# Study on Indoor Fire Evacuation Path Planning Method Based on the Grey Wolf Optimization Algorithm

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**Abstract.** In pursuit of enhancing the efficiency of indoor fire evacuation path planning and reducing crowd density, this paper introduces an advanced evacuation path planning method based on the Grey Wolf Optimizer (GWO) algorithm. Initially, a grid-based approach is utilized to model the fire scenario. Subsequently, a path planning problem is formulated that incorporates the effects of CO concentration and crowd density. This model integrates the relationship between crowd density and evacuation speed, employing a Gaussian plume model to quantify the impact of crowd density and smoke hazards on individuals. The GWO algorithm is then introduced to solve this optimization problem, aiming to derive an optimal evacuation plan that comprehensively considers path length, smoke concentration, and crowd density. The model is validated across four distinct environmental scenarios. The experimental results demonstrate that the proposed method effectively identifies the shortest evacuation path and boasts rapid convergence rates while avoiding local optima. In non-fire scenarios, the method reduces the optimization cycle by 10%-25% and shortens path length by 10%-25% compared to other algorithms. During fire incidents, optimization cycles and path lengths are reduced by 10%-20%. These improvements enhance evacuation safety and efficiency while providing flexibility across settings, from indoors to commercial areas. This study offers valuable tools and insights for urban fire emergency management and safety planning.

**Keywords:** Indoor Fire, Path Planning, Smoke Environment, GWO Algorithm.

## 1. Introduction

With societal progression and improved living standards, interior decoration and smart devices increasingly integrate into people's environments [1]. This proliferation, especially indoors, poses significant fire hazards due to the widespread use of decorations and electrical equipment. The inherent complexity and limited space of indoor settings heighten fire risks. Once a fire ensues, it spreads rapidly, causing temperature spikes and a swift increase in noxious gases, potentially leading to substantial casualties and economic losses. Thus, research into indoor path planning in fire scenarios is imperative.

Path planning in fire scenarios involves two main steps: environmental modeling and constructing a mathematical model. Fang et al. [2] used a hierarchical directional network and the Hierarchical Multi-Objective Evacuation Routing Problem (HMERP) algorithm, based on Ant Colony Optimization (ACO), to optimize evacuation routes in stadiums, focusing on spatial and temporal aspects. However, these studies neglected smoke impact, making their models less representative. Liao et al. [3] utilized PyroSim to model buildings and proposed a Dijkstra algorithm-based fire evacuation indicator system to integrate theory and functional modules. Xu et al. [4] conducted fire simulations with PyroSim and introduced an Improved Ant Colony Optimization (IACO) algorithm to enhance supermarket evacuations. Yet, these studies also overlooked crowd density effects. Therefore, a model incorporating smoke dispersion and crowd density is essential for path planning.

Common global path planning methods include Dijkstra's algorithm [5], Floyd's algorithm [6], A* algorithm [7], and Particle Swarm Optimization (PSO) [8]. Significant advancements have applied these to emergency fire path planning. Nima [9] used Dijkstra's method in a processing plant fire to minimize casualty risk and update evacuation plans, but its high complexity limits applicability. Zhu et al. [10] applied the A* algorithm for forest fire rescue, which, though feasible, is prone to local optima. Thus, more efficient algorithms are needed to enhance optimization.

In summary, this paper develops an indoor fire path planning method using GWO, considering smoke concentration and crowd density. It first employs a grid-based approach for fire scenario modeling. A path planning model is then formulated, incorporating the effects of smoke dispersion and crowd density on evacuation speed. This model uses Gaussian plume modeling and density-based evacuation speed patterns to quantify these impacts. The GWO algorithm solves this optimization problem, achieving an optimal evacuation strategy that considers path length, smoke concentration, and crowd density. The proposed GWO-based method demonstrates excellent convergence speed and solution precision, providing valuable insights for indoor fire evacuation planning.

## 2. Problem description and model development

### 2.1. Problem description

Under specific idealized assumptions, designing evacuation routes during an indoor fire involves determining the optimal path within a limited timeframe using data from fire detection equipment, including fire source location, gas concentration, and crowd distribution. This guides individuals to exit swiftly and safely, enhancing evacuation efficiency. Since the building's internal structure and related information are known in advance, this issue is within global path planning. Essential information for establishing evacuation routes includes:

(1) Map environment and real-time fire parameters: A comprehensive understanding of the indoor layout, pathways, and safety exits, along with real-time data on fire source and crowd distribution, is necessary.

(2) Evacuation influencing factors and classification: Fire source location, toxic gas concentration, and crowd density are critical. These factors are graded to assess the safety and feasibility of different paths.

(3) Understanding optimal evacuation paths: The best path considers safety, passage conditions, and efficiency, not just distance.

By thoroughly considering these characteristics, it is possible to design optimal evacuation routes for individuals in indoor settings during a fire, ensuring they can evacuate the area swiftly and safely.

### 2.2. Environment modeling

In environment modeling, common methods include the grid method, topological analysis, machine vision, and free space depiction. The grid method is popular due to its simplicity. This study uses grid-based technology to digitally represent indoor scenes, converting maps into grids, as illustrated in Figure 1.

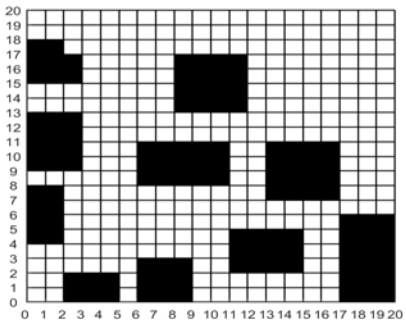



**Figure 1:** Evacuation area map model

As depicted in Figure 1, each cell can move to its eight adjacent neighboring cells. Black cells represent obstacles, such as walls or furniture, which are impassable areas, while white cells denote open passages, representing freely navigable spaces. Starting from the top-left corner and proceeding left to right, row by row, each cell can be identified with a specific number. The grid map dimensions are in rows and columns, and the coordinates of each cell's center can be calculated using the following formula:

$$\begin{cases} x_i = \text{mod}(i-1, col) + 0.5 \\ y_i = row - \text{ceil}(i / col) + 0.5 \end{cases} \tag{1}$$

In this equation, "mod" denotes the modulus function, and "ceil" represents the ceiling function used for rounding up.

### 2.3. Mathematical model of fire scenarios

In fire emergencies, panicked individuals often exhibit irrational following behaviors. Structural characteristics of buildings, like narrow passages and complex layouts, cause crowding and bottlenecks during evacuations. This reduces efficiency and increases stampede risks. To address this, the study uses a crowd density influence coefficient to evaluate how varying density conditions affect evacuation speed, as shown in the formula:

$$f_p = \begin{cases} 1, & \rho_p < 1.18 \\ 0.797 - 0.313\ln\rho_p - 0.0138\rho_p, & 1.18 \le \rho_p < 6 \\ 0, & \rho_p > 6 \end{cases} \tag{2}$$

where $\rho_p$ represents crowd density, measured in persons/m². According to the National Fire Protection Association, 80% of fire casualties result from toxic smoke inhalation, such as carbon monoxide (CO), hydrogen chloride (HCl), and sulfur dioxide ($SO_2$), with CO being the primary cause of injuries and fatalities. The Gaussian dispersion model, a commonly used analytical tool in studying non-heavy gas diffusion, includes the Gaussian plume model, which is suitable for continuous point source emissions. This model is chosen to estimate CO concentration changes:

$$C(x_0, y_0, z, H) = \frac{Q_c}{2\pi\delta_{y_0}\delta_z} exp\left[-\frac{y_0^2}{2\delta_{y_0}^2}\right] \begin{Bmatrix} exp\left[-\frac{(z-H)^2}{2\delta_z^2}\right] + \\ exp\left[-\frac{(z+H)^2}{2\delta_z^2}\right] \end{Bmatrix} \tag{3}$$

where:

$$\delta_{y_0} = \gamma_1 x_0^{\alpha_1} \tag{4}$$

$$\delta_z = \gamma_2 x_0^{\alpha_2} \tag{5}$$

where $C$ represents gas concentration at a given coordinate, $Q_c$ is the gas emission rate per unit time, and $H$ is the effective emission height. $x_0$, $y_0$, and $z$ denote the downwind, crosswind, and vertical distances from the emission source to the observation point, respectively. $u$ is the wind speed, and $\delta_{y_0}$, $\delta_z$ are the horizontal and vertical dispersion parameters. $\alpha_1$, $\alpha_2$, $\gamma_1$, and $\gamma_2$ represent regression exponents and coefficients determined by atmospheric stability.

According to national standards on CO concentration effects, the impact on evacuees is classified into three levels, as shown in Table 1.

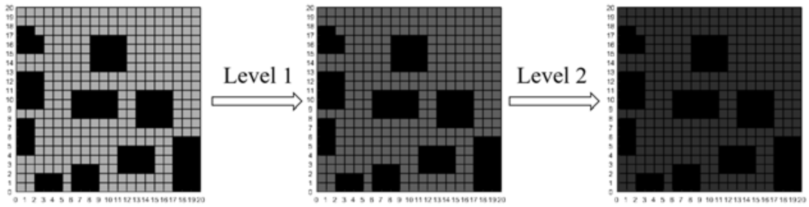
**Table 1:** Impact of CO concentration on evacuation

| Level/S | CO concentration (C) (g/m³) | Evacuation status |
|---|---|---|
| 0 | C≤5×10$^{-6}$ | Normal |
| 1 | 5×10$^{-6}$<C≤50×10$^{-6}$ | Restricted |
| 2 | C>50×10$^{-6}$ | Prohibited |

The harm CO causes depends on its concentration and the exposure time. When (C > 50) g/m³, the grid is treated as an obstacle; when (C < 50) g/m³, the impact of CO concentration and crowd density on the evacuation process is quantified by:

$$L_{ij} = \left| \int_{x_i}^{x_j} \frac{C(x, y(x), z, H)dx}{f_p} \right| \tag{6}$$

where $L_{ij}$ denotes the equivalent distance between grid (i) and (j). A smaller $L_{ij}$ value indicates lower CO concentration and shorter evacuation time. Figure 2 illustrates the effect of different CO concentration levels on the indoor environment.




(a)Level-0 (b) Level-1 (c) Level-2

**Figure 2:** Indoor environment effects at different CO concentration levels

In summary, the fire evacuation path planning problem is an optimization task to find a safe route on a map, minimizing toxic gas exposure while maximizing evacuation efficiency.

## 3. Indoor fire path planning method based on the GWO algorithm

### 3.1. Standard GWO algorithm

The GWO [11] is inspired by the social hierarchy and hunting strategies of grey wolves, aiming to achieve optimal search by simulating their tracking and hunting behavior. In the GWO algorithm, grey wolves are classified into four types to mimic this hierarchy:

$\alpha$ : The leaders primarily responsible for decision-making and disseminating commands to the rest of the pack.

$\beta$ : The subordinate wolves that assist the alpha in decision-making and other group activities.

$\delta$ : Scouts, sentinels, elders, and hunters that constitute this level.

$\omega$ : The lowest ranking wolves, playing the role of "scapegoats" and yielding to all higher-ranking wolves.

In the GWO algorithm, $\alpha$ , $\beta$ , $\delta$ , and $\omega$ represent the best, second best, third best, and candidate solutions, respectively, as shown in Figure 3.

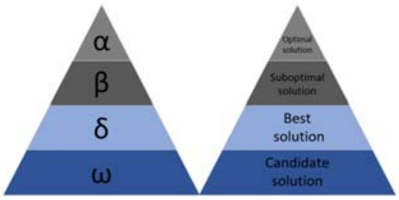



**Figure 3:** GWO hierarchy

The GWO algorithm simulates three primary phases of grey wolf hunting:

Prey Searching: Wolves use $\alpha$ , $\beta$ , and $\delta$ positions to disperse and locate potential prey, then converge to capture it. Mathematically, this is represented using a divergence model, applying a coefficient A with random values greater than 1 or less than -1 to force wolves away from the prey. This aids exploration and allows GWO to perform a global search. As shown in Figure 4, |A|>1 encourages grey wolves to stray from the prey, aiming to find more robust prey.

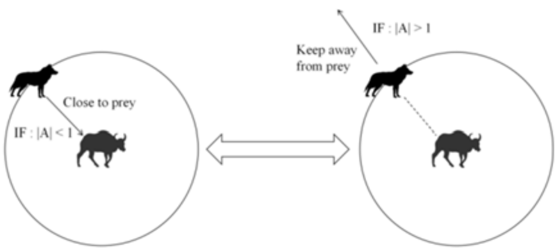



**Figure 4:** GWO searching

Another component enhancing GWO exploration is the coefficient C, a random number in [0,2]. This assigns random weight to prey's position, amplifying C>1 or diminishing C<1 its influence on wolves' next position. Calculations for A and C are:

$$A = 2a \cdot r_1 - a \tag{7}$$

$$C = 2 \cdot r_2 \tag{8}$$

where $r_1$ and $r_2$ are random values within [0,1]. To simulate approaching the prey, A is a random value within the interval ([-a, a]), where (a) is a convergence factor that decreases linearly from 2 to 0 over the course of iterations.

$$a = 2\left(1 - \frac{t}{t_{\max}}\right) \tag{9}$$

where $(t)$ is the current iteration and $(t_{max})$ is the maximum number of iterations.

(1) During the hunting process, grey wolves gradually approach their target, forming an encircling posture. This behavior is mathematically modeled by calculating the distance (D) between the current position of a grey wolf and the prey:

$$D = \left|C \cdot X_p(t) - X(t)\right| \tag{10}$$

The position update rule for grey wolves is as follows:

$$X(t+1) = X_p(t) - A \cdot D \tag{11}$$

Where X denotes the wolf's position, t the current iteration, and P the prey's position. The wolf pack advances by adjusting positions toward P based on their location and the random vector C. Movement direction is influenced by C, while step size is determined by the distance to the target and vector A. Linear diminution reflects decreasing randomness and step size with each iteration, approximating the optimal solution.

In pursuing prey, gray wolves can locate and attack their target, discerning the prey's (optimal solution) position. Once identified, $\beta$ and $\delta$ wolves, under the leadership of $\alpha$, guide the pack in encircling the prey. In optimization problems, the exact position is unknown. To mimic their hunting, we assume $\alpha$, $\beta$, and $\delta$ have heightened ability to locate the prey. Thus, in each iteration, the top three wolves are retained, and their positions update other agents, including $\omega$. The mathematical model of their tracking is:

$$\begin{cases} D_\alpha = \left|C_1 \cdot X_\alpha - X\right| \\ D_\beta = \left|C_2 \cdot X_\beta - X\right| \\ D_\delta = \left|C_3 \cdot X_\delta - X\right| \end{cases} \tag{12}$$

Where $D_\alpha$, $D_\beta$, and $D_\delta$ represent distances between $\alpha$, $\beta$, and $\delta$ wolves and others. Positions $X_\alpha$, $X_\beta$, and $X_\delta$ denote current locations. Vectors $C_1$, $C_2$, and $C_3$ are stochastic, while $X$ is the wolf's current position. When $|A| > 1$, wolves disperse to search broadly; when $|A| < 1$, they focus on specific regions. The update rule is:

$$\begin{cases} X_1 = X_\alpha - A_1 D_\alpha \\ X_2 = X_\beta - A_2 D_\beta \\ X_3 = X_\delta - A_3 D_\delta \end{cases} \tag{13}$$

$$X(t+1) = \frac{X_1 + X_2 + X_3}{3} \tag{14}$$

Where $X_\alpha$, $X_\beta$, and $X_\delta$ denote the positions of $\alpha$, $\beta$, and $\delta$ wolves. The vectors $X_1$, $X_2$, and $X_3$ indicate step size and direction, while $X(t+1)$ is the wolf's final position. The large data prediction model for electricity consumption is implemented in Clementine software.

### 3.2. Algorithmic procedure

Based on the previous analysis, the specific implementation steps of the GWO for path planning are as follows:

(1) Constructing the environmental map: Establish a two-dimensional static grid-based model, incorporating fire data, Gaussian plume dispersion, and population density models. Set start and end points and configure models and algorithm parameters.

(2) Initialization of positions and fitness calculation: Randomly initialize grey wolf positions within bounds. Compute fitness for each wolf, retaining the top three positions ($\alpha$, $\beta$, $\delta$).

(3) Path selection and local update: Select the next grid cell based on path rules, adding cells to a tabu list. Update positions and fitness values.

(4) Endpoint evaluation and path recording: Check if wolves reach the endpoint. If so, record the path and length; if not, return to step 3.

(5) Iteration completion and global update: Assess if all wolves completed the iteration. If so, record optimal path and time; if not, return to step 3.

(6) Maximum iteration check: If the max iterations are reached, smooth the optimal path and conclude planning; if not, return to step 2.

Figure 5 illustrates the flowchart of the GWO algorithm utilized for planning evacuation paths.

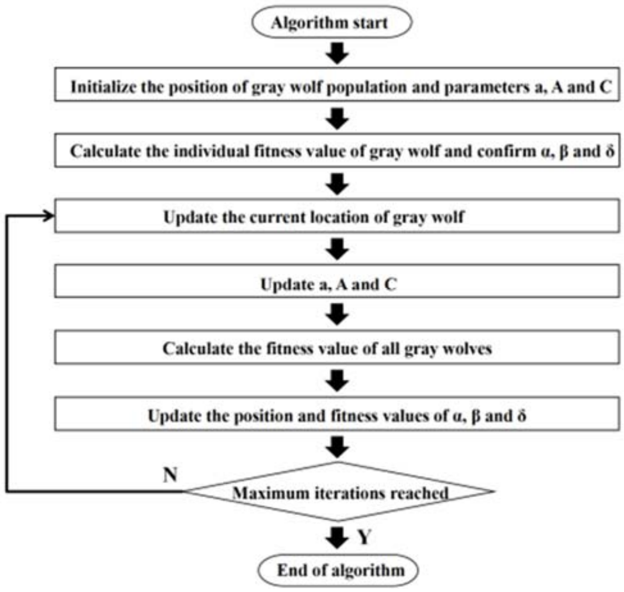



**Figure 5:** Steps of the GWO algorithm

## 4. Experiment and analysis

### 4.1. Simulation environment

To comprehensively evaluate the effectiveness, applicability, and scalability of the GWO, four different-sized environmental models were constructed. The map sizes include $10\times10$, $20\times20$, $30\times30$, and $40\times40$, with each grid cell measuring 1m per side. The starting point for all models is Grid 1, with endpoints at Grids 10, 20, 30, and 40, respectively. The environmental scenarios encompass situations both with and without fire occurrences.

The algorithm parameters for the simulation experiments are set as outlined in Table 2: the maximum number of iterations (N) is set to 100, the population size (M) is 50, the dimensionality of the population is 2, with a convergence factor in the range (0, 2). The perturbation factors $A_1$, $A_2$, $A_3$ are set in the range (-2, 2), and the factor $C_1$, $C_2$, $C_3$ is set in the range (0, 2).

**Table 2:** GWO algorithm parameter settings

| Parameter name | Parameter value |
|---|---|
| Maximum iterations (N) | 100 |
| Population dimension | 2 |
| Population size (M) | 50 |
| Convergence factor | (0,2) |
| Perturbation factors $A_1$, $A_2$, $A_3$ | (-2,2) |
| Perturbation factors $C_1$, $C_2$, $C_3$ | (0,2) |

All experiments were conducted using simulation software Matlab 2022b. The specific hardware configuration is detailed in Table 3:

**Table 3:** Experimental hardware configuration

| Configuration | Model |
|---|---|
| CPU | i7-12700H |
| CPU frequency | 2300Mhz |
| GPU model | NVIDIA GeForce RTX 3060 |
| GPU memory | 6144MB |
| System | Win11 |

### 4.2. Algorithm verification

#### 4.2.1 Scenario one: No fire occurrence

To evaluate the GWO's effectiveness in convergence speed and global search, a comparative study was conducted with Particle Swarm Optimization [12], Genetic Algorithm [13], Whale Optimization [14], and Sparrow Search [15] across four scenarios. Using parameters from the previous section, MATLAB simulations compared the path planning results. The results are depicted in Figures 6, 7, 8, and 9, and summarized in Table 4.

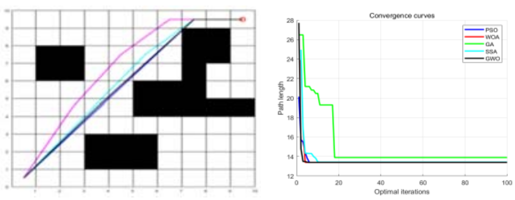


**Figure 6:** Results on a 10×10 grid map

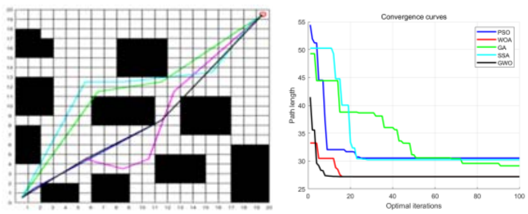


**Figure 7:** Results on a 20×20 grid map

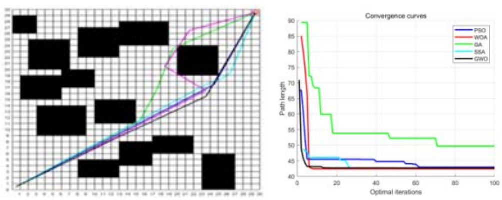


**Figure 8:** Results on a 30×30 grid map

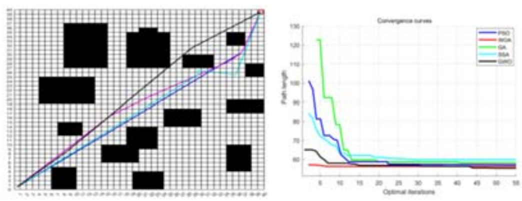


**Figure 9:** Results on a 40×40 grid map

**Table 4:** Performance comparison of five algorithms across four grid maps

| Scale | Metric | GWO | GA | PSO | WOA | SSA |
|---|---|---|---|---|---|---|
| 10×10 | Optimal iterations/n | 3 | 9 | 7 | 8 | 21 |
| | Path length/m | 12.69 | 13.04 | 12.97 | 12.89 | 12.91 |
| 20×20 | Optimal iterations/n | 31 | 44 | 42 | 42 | 38 |
| | Path length/m | 27.14 | 33.42 | 31.28 | 27.07 | 29.87 |
| 30×30 | Optimal iterations/n | 15 | 49 | 41 | 15 | 27 |
| | Path length/m | 57.49 | 68.07 | 59.83 | 57.43 | 65.91 |
| 40×40 | Optimal iterations/n | 13 | 87 | 23 | 15 | 27 |
| | Path length/m | 57.31 | 61.54 | 58.12 | 58.47 | 60.59 |

In this series of experiments, as shown in Figures 6(a), 7(a), 8(a), 9(a), and Table 4, the number of grid cells traversed by the Genetic Algorithm, Particle Swarm Optimization, Whale Optimization, and Sparrow Search is significantly higher than that of the GWO, indicating redundant pathways. The convergence curves in Figures 6(b), 7(b), 8(b), and 9(b) show that GWO rapidly identifies the shortest optimal path compared to others in early iterations.

This suggests that wolves' positional information swiftly converges near the optimal region early on, providing a high-quality initial solution for further refinement. In the mid-iteration phase, adaptive adjustments of the convergence factor and feedback mechanism balance local exploitation and global exploration. Consequently, GWO exhibits faster convergence, needing fewer iterations to find the optimal path compared to other algorithms. Moreover, the results on path length show that GWO has robust global search capabilities, locating a shorter evacuation path than other algorithms. These findings affirm the GWO's effectiveness and practicality.

### 4.2.2 Scenario two: fire occurrence

To assess the GWO's applicability and superiority in fire scenarios, simulations were conducted on grid maps $10\times10$, $20\times20$, $30\times30$, and $40\times40$, considering a single exit and multiple fire points. The algorithm's effectiveness was validated by comparing optimal paths under various conditions. In single-exit maps, evacuation starts at Grid 1, with exits at Grids 10, 20, 30, and 40.

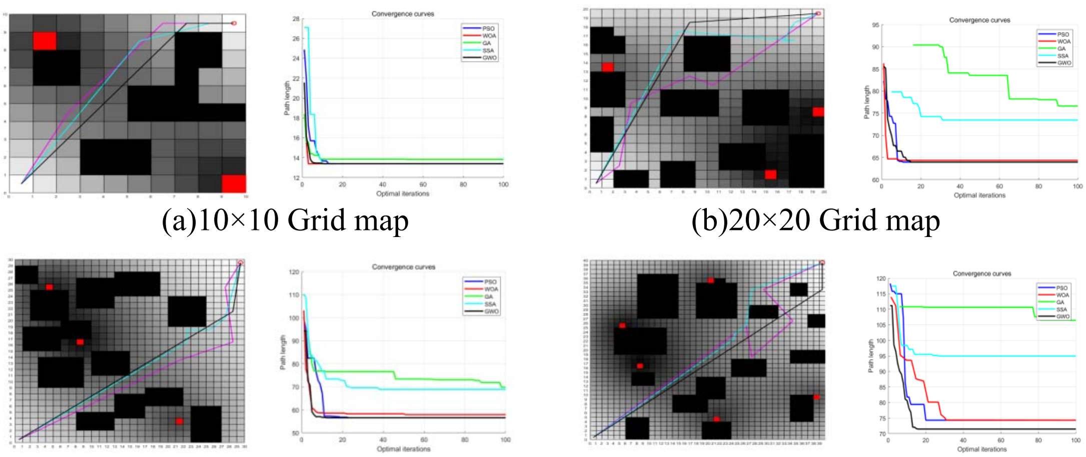
Additionally, the parameters $\varepsilon_1$ and $Q_1$ were reset to $5\times10^{-6}$ and 1. An equivalent distance replaced the traditional Euclidean distance in the heuristic function. The CO diffusion model is given by $5\times10^{-6}$, with the CO concentration in unaffected areas set to 0, and a population density of 5.8 people/m² in densely populated regions. Other parameters were set as follows: ($Q_c$=0.1 g/m$^{\wedge 3}$), (H=2 m), (u=1 m/s). Considering the average breathing height of evacuees, (z) was set to 1.6 m. When the atmospheric stability class is B, the values for $\alpha_1$, $\alpha_2$, $\gamma_1$, $\gamma_2$ are as per Tables 5 and 6. The final optimal evacuation path planning results are shown in Figure 10 and Table 7.

**Table 5:** Horizontal dispersion parameters

| Downwind distance (m) | $\gamma_1$ | $\alpha_1$ |
|---|---|---|
| $>1000$ | 0.396353 | 0.865014 |
| $\leq 1000$ | 0.281846 | 0.914370 |

**Table 6:** Vertical dispersion parameters

| Downwind distance (m) | $\gamma_2$ | $\alpha_2$ |
|---|---|---|
| $>500$ | 0.127190 | 0.941015 |
| $\leq 500$ | 0.0570251 | 1.09356 |




(a)10×10 Grid map (b)20×20 Grid map

(c)30×30 Grid map (d) 40×40 Grid map

**Figure 10:** Comparison of fire evacuation paths under different environmental conditions

**Table 7:** Equivalent path distances for four maps considering fire environment

| Scale | Metric | GWO | GA | PSO | WOA | SSA |
|---|---|---|---|---|---|---|
| 10×10 | Optimal iterations/n | 3 | 21 | 9 | 3 | 17 |
| | Path length/m | 13.42 | 14.22 | 14.11 | 13.42 | 14.11 |
| 20×20 | Optimal iterations/n | 36 | 44 | 43 | 41 | 19 |
| | Path length/m | 27.89 | 32.11 | 30.12 | 27.13 | 29.97 |
| 30×30 | Optimal iterations/n | 17 | 20 | 7 | 21 | 23 |
| | Path length/m | 63.71 | 79.13 | 75.13 | 63.54 | 81.79 |
| 40×40 | Optimal iterations/n | 15 | 55 | 38 | 17 | 50 |
| | Path length/m | 72.31 | 97.23 | 101.12 | 72.31 | 101.12 |

Figure 10 illustrates post-fire evacuation routes using solid lines in various colors. The red grid indicates the fire source, black grids are impassable obstacles, and shades of gray show smoke concentrations, as detailed in Figure 2. Individuals start at Grid 1, with exits at Grids 10, 20, 30, and 40. Results from Figure 10 and Table 7 show that the GWO algorithm charts an optimal path, minimizing CO concentration and avoiding high-density areas based on current data. These findings validate the GWO algorithm's robust planning capabilities in fire scenarios, swiftly devising routes with minimal CO exposure and crowd density.

## 5. Conclusions

This study addresses the high-risk, rapid spread, and severe consequences of indoor fires by proposing a GWO-based path planning method. Initially, a grid method models fire scenarios. Considering smoke and crowd density's impact on safety and efficiency, a model integrating CO concentration and crowd density is constructed. By incorporating evacuation speed patterns related to crowd density and a Gaussian smoke plume model, potential hazards are quantified. The GWO algorithm solves the optimization problem by considering path length, smoke concentration, and crowd density comprehensively. Validated across four scenarios, results show the method finds the shortest path with rapid convergence and avoids local optima. Compared to other algorithms, iteration time is reduced by 10%-20%, and path length by 10%-20%. This approach is applicable to indoor and commercial street fire scenarios. Future work will explore further optimization of the GWO algorithm to enhance computational efficiency and adaptability. Additionally, integrating real-time data and advanced sensor technologies could improve responsiveness in dynamic fire situations. Expanding the model to consider multi-story buildings and complex urban environments offers another promising direction. These efforts aim to refine evacuation strategies, contributing to safer and more resilient urban safety planning.

## References

[1] Wang D L, Ge X Y, Zhou X C. Design of indoor emergency fire alarm system based on wireless transmission of sensor data[J]. Wireless Internet Science and Technology, 2024, 21(22): 37-40.

[2] Fang Z X, Zong X L, Li Q Q, et al. Hierarchical multi-objective evacuation routing in stadium using ant colony optimization approach[J]. Journal of Transport Geography, 2010, 19(3): 443-451.

[3] Liao H M, Zhu Y Q, Chen Z P. A fire disaster dynamic evacuation in-dicating system based on the Dijkstra algorithm[J]. Journal of Safety and Environment, 2021, 21(4): 1676-1683.

[4] Xu L, Huang K, Liu J P, et al. Intelligent planning of fire evacuation routes using an improved ant colony optimization algorithm[J]. Journal of Building Engineering, 2022, 61(1): 105208-105208.

[5] Bhat R, Rao K, Kamath R, et al. Comparative analysis of bellman-ford and dijkstra's algorithms for optimal evacuation route planning in multi-floor buildings[J]. Cogent Engineering, 2024, 11(1): 2319394-2319404.

[6] Mohd N A, Shariff S R, Supadi S S, et al. Modelling the shortest path for inner warehouse travelling using the floyd-wWarshall algorithm[J]. Mathematics, 2024, 12(14): 2698-2717.

[7] Zhang B, Cai X F, Li G Q, et al. A modified A* algorithm for path planning in the radioactive environment of nuclear facilities[J]. Annals of Nuclear Energy, 2025, 214(1): 111233-111242.

[8] Zou Z Y, Zeng H, Zheng X D, et al. Research on multi-center path optimization for emergency events based on an improved particle swarm optimization algorithm[J]. Mathematics, 2025, 13(4): 654-676.

[9] Khakzad N. A methodology based on Dijkstra's algorithm and mathematical programming for optimal evacuation in process plants in the event of major tank fires[J]. Reliability Engineering and System Safety, 2023, 236(1): 109291-109302.

[10] Zhu Y L, Zhang G, Chu R. Research on escape route planning analysis in forest fire scenes based on the improved A* algorithm[J]. Ecological Indicators, 2024, 166(1): 112355-112370.

[11] Li B, Hao Y X, Cui Y Y, et al. An improved grey wolf algorithm and its localization research in complex indoor environments[J]. Scientific Reports, 2025, 15(1): 7329-7352.

[12] Pan Y, Wen J, Zhang Y, et al. Ultra-compact asymmetric polarization beam splitter based on hybrid plasmonic waveguide and subwavelength grating utilizing particle swarm optimization algorithm[J]. Optics Communications, 2025, 582(1): 131624-131633.

[13] Chen L D, Zhu Y F, Lee G Y, et al. Two-step genetic algorithm for dynamic route optimization of electric vehicles based on demand analysis[J]. Arabian Journal for Science and Engineering, 2025, 10076(25): 1-17.

[14] Shafieenejad I. Maximizing the velocity deflection of asteroid didymos using the whale optimization algorithm[J]. Planetary and Space Science, 2025, 258(1): 106075-106085.

[15] Zhang W J, Yan H J, Xiang L L, et al. Wind power generation prediction using LSTM model optimized by sparrow search algorithm and firefly algorithm[J]. Energy Informatics, 2025, 8(1): 35-52.