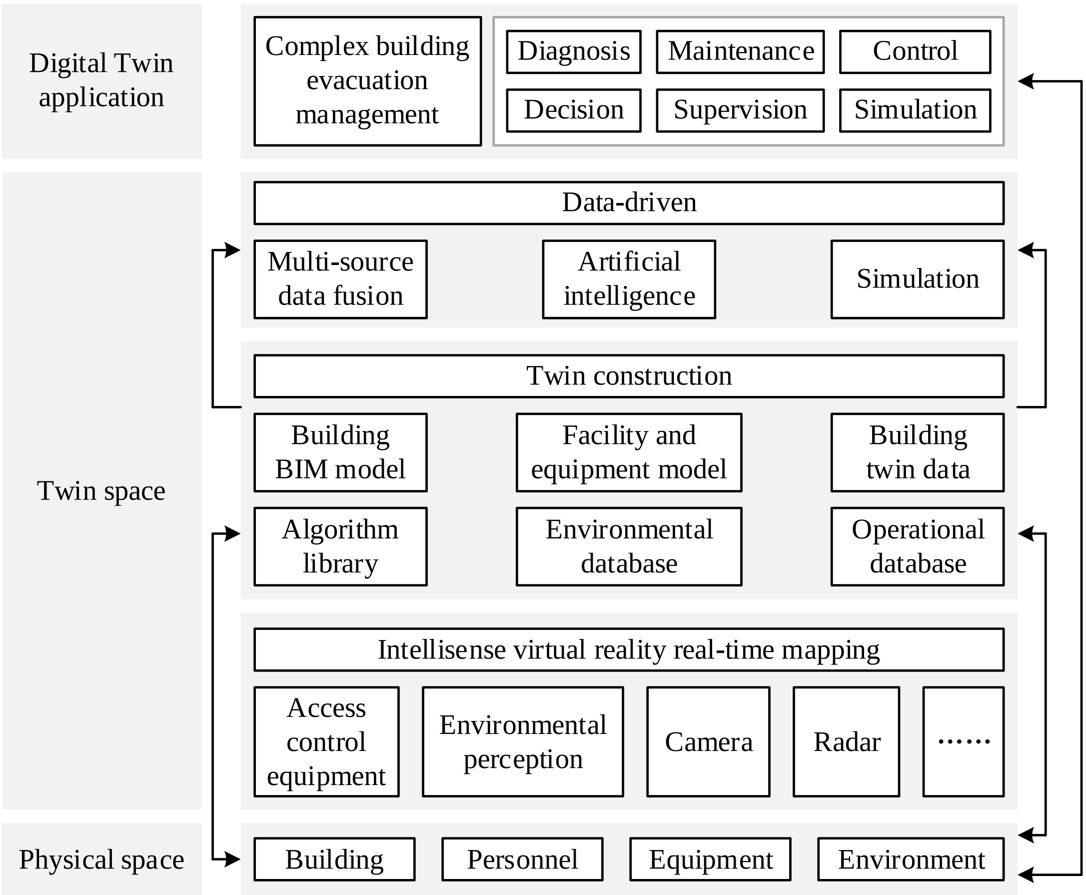

Figure 1: Twin framework for building fire evacuation figures

3 Design of Adaptive PSO Algorithm Integrating Fire Dynamic Information (APSO-FD)

To accurately respond to the dynamic fire evacuation scenarios and overcome the inherent limitations of the standard particle swarm optimization algorithm (PSO) in such applications, this study designs and implements an adaptive particle swarm optimization algorithm (APSO-FD) that deeply integrates the dynamic information of the fire environment. This algorithm aims to achieve an efficient unity of real-time performance, safety and global optimality in evacuation path planning by constructing an fitness evaluation system that responds to environmental changes in real time and implementing a precise parameter adaptive control strategy.

3.1 Standard Particle Swarm Optimization Algorithm and Its Limitations

3.1.1 Basic Principles of the PSO Algorithm

Particle Swarm Optimization algorithm, often abbreviated as PSO, is a swarm intelligence optimization technique derived from the simulation of social behaviors such as foraging of bird flocks in nature. This algorithm was first proposed by Kennedy and Eberhart in the mid-1990s. Its core idea lies in using the collaboration and information sharing mechanism among individuals in the group to search for the optimal solution to complex problems. The PSO algorithm has been widely applied and verified in many optimization fields of scientific research and engineering practice due to its characteristics such as intuitive concept, fewer parameters and easy programming implementation.

The inspiration of the PSO algorithm comes from the observation and abstraction of the predatory behavior patterns of bird groups. Imagine a flock of birds randomly searching for food in an area where there is only one source of food. None of the birds know exactly where the food is, but they know how far the current position is from the food. In this situation, the easiest and most effective strategy is to follow the bird that is currently closest to the food for the search.

The PSO algorithm is precisely based on this kind of group collaboration model, comparing the potential solutions of the optimization problem to "particles" in the search space. Each particle is assigned specific attributes to guide its exploration behavior in the solution space. The core concepts are defined as follows:

Particle: As the basic search unit in the optimization process, each particle characterizes a potential solution to the problem. In the d-dimensional search space, it has no physical mass or volume and is simply regarded as an intangible point.

Population: The set of all particles that perform the collaborative search task, and its size is denoted as -N. Population size is an important parameter that affects the search performance and computational cost of an algorithm.

Position: Describes the particle in. D. The state vector of the state in the dimensional solution space, the position vector of i particles is expressed as $x_i = (x_{i1}, x_{i2}, \ldots, x_{iD})$. Each component x_{id} of this vector represents the current value of a parameter to be optimized for the problem. The superiority or inferiority of particle positions is evaluated by the Fitness function fitness.

Velocity: The velocity vector that characterizes the magnitude and direction of a particle's tendency to move in the solution space. The velocity vector of the i th particle is expressed as $v_i = (v_{i1}, v_{i2}, \ldots, v_{iD})$. This vector directly determines the amplitude and direction of the position update of the particle in the subsequent iterations.

Individual optimal $pbest_i$: Records the position vector that has the best fitness value among all the positions visited by the I th particle since the search was initiated. This constitutes the historical optimal experience or memory of the particle itself.

Global optimal $gbest$: It records the best position vector found so far among all members of the entire particle population, that is, the one with the best fitness among all $pbest_i$. This represents the optimal information shared by the group.

The optimization dynamics of PSO lies in the fact that each particle is simultaneously "attracted" by its own historical optimum, $pbest_i$, and the global optimum of the population, $gbest$, during the iterative process, and by adjusting its own velocity v_i. To update its position x_i, thereby achieving a balance between exploring the unknown area and utilizing the known information, and driving the entire population to move towards a better solution domain.

3.1.2 Limitations of Standard PSO in Dynamic Fire Evacuation Path Planning

Although the standard particle swarm optimization algorithm has demonstrated its optimization capabilities in many fields, when it is directly applied to the specific and demanding scenario of dynamic fire evacuation, its inherent characteristics bring a series of challenges, which constitute the direct motivation for its improvement.

(1) Convergence issue: Premature convergence and local optimal trap analysis

The primary challenge faced by the standard PSO algorithm in the optimization process is the risk of premature convergence. This phenomenon refers to the fact that before the global optimal solution is fully explored, the entire particle population gathers too quickly into one or a few non-global optimal regions, thus losing the possibility of further exploration of better solutions.

Specifically in the application of fire evacuation path planning, the complex spatial structure inside the building and the dynamically changing fire environment jointly constitute an extremely complex search space that may contain numerous local optimal solutions. For example, a path that initially seems the shortest and far from the fire source might be a local optimal solution, but it could lead to a bottleneck area that will be blocked by the fire or smoke in the future. If the standard PSO converges prematurely to such paths and fails to discover other paths that are slightly longer initially but safer globally, a local optimal trap will be formed.

The consequence of getting trapped in local optimum is particularly serious in the scenario of fire evacuation. It may cause the evacuation path planned by the algorithm to guide people to a temporary safe area. However, as the fire situation worsens, this area eventually turns into a dangerous zone, making it impossible for people to continue evacuating.

(2) Insufficient dynamic adaptability: The response to dynamic environmental changes is lagging behind

The insufficient adaptability of the standard PSO algorithm in dealing with dynamic environmental changes is another core limitation of its application in fire evacuation. The design basis of a standard PSO typically assumes that the objective function or fitness landscape is static and invariant. The algorithm guides the search direction based on the particle historical optimum $pbest$ and the $gbest$ historical optimum best, which reflect the superiority or weakness of the solution in past environmental states.

However, the fire evacuation environment is precisely a highly dynamic system. Factors such as the location of the fire source, the speed of fire spread, the concentration and distribution of smoke, changes in visibility, temperature rise, and possible channel blockage or structural damage are all changing the safety and passage efficiency of each node and path segment in the evacuation path network in real time, thereby leading to drastic changes in the adaptability landscape over time.

(3) Parameter Dependency and Setting Difficulties

The performance of the standard PSO algorithm has a strong dependence on the values of its internal control parameters. For the problem of dynamic fire evacuation path planning, the challenge of parameter setting is even more severe. Since the fire environment itself is dynamically evolving, different stages may have different requirements for the search behavior of the algorithm. This dependence on the setting of static parameters makes the standard PSO less robust when facing complex and changeable fire scenarios. The algorithm may perform well at one stage, but its performance drops sharply at another. Therefore, the lack of an effective parameter adaptive adjustment mechanism is a practical operational difficulty when standard PSO are directly applied to dynamic fire evacuation route planning.

(4) Search for the problem of diversity attenuation

The standard PSO algorithm generally has the problem that the search diversity gradually decays during the iterative process. Although this aggregation behavior is the basis for the algorithm to converge to the optimal solution, if the diversity is lost too early or too quickly, it will damage the global search performance of the algorithm, especially in a dynamic environment. This inherent characteristic limits the algorithm's ability to quickly find brand-new solutions when the environment undergoes drastic changes, making it inadequate in the dynamic fire evacuation path planning that requires continuous exploration and adaptation. Therefore, how to maintain moderate population diversity while ensuring effective optimization is one of the key considerations for improving PSO to adapt to dynamic environments.

3.2 The Design of APSO-FD Algorithm

3.2.1 Construction of Fitness Function

The optimization direction of the APSO-FD algorithm is precisely guided by its Fitness Function. The design of the fitness function must comprehensively reflect the key evaluation dimensions of the advantages and disadvantages of the fire evacuation path to ensure that the algorithm can find the path solution that truly meets the requirements of safe and efficient evacuation.

The core indicators for path evaluation selected in this study cover the geometric length of the path $L(P)$, the path safety risk $S(P,t)$, and the expected travel time $T(P,t)$. The path length reflects the basic travel distance. Safety risk quantifies the extent to which a path is exposed to dangerous factors such as high temperatures and smoke. Estimated travel time takes into account the length of the path, the impact of the environment on speed, and potential congestion. These three indicators together form the basis for evaluating the overall performance of evacuation routes.

The quantification and integration of fire environmental impact parameters is the key to achieving the dynamic response of the fitness function. This study utilizes the real-time data provided by the digital twin platform to accurately calculate the comprehensive risk index $H_{ij}(t)$ and the passage difficulty level $\zeta_{ij}(t)$ of each section (i, j) on the path at time t, and then obtains the equivalent step size $D_{ij}(t)$ of the passage path calculation that integrates length, risk and passage difficulty. The equivalent step size $D_{ij}(t)$ has become the core metric for measuring the comprehensive cost of the passing section (i, j), which directly maps the dynamic changes of the environment to the evaluation value of the path.

Based on the above metrics, the Fitness function Fitness(P) constructed in this study takes minimizing the total equivalent length of the path as the optimization objective and integrates the penalty mechanism for the infeasibility of the path. Its mathematical expression is defined as the sum of the equivalent step lengths $D_{ij}(t)$ of all component sections (i, j) on path P, plus a term $Penalty(P)$ used to punish paths that violate the constraints:

$$Fitness(P) = \sum_{(i,j)\in P} D_{ij}(t) + Penalty(P) \tag{2}$$

Among them, when the path ·P crosses static obstacles or real-time high-risk areas, Penalty(P) takes a sufficiently large positive value to ensure that such paths are effectively excluded during the optimization process. The design of this fitness function ensures that the APSOFD algorithm can actively avoid dangers and find the safe evacuation path with the lowest comprehensive cost during optimization.

3.2.2 Adaptive Parameter Adjustment Strategy

The static Settings of the parameters of the standard PSO algorithm are difficult to adapt to the drastic dynamic changes in the fire environment. To this end, the APSO-FD algorithm adopts an advanced parameter adaptive adjustment strategy. The core lies in enabling the inertia weight a to dynamically respond to the search process and environmental risks, thereby intelligently balancing global exploration and local development.

The dynamic inertia weight ω adjustment mechanism designed in this study integrates iterative information and environmental risk feedback. The inertia weight ω maintains a relatively high value in the early stage of iteration to encourage global exploration.

Subsequently, it decreases nonlinearly with the increase of the number of iterations k to enhance the convergence in the later stage. The form of its base decay is set as:

$$\omega_{base}(k) = \omega_{max} - (\omega_{max} - \omega_{min}) \times (k / K_{max})^{p} \tag{3}$$

Here, ω_{max} and ω_{min} define the value range of ω, K_{max} is the preset maximum number of iterations, and p is the exponent for controlling the attenuation rate. On this basis, this algorithm further introduces the adjustment term based on real-time environmental risks. For each particle i, the average risk $H_{avg}(P_i, t)$ of the path segment it is going to explore is evaluated in real time. When $H_{avg}(P_i, t)$ increases significantly, it means that the particles are tending towards the dangerous area. At this time, their escape and exploration capabilities need to be enhanced.

Therefore, the final dynamic inertia weight $\omega(i, k+1)$ is designed as a combination of the base attenuation weight and the risk adjustment term:

$$\omega(i, k+1) = \omega_{base}(k) + \alpha \times Sigmoid(H_{avg}(P_i, t)) \tag{4}$$

Among them, α is the risk influencing factor. The Sigmoid-function maps the risk degree to the appropriate adjustment interval, ensuring that when the risk increases, the inertia weight increases accordingly, driving the particles to undergo stronger exploratory movement.

Learning factors c_1 and c_2 are equally crucial for balancing individual cognition and social learning. In the APSO-FD algorithm, a strategy of synchronous adjustment with the number of iterations is adopted. The cognitive factor c_1 decreases linearly with the iterations from a larger initial value, while the social factor c_2 increases linearly with the iterations from a smaller initial value. This design simulates the natural transformation of the optimization process from emphasizing individual exploration to focusing on group convergence.

$$\begin{aligned} c_1(k) &= c_{1,start} - (c_{1,start} - c_{1,end}) \times (k / K_{max})\$\$\$\$c_2(k) \\ &= c_{2,start} + (c_{2,end} - c_{2,start}) \times (k / K_{max}) \end{aligned} \tag{5}$$

Here $c_{1,start}, c_{1,end}, c_{2,start}, c_{2,end}$, they are the initial and final values of c_1 and c_2 respectively.

Through the collaborative adaptive adjustment of the above-mentioned inertia weight and learning factors, the APSO-FD algorithm can intelligently switch its search mode according to the optimization process and real-time environmental risks, significantly improving its robustness and optimization efficiency in the dynamic fire environment.

3.2.3 Particle Coding and Constraint Processing

This study determines to adopt the encoding method based on node sequences. In a grid-based or topological networked building environment, each passable position is assigned a unique node number. The position vector x of the particle, which is an ordered sequence of node numbers x_i, is $x_i = (node_1, node_2, \ldots, node_L)$. The sequence $node_1$ directly defines a path from the starting node to the ending $node_L$. The dimension of the particle vector. D corresponds to the maximum allowed number of path steps L_{max}.

The feasibility of the path is jointly guaranteed by the penalty mechanism in the fitness function and the particle movement restriction. Path connectivity requires that adjacent nodes in the sequence $node_j, node_{j+1}$ must be directly accessible on the map. Obstacle avoidance constraints prohibit paths from crossing static obstacles such as walls and real-time fire hazard $H_{ij}(t)$. Dynamic hazard areas that exceed the safety threshold. Any path that violates these constraints will be subject to a huge $Penalty(P)$ in fitness calculations, causing it to be naturally eliminated in the course of evolution. please

The boundary processing mechanism of particle motion is crucial for maintaining the stability of the algorithm and the effectiveness of the solution. Position boundary processing ensures that particle x is always within the valid area defined by the map. When a particle attempts to move beyond the boundary or enter an impassable area, a boundary absorption strategy is adopted, that is, the particle is placed at the nearest effective point on the boundary it attempts to cross.

Velocity boundary processing prevents the particle step size from being too large by setting a maximum velocity limit. After each velocity update, each component store of the velocity vector V_{max} is checked. If its absolute value exceeds V_{max}, saturation processing is carried out:

$$v_{id}^{k+1} = sign(v_{id}^{k+1}) \times \min(|v_{id}^{k+1}|, V_{max}) \tag{6}$$

This mechanism ensures the smoothness of particle movement and the controllability of the search process. To sum up, the APSO-FD algorithm has formed an optimized solution for the dynamic fire evacuation path planning problem through elaborately designed fitness functions, dynamic parameter adjustment strategies, and rigorous coding and constraint processing.

4 Simulation and analysis of evacuation in complex building fire environments

4.1 Performance Evaluation of Evacuation Path Dynamic Planning

In order to verify the effectiveness of this paper's optimized particle swarm algorithm in the dynamic planning of fire evacuation paths, MATLAB R2023a is used to compare and analyze the original particle swarm algorithm, the original ant colony algorithm and the improved particle swarm algorithm of this paper. The experiment is set in a 40m×40m environment map, the starting point is set as (1, 1), and the end point is set as (38, 39). The comparison results of the convergence curves of the three algorithms are shown in Fig. 2. The comparison results show that the improved wolfpack algorithm outperforms the original wolfpack algorithm and the original ant colony algorithm in terms of the number of iterations and the path length, which reduces 9 and 17 iterations respectively, and shortens the path by 15.46 and 17.73 m. The algorithm in this paper demonstrates a better computing speed, path optimization ability and path smoothness.

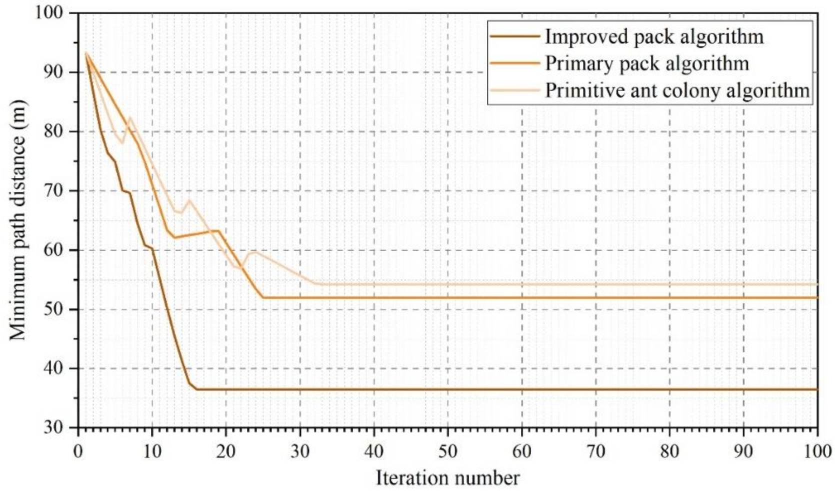

Figure 2: The convergence curve compares the results

Various fire product parameters change with the fire development process. In order to verify the effectiveness of the improved particle swarm algorithm in the case of fire spreading, MATLAB R2023a software is used to simulate and experimentally compare the evacuation paths for the three fire periods of 120, 240, and 360s.

Figure 3 shows the convergence curves of the improved particle swarm algorithm for the three fire periods. From the figure, it can be seen that in terms of evacuation time, as the fire spreads, the evacuation speed of the personnel slows down significantly, and the evacuation time for the 3 fire periods is 25.67, 52.09 and 88.46 s. This is because the material produced by the fire gradually increases, thus the degree of influence on the evacuees is increasing, which leads to an increase in the evacuation time. The above results show that the improved particle swarm algorithm can realize the dynamic planning of fire evacuation routes.

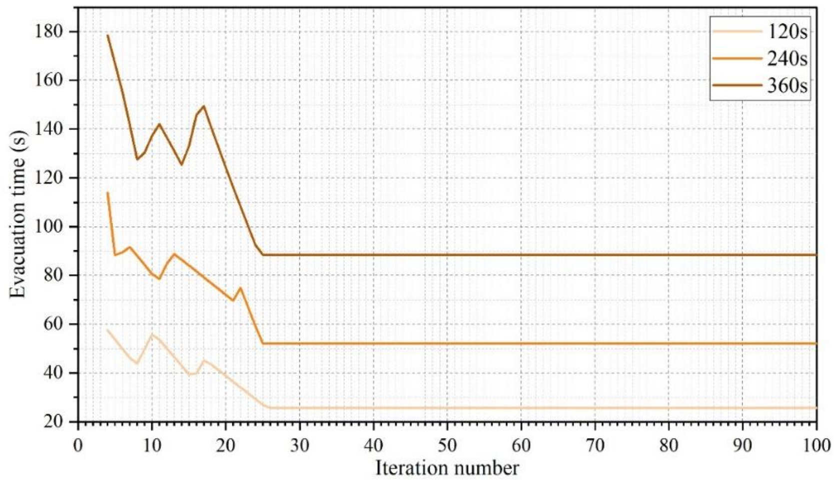

Figure 3: Three fire periods of improved the convergence of the particle swarm algorithm

4.2 Comparison of evacuation times on medium-sized road networks

In this paper, a medium-sized road network with 67 nodes and 99 paths is used to validate the effectiveness of this paper's digital twin combined with the improved algorithm. The marginal constraint of the model is the capacity of the evacuated paths. In order to ensure that the experiment is closer to the actual situation, the simulation software is used to generate the length (Unit: m) as well as the width (Unit: m) of the evacuated road sections. The roadway capacity is generated according to the roadway width, and the roadway passing time length is randomly generated in ascending order in the interval [4, 180]. The original particle swarm algorithm and the original ant colony algorithm are also chosen to compare with the method of this paper.

Figure 4 shows the time spent on each road segment of the fire evacuation paths of the three methods. According to the data in the figure, the improved particle swarm algorithm combined with the digital twin evacuation framework in this paper provides the optimal fire evacuation path, and the optimal path includes 15 nodes and 14 road segments, and the total evacuation time is about 635s. The evacuation paths generated by the original particle swarm algorithm and the original ant colony algorithm consist of 17 and 19 sections, respectively, and the total evacuation time is 853 and 946 s. It can be seen that the improved algorithms in this paper achieve better results in terms of evacuation sections as well as evacuation time.

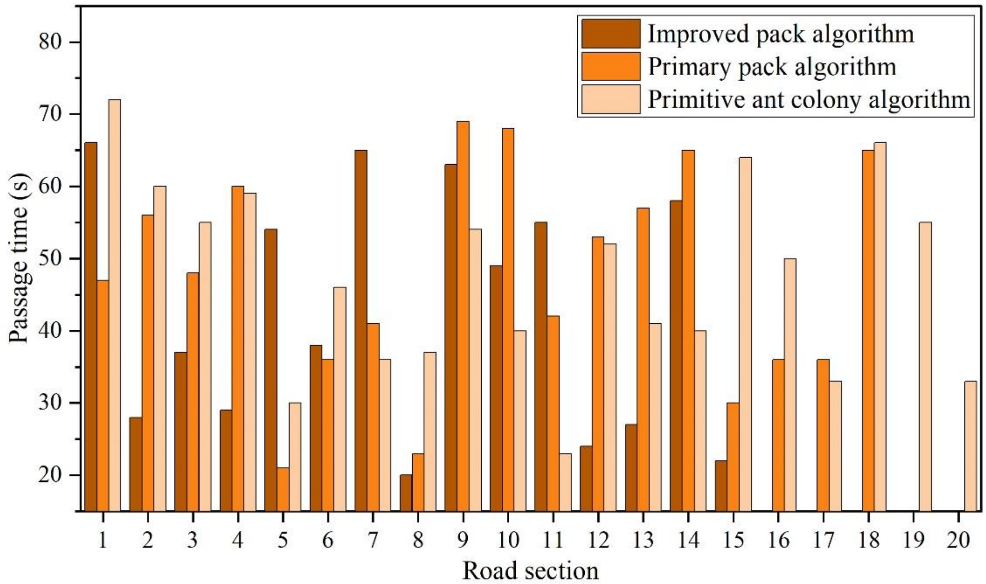

Figure 4: Three kinds of algorithm fire evacuation path

4.3 Evacuation distance and time optimization

A commercial building is taken as the object of study and geometric modeling is established. The commercial building is a comprehensive building with classrooms, offices, restaurants, swimming pools, dormitories, etc. The main body of the project is a frame concrete structure with a large number of combustible materials, which is characterized by difficulties in extinguishing and escaping. The height of the building is 33m, the height of the 1st floor above ground is 4.5m, the height of the 2nd and 3rd floors above ground is 4m, and the height of the 4th to 10th floors above ground is 3.5m. Each floor has a floor area of approximately 3,490m^2. The window size is 1m x 1.5m and the room door size is 1.5m x 2m.

In order to study the most real fire situation, the smoke exhaust and sprinkler system is set up in the building to simulate the solid space fire coupled with the ignition point, smoke exhaust, sprinkler, thermocouple, etc. The outside temperature is set to be 23°C, and the wind speed is set to be 0 m/s. In order to simulate the fire as close as possible to the actual fire, the first grid is set up for the 1~5 floors, and the size of the grid is 2 m × 2 m × 2 m. The second grid is set up for the 6-10 floors, and the size of the grid is 1.5 m × 1.5 m × 1.5 m. The simulation time is set to be 600 s. Layers 6 to 10 are set as the second grid, with a grid size of 1.5m×1.5m×1.5m, and the simulation time is set to 600s.

The setting of the fire scene follows the most unfavorable principle, and real fire situations are selected for the design, and the fire sources are located in 10 different rooms on the 5th, 6th and 7th floors to simulate 10 different fire situations. In order to simulate the realism of fire occurrence, daily utensils such as sofa, desk, bed, etc. are set up in the building, and a smoke detection point is set up at the left stairway. The evacuation paths were planned using the improved particle swarm algorithm described above. The topological undirected graphs in each floor were first represented as matrices with the numbers in the matrices representing the distance between their row labeled node numbers and their column labeled node numbers.

Fig. 5 shows the distance and time saved by the optimized paths of this paper's method for 10 fire scenarios. From it, it can be seen that for 10 different scenarios of fire, the improved algorithm of this paper can save 18.2~24.4m of evacuation distance. Taking the evacuation speed of 2m/s as an example, the optimized evacuation time of the algorithm can save 9.1~12.2s. Based on the digital twin 3D digital mirror model, when the evacuation paths are formulated, the combination of real-time sensors monitoring the fire development, indoor fire temperature, visibility, CO volume fraction and other characteristic values, as well as the location of people, can effectively avoid blind escape due to the uncertainty of the dangerous location of the scene. The blind escape due to the uncertainty of the hazardous location at the scene can be effectively avoided.

It can be seen that the improved algorithm in this paper can effectively reduce the evacuation distance of the trapped personnel, reduce the evacuation time and improve the evacuation efficiency. At the same time, the dynamic evacuation guidelines of fire safety based on digital twins can effectively help trapped people understand the location of the danger, plan the evacuation path, and improve the escape efficiency.

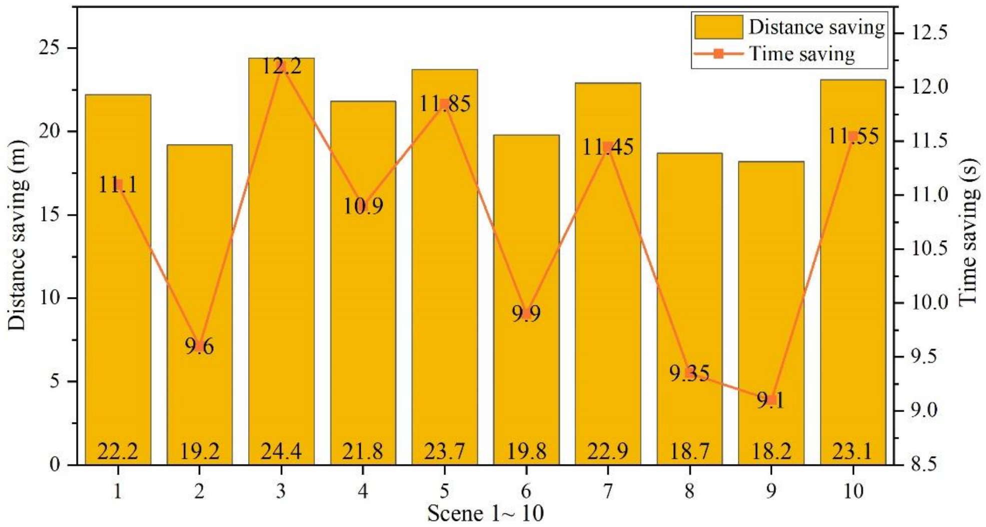

Figure 5: The effect of path optimization is analyzed

4.4 Simulation of evacuation from a fire environment

The improved algorithm of this paper is imported into MATLAB R2023a software, and combined with the digital twin evacuation framework, the fire evacuation model is constructed by setting up floors and stairs. The study designed a commercial building with 5 floors, each floor including 5 Exit, and lightened some components of the actual building such as walls, columns, and doors. In order to realistically restore the environment of the commercial complex, the study sets the personnel characteristic parameters as follows:

1) Personnel composition. Young people predominate in the commercial complex, followed by children and the elderly.

2) Number of personnel. The number of evacuees on the floors of the commercial complex

is related to the floor area of each floor, and the number of evacuees on each floor is calculated according to the ratio of personnel density stipulated in the Building Design Fire Prevention Code GB50016-2014. In this paper, a total of 2865 people are set, and the number of people on each floor from 1 to 5 is 535, 593, 578, 592 and 567 respectively.

3) Evacuation speed. The evacuation speed of people of different ages is different, and their reactions during the evacuation process are also different. Young people have strong mobility and fast escape speed, men are set to 2.5m/s, women are set to 2m/s. Elderly people, due to lack of health, are slow to act and slow to react during evacuation, they are set to 1.3m/s. Children, when responding to emergencies, have a panic mentality, and are prone to crying and shouting during evacuation, they are set to 1.5m/s.

The fire source point of the commercial building is located near the atrium, close to the exit Exit1, during the evacuation process, the personnel should avoid the fire source point, so the available safety exits are Exit2, Exit3, Exit4, Exit5.The total number of evacuees in the commercial complex is 2865 people, and the evacuation time used is 326.2s.The changes in the number of evacuees and the number of remaining personnel are shown in Fig. 6, and it can be seen that in the first 30s, the number of personnel in the first 30s is 1.5m/s, and it is set at 1.5m/s. It can be seen that the evacuation rate is faster in the first 30s, with a total of 634 people evacuated, because the evacuation of people on the first floor has been completed, and some of the people on the second floor have been evacuated to the outdoor area. The evacuation rate decreases from 30s onwards, this is because most of the personnel are congested in the stairway and cannot be evacuated, and the evacuation rate decreases as time goes by with fewer evacuees. The improved particle swarm intelligence optimization algorithm incorporating the digital twin concept shows high personnel evacuation efficiency.

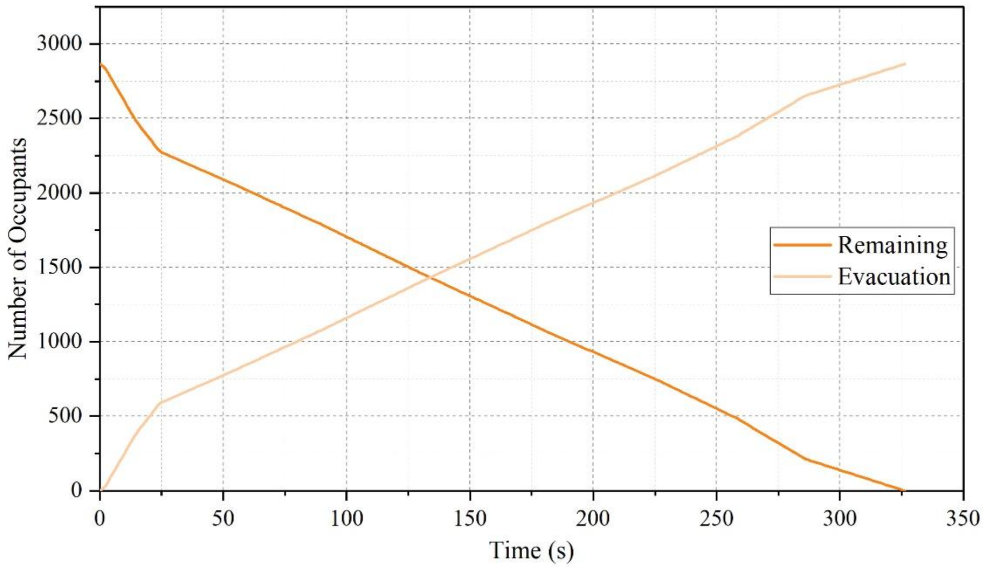

Figure 6: Number of evacuated personnel and the number of residual personnel

5 Conclusion

This research designs a framework for evacuating people from complex building fire environments based on the digital twin five-dimensional model, which can implement the collection of various types of safety information in the building and transmit them to the twin space through the network for twinning applications. Meanwhile, the particle swarm intelligent optimization algorithm was improved to enhance the dynamic optimization seeking ability of the algorithm by introducing fire environment influence parameters. The digital twin fire evacuation framework is integrated with the improved intelligent optimization algorithm, and simulation experiments are designed to analyze and explore the effect of people evacuation in fire environment.

The improved wolfpack algorithm reduces 9 iterations in evacuation path convergence compared with the original wolfpack algorithm, and the planning path distance is shortened by 15.46 m. As the fire spreads, the evacuation of personnel slows down, and the evacuation time reaches 88.46 s when the fire occurs for 360 s. On the evacuation of a medium-sized road network, the method proposed in this paper combining the digital twin technology with the intelligent optimization algorithm provides the paths with evacuation times of about 635 s, which is better than the comparison algorithm with 853 and 853 s, respectively. better than the comparison algorithm's 853 and 946 s. In the simulated 10-medium fire scenarios, the method saves 9.1 to 12.2 s of evacuation time. In addition, evacuating 2865 people in the fire simulation only took about 326s, which is more efficient.

Although this study has achieved some results in the field of fire emergency evacuation, there are still many directions that deserve further exploration. Future research could further extend the digital twin technology by extending its application to safety management throughout the building life cycle, thus realizing a wider range of monitoring and warning functions.

About the Author

Yuwen Chen (born in Fuzhou, Fujian Province, China in 1999) is a Master's candidate in Control Science and Engineering at Xiamen University. Her research focuses on digital twin, combining IoT sensing networks and machine learning algorithms.

References

[1] Lotfabadi, P. (2014). High-rise buildings and environmental factors. Renewable and Sustainable Energy Reviews, 38, 285-295.

[2] Li, G. Q., Zhang, C., & Jiang, J. (2018). A review on fire safety engineering: Key issues for high-rise buildings. International journal of high-rise buildings, 7(4), 265-285.

[3] Dundar, U., & Selamet, S. (2023). Fire load and fire growth characteristics in modern high-rise buildings. Fire safety journal, 135, 103710.

[4] Yan, Z., Wang, Y., & Chao, L. (2023). Simulation study on fire and evacuation of super high-rise commercial building. Case Studies in Thermal Engineering, 52, 103519.

[5] Zhang, X. (2017). Study on rapid evacuation in high-rise buildings. Engineering science and technology, an international journal, 20(3), 1203-1210.

[6] Kodur, V. K. R., Venkatachari, S., & Naser, M. Z. (2020). Egress parameters influencing emergency evacuation in high-rise buildings. Fire technology, 56, 2035-2057.

[7] Dewan, R. (2022). Evacuation methods during fire in high-rise buildings: A review. Sustainable Infrastructure Development: Select Proceedings of ICSIDIA 2020, 269-279.

[8] Jevtic, R. B. (2019). Fire and evacuation in high residential buildings. Facta Universitatis, Series: Working and living environmental protection, 123-134

[9] Lyu, Y., & Wang, H. (2025). Fire Evacuation for People with Functional Disabilities in High-Rise Buildings: A Scoping Review. Buildings, 15(4), 634.

[10] Poliakova, T., & Grigoryan, M. (2018). Fire safety issues in the design and construction of high-rise buildings. In MATEC Web of Conferences (Vol. 196, p. 02014). EDP Sciences.

[11] Yan, Z., Wang, Y., Chao, L., & Guo, J. (2024). Study on Evacuation Strategy of Commercial High-Rise Building under Fire Based on FDS and Pathfinder. CMES-Computer modeling in engineering & sciences, 140(2).

[12] Liu, X., Zhang, H., & Zhu, Q. (2012). Factor analysis of high-rise building fires reasons and fire protection measures. Procedia Engineering, 45, 643-648.

[13] Akashah, F. W., Baaki, T. K., Anuar, M. F., Azmi, N. F., & Yahya, Z. (2020). Factors affecting adoption of emergency evacuation strategies in high-rise office buildings. Journal of Design and Built Environment, 20(3), 1-21.

[14] Chen, Y., Wang, C., Yap, J. B. H., Li, H., Hu, H. S., Chen, C. C., & Lai, K. K. (2020). Fire Evacuation Process Using Both Elevators and Staircases for Aging People: Simulation Case Study on Personnel Distribution in High - Rise Nursing Home. Discrete Dynamics in Nature and Society, 2020(1), 5365126.

[15] Zhang, Y., Ding, Y., Chraibi, M., & Huang, X. (2025). Multi-scale analysis of fire and evacuation drill in a multi-functional university high-rise building. Developments in the Built Environment, 21, 100626.

[16] Song, L. Z., Zhu, J., Liu, S. T., & Qu, Z. J. (2022). Recent fire safety design of high-rise buildings. J. Urban Dev. Manag, 1(1), 50-57.

[17] Wang, J., Yuan, D., Liu, D., Zhou, T., & Liu, W. (2025). Fire Safety Literacy of Personnel in High-Rise Buildings: A Survey Study. Fire, 8(2), 40.

[18] Rasa, A. R., Xia, L., Song, X., Yu, H., Karim, R., Zhang, J., & Song, W. (2024). Understanding human-obstacle interaction dynamics on staircases: Implications for emergency evacuation and fire safety in high-rise buildings. Journal of Building Engineering, 98, 111082.

[19] Jehangir Arshad,Ch. Ahsan Abbas Sheheryar,Mohammad Khalid Imam Rahmani,Abdul Qayyum,Roumaisa Nasir,Sohaib Tahir Chauhdary & Khalid Jaber Almalki. (2025). Simulink-Driven Digital Twin Implementation for Smart Greenhouse Environmental Control. Egyptian Informatics Journal,30,100679-100679.

[20] Maira Alvi,Hrishikesh Dutta,Roberto Minerva,Noel Crespi,Syed Mohsan Raza & Manoj Herath. (2025). Global perspectives on digital twin smart cities: Innovations, challenges, and pathways to a sustainable urban future. Sustainable Cities and Society,126,106356-106356.