Alexandria Engineering Journal 107 (2024) 652–664

Contents lists available at ScienceDirect

Alexandria Engineering Journal

journal homepage: www.elsevier.com/locate/aej

Original Article

Fire emergency management of large shopping malls: IoT-based evacuee tracking and dynamic path optimization

Ziyang Zhang, Lingye Tan *, Robert L.K. Tiong

School of Civil and Environmental Engineering, Nanyang Technological University, Singapore, 639798, Singapore

ARTICLE INFO

Keywords:
IoT-based evacuation
Deep learning
Fire emergency management
Real-time path optimization
Evacuee tracking system

ABSTRACT

As urbanization accelerates and buildings become more complex, fire emergency evacuation has become increasingly challenging. Traditional evacuation plans often struggle with slow response times and suboptimal path planning in real-time dynamic and complex fire scenarios. To address these issues, this study proposes the IoT-based DWM-Evac model for fire emergency evacuation path planning. The model leverages IoT technology by using various sensors placed inside buildings to monitor fire incidents and spread in real-time, collecting critical data such as temperature, smoke concentration, and flame location. It integrates Dynamic Graph Neural Networks (DGNN), Whale Optimization Algorithm (WOA), and Markov Decision Process (MDP) to enhance path efficiency and safety. Experimental results indicate that the DWM-Evac model achieves an average evacuation time of 315 s in a virtual mall environment, 25 s shorter than traditional plans, with an average path length of 255 meters and a path safety score of 0.92, higher than the traditional plan's 0.88. The application of IoT in fire emergency management not only improves response speed but also optimizes path planning, significantly enhancing personnel safety.

1. Introduction

In the process of modern urbanization, with the increase of population density and the complexity of building structure, the risk of fire in high-density public places such as large shopping malls is increasing [1]. How to effectively organize personnel evacuation and reduce casualties and property losses in the case of a fire emergency has become a key challenge in urban safety management [2]. Traditional fire evacuation methods, usually relying on the preset static evacuation path, cannot respond to the dynamic changes of the fire site in time [3]. Due to the lack of real-time data support of these methods, the evacuation path planning is not flexible enough and cannot be adjusted in time according to the actual situation of fire spread, resulting in low evacuation efficiency and potential chaos [4].

The development of the Internet of Things (IoT) technology has provided innovative solutions to this problem. By installing various sensors inside the building, the Internet of Things can monitor the occurrence and development of fires in real time, and transmit key data such as temperature, smoke concentration, and flame location to the central control system through the wireless network [5]. Based on these real-time data, the evacuation path can be dynamically adjusted to improve the efficiency and safety of evacuation [6]. Compared with the traditional methods, the Internet of Things technology can not only provide more accurate on-site information, but also realize the rapid optimization of the evacuation path at the moment of fire occurrence, effectively avoiding the delay and danger caused by the information lag in the evacuation process [7].

methods and the advantages of IoT technology, this study proposes a model of fire-site evacuation tracking and path optimization driven by iot-aware data, called DWM-Evac (Dynamic Graph Neural Network-Whale Optimization Algorithm-Markov Decision Process Evacuation Model). The model combines three advanced technologies, dynamic graph neural network (DGNN), whale optimization algorithm (WOA) and Markov decision process (MDP), to realize real-time optimization and dynamic adjustment of evacuation path at the fire site. DGNN provides the evacuation path planning structure in real time [8]; WOA optimizes the global path to find the optimal evacuation path; MDP further optimizes the evacuation strategy to ensure the flexibility and effectiveness in the evacuation process [9].

The main contributions of this paper are as follows:

- The DGNN integrating real-time IoT sensor data is designed to dynamically update the evacuation path graph structure at the fire scene. This component reflects changes in the fire scene in real-time and provides a more accurate foundation for evacuation path planning.

* Corresponding author.
E-mail addresses: ziyang004@e.ntu.edu.sg (Z. Zhang), lingye001@e.ntu.edu.sg (L. Tan), clktiong@ntu.edu.sg (R.L.K. Tiong).

https://doi.org/10.1016/j.aej.2024.08.107
Received 6 August 2024; Received in revised form 19 August 2024; Accepted 29 August 2024
Available online 12 September 2024

- The WOA is utilized for global optimization of evacuation paths, ensuring their efficiency and safety. By simulating the predatory behavior of whales, this algorithm can find the optimal evacuation path in a complex and changing environment.
- The MDP is combined for strategy optimization and dynamic decision-making, further enhancing evacuation efficiency. This ensures that evacuation strategies can be adjusted promptly in response to dynamic changes at the fire scene, maximizing the safety of individuals.

The structure of this paper is as follows: Section 2 introduces related work, including the application of IoT in fire emergency evacuation, the application of Dynamic Graph Neural Networks in path planning, and the use of optimization algorithms and Markov Decision Processes in evacuation path optimization. Section 3 details the overall architecture and components of the DWM-Evac model. Section 4 describes the experimental setup, datasets, performance testing metrics, and analysis of the experimental results. Section 5 summarizes the main contributions of this paper, discusses its limitations, and suggests directions for future research.

2. Related work

Addressing the problem of fire emergency evacuation path planning, IoT technology, deep learning, and multi-agent systems provide crucial technical support from various aspects such as monitoring and early warning, path planning, and individual behavior simulation. These technologies also offer theoretical and technical foundations for the DWM-Evac model proposed in this paper.

2.1. IoT in fire evacuation

In recent years, the application of IoT technology in fire emergency management has received widespread attention. IoT employs various types of sensors installed within buildings, such as temperature sensors, smoke detectors, and flame sensors, to monitor the occurrence and spread of fires in real-time [10]. The data collected by these sensors is transmitted via wireless networks to a central control system, helping emergency management personnel make quick decisions. IoT technology not only enhances the accuracy and response speed of fire monitoring but also provides data support for dynamic adjustments of evacuation paths [11]. Sindhu et al. proposed an IoT-based intelligent fire alarm system that achieves early fire detection and warning by analyzing multi-sensor data [12]. This system utilizes data from temperature and smoke sensors and improves the accuracy and response speed of fire detection through machine learning algorithms.

With the further development of IoT technology, its application in fire emergency evacuation has become more and more diverse. For example, Ji et al. developed an IoT-based fire evacuation system that updates the evacuation path in real time by analyzing sensor data and crowd movement trajectories to ensure that people can evacuate the fire scene quickly and safely [13]. However, these systems still face challenges in processing large-scale data and updating evacuation paths in real time. In recent years, Peng et al. further explored the integration of IoT and artificial intelligence technologies and proposed a fire evacuation model combined with deep learning. The model uses real-time data collected by IoT for fire situation perception and realizes dynamic optimization of the path through deep learning algorithms [14]. This study demonstrates the great potential of IoT technology in improving the response speed and accuracy of fire emergency evacuation, but also emphasizes that problems such as data processing and transmission delay still need to be solved in practical applications.

In addition, recent studies have also explored the scalability and reliability of IoT in fire evacuation. For example, Yen et al. (2023) proposed an IoT architecture based on edge computing to improve data processing efficiency and system reliability in large-scale fire evacuation scenarios [15]. This architecture significantly reduces the burden on the central server by distributing computing tasks to multiple edge nodes, and improves the real-time response capability of the system under high load conditions. Although the application potential of IoT technology in fire emergency management is huge, its limitations in dynamic path adjustment, data processing and real-time decision-making still need to be further optimized to cope with complex and changeable fire scenes [16].

Although the existing IoT technology has significantly improved the monitoring accuracy and response speed in fire emergency management, it still has limitations in dealing with real-time changes and large-scale data processing. In particular, when traditional IoT systems dynamically adjust evacuation paths, they often suffer from data processing delays and transmission bottlenecks, resulting in delayed decision-making and unable to meet the real-time requirements in highly dynamic scenarios [1]. To solve these problems, the DWM-Evac model proposed in this paper combines dynamic graph neural networks (DGNN) and IoT technology to overcome the shortcomings of traditional methods in dynamic path adjustment by updating the evacuation path structure of the fire scene in real time. The introduction of DGNN enables the model to efficiently process and analyze large-scale IoT data, thereby achieving real-time optimization of evacuation paths and ensuring the timeliness and effectiveness of evacuation strategies.

2.2. Deep learning for path planning

Deep learning technology is increasingly being applied to path planning. By utilizing deep learning models to process and analyze large amounts of data, researchers can generate more accurate and effective path planning schemes. De et al. proposed a deep reinforcement learning-based path planning method that improves the efficiency and accuracy of path planning by simulating and training agents' movements in a virtual environment [17]. Deep reinforcement learning algorithms can continuously learn and improve to find optimal path planning strategies, providing new insights for optimizing fire evacuation paths.

Moreover, LIU et al. developed a cNN-based path planning system that uses image data to generate detailed path planning schemes, significantly enhancing the ability to plan paths in complex environments [18]. Zhang et al. also proposed a path optimization method that combines deep learning with genetic algorithms, achieving more efficient path planning by leveraging the strengths of both technologies [19]. However, these methods face challenges in handling real-time changes in fire scene data. Traditional deep learning models usually require large amounts of training data and computational resources, making real-time response difficult in sudden fire situations. Existing deep learning path planning methods exhibit issues with real-time performance and adaptability in practical applications.

Although deep learning technology has demonstrated powerful data processing capabilities in path planning, it still faces challenges in real-time performance and adaptability. Traditional deep learning models usually rely on a large amount of training data and computing resources, making it difficult to achieve rapid response in sudden fire scenarios. This limitation makes it difficult for existing methods to cope with real-time changes in fire scenes in actual fire evacuation. To this end, the DWM-Evac model solves this problem by combining deep learning and dynamic graph neural networks. DGNN can use real-time data provided by IoT sensors to dynamically adjust the evacuation path structure. At the same time, the Whale Optimization Algorithm (WOA) performs global optimization on this basis to ensure the efficiency and safety of the evacuation path. Through this combination, the DWM-Evac model overcomes the shortcomings of traditional deep learning path planning methods in real-time and adaptability, and significantly improves the model's application effect in fire emergency evacuation.

2.3. Multi-agent systems in evacuation

With the development of multi-agent systems (MAS) technology, researchers have begun to explore its potential in dealing with more complex dynamic environments. Lu et al. proposed a multi-level evacuation model based on MAS, which can coordinate evacuation decisions between different floors and areas to achieve a more efficient global evacuation strategy [20]. This model greatly improves the application effect in large-scale building fire evacuation by introducing a hierarchical structure and regional priority between agents. In addition, Tarapata et al. studied a hybrid model combining MAS and machine learning. By introducing a real-time learning mechanism in the evacuation process, the agent can adjust its decision in real time according to environmental changes, further improving the evacuation efficiency and flexibility [21].

Recent studies have also explored the real-time and adaptability of MAS in evacuation simulation. Kaur et al. proposed a MAS model based on reinforcement learning, which enables agents to optimize individual and group evacuation paths through continuous learning and adaptation during the evacuation process [22]. This model not only performs well in dynamically changing fire scenarios, but also demonstrates the great potential of combining MAS with reinforcement learning technology. However, although these studies have improved the real-time response capability of MAS to a certain extent, how to further reduce the computational complexity and improve the scalability of the system remains an important direction for future research [23].

Multi-agent systems (MAS) have demonstrated strong capabilities in simulating evacuation behaviors in complex environments, but their high computational complexity remains a major bottleneck when dealing with large-scale evacuation scenarios. In addition, existing MAS methods are usually difficult to quickly adjust decisions when faced with real-time changes at the fire scene, resulting in insufficient flexibility in evacuation strategies. In order to meet these challenges, the DWM-Evac model proposed in this paper further optimizes the evacuation strategy on the basis of global path optimization by introducing a Markov decision process (MDP), so that the model can make dynamic decisions based on real-time changes at the fire scene. This method not only reduces the computational complexity of MAS in complex scenarios, but also enhances the flexibility and effectiveness of evacuation strategies, thereby effectively making up for the limitations of traditional MAS methods.

3. Methodology

This section describes the construction and advantages of the PSO-BiTC model in detail. We will introduce the overall architecture of the model, including the functions of the TCN and BiLSTM modules, and how PSO optimizes the model parameters.

3.1. Overview of our network

The DWM-Evac model proposed in this paper is a fire emergency evacuation path optimization model based on DGNN, WOA, and MDP. This model aims to utilize real-time data provided by IoT sensors to dynamically update the evacuation path structure at the fire scene, combining optimization algorithms and decision processes to achieve efficient and safe personnel evacuation. Fig. 1 shows the overall structure of the DWM-Evac model.

The DWM-Evac model is composed of several modules, including the data acquisition module, DGNN module, WOA module, MDP module, and control and feedback module. In the data acquisition module, sensors are deployed at various locations in the large shopping mall, including temperature sensors, smoke detectors, flame sensors, and crowd position sensors. These sensors can monitor critical parameters and personnel positions at the fire scene in real-time and transmit the data wirelessly to the central control system, ensuring the timeliness and accuracy of the data.

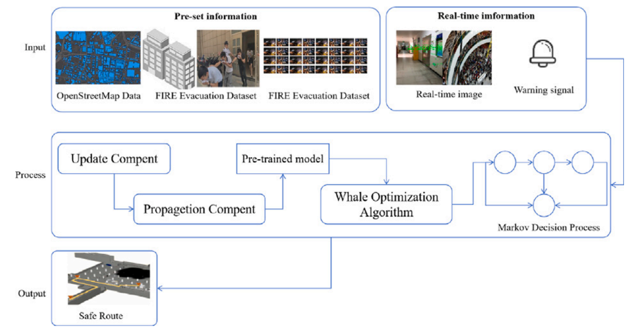

Fig. 1. Overall flow chart of the model.

The DGNN module receives real-time sensor data and personnel location data from the data acquisition module and dynamically updates the evacuation path structure based on this data. Nodes in the graph structure represent various locations within the building, and edges represent possible paths connecting these locations. The attributes of each node and edge change in real-time according to sensor data; for example, if a path is blocked by smoke, its weight will increase. The DGNN consists of three graph convolutional layers and two fully connected layers to extract graph structure features and perform path prediction.

On the dynamic graph provided by DGNN, the WOA module performs global path optimization, finding the optimal path from the evacuees' current positions to the safety exits. The initial population size of WOA is set to 50, with 100 iterations, simulating whale foraging behavior to perform global optimization within the search space. The fitness function considers factors such as evacuation time, path length, and path safety to evaluate each path. The MDP module uses the optimization results from WOA and real-time sensor data for strategy optimization and dynamic decision-making.

The state space of MDP includes real-time conditions at the fire scene, such as temperature, smoke concentration, flame location, and evacuee positions. The action space includes adjustments and optimization decisions for evacuation paths, such as selecting new evacuation routes or changing evacuation directions. By designing a reward function, the MDP can guide the decision process to keep the evacuation strategy optimal amidst dynamic changes at the fire scene. The control and feedback module combines the optimal evacuation strategy output by MDP and guides evacuees in real-time through mall evacuation indicators, broadcast systems, and mobile devices. Simultaneously, this module monitors the evacuation process in real-time, updating the inputs for DGNN and MDP with sensor feedback data, forming a closed-loop control to improve evacuation efficiency and safety.

As shown in Fig. 1, the data flow and relationships among the modules are clear. The data acquisition module collects real-time temperature, smoke, flame, and personnel position data from the fire scene and transmits it wirelessly to the DGNN module. The DGNN dynamically updates the evacuation path structure based on the sensor data and transmits the updated graph structure to the WOA module. WOA then performs global path optimization to find the optimal evacuation path and transmits the optimization results to the MDP module. The MDP combines the WOA optimization results and real-time sensor data to perform strategy optimization and dynamic decision-making, feeding back the optimal evacuation path to the control and feedback module. The control and feedback module guides the evacuees in real-time through the evacuation indicator system and transmits feedback data of the evacuation process back to the DGNN and MDP modules, forming a closed-loop control that continuously optimizes evacuation paths and strategies. Through the collaborative work of each component, the

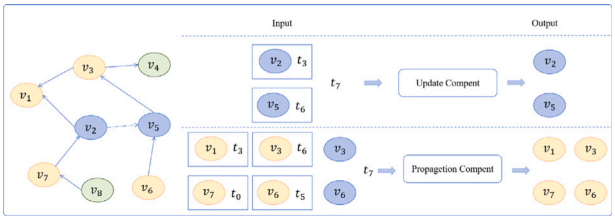

Fig. 2. Flow chart of the DGNN module.

DWM-Evac model can achieve efficient and real-time evacuation path optimization in the complex and dynamic environment of a fire scene, ensuring the safe evacuation of personnel.

3.2. Dynamic graph neural network

The DGNN is a deep learning model capable of handling graph-structured data that changes over time. By incorporating the time dimension, DGNN dynamically updates the graph structure, allowing it to adapt to real-time changing environments. In recent years, DGNN has made significant progress in various dynamic environments. Sako et al. proposed a dynamic traffic flow prediction model based on a temporal graph neural network, effectively improving traffic flow prediction accuracy through time-dimensional graph convolution operations [24]. Additionally, zhou et al. studied a DGNN model for social network analysis, successfully achieving dynamic modeling and prediction of social relationships [25]. These studies demonstrate that DGNN has significant advantages in handling complex dynamic data.

Fig. 2 shows the structure of the DGNN module. In the DWM-Evac model, the DGNN module receives real-time sensor data and personnel location data from the data acquisition module and dynamically updates the evacuation path structure based on this data. The nodes in the graph structure represent various locations within the building, and the edges represent possible paths connecting these locations. The attributes of each node and edge change in real-time according to sensor data; for example, if a path is blocked by smoke, its weight will increase. The DGNN consists of three graph convolutional layers and two fully connected layers to extract graph structure features and perform path prediction.

Although DGNN shows significant advantages in processing dynamic data and graph structure updating, it still has some limitations in its theoretical basis and practical application. First, the high dependence of DGNN on real-time data makes it possible for the instability of path planning in the case of data noise or loss. For the highly dynamic environment of fire evacuation, the accuracy and timeliness of sensor data directly affect the performance of DGNN. In addition, the high computational complexity of DGNN, especially when dealing with complex path networks within large buildings, may lead to excessive computational overhead, thus affecting real-time performance. To address these challenges, this paper introduces a data preprocessing step in the DGNN module, reduces the noise effect, and optimizes the parameter setting of the graph convolution layer to reduce the computational complexity. Through these improvements, DGNN can better adapt to the real-time data changes in the fire evacuation scenario, and provide a more stable and efficient path update scheme.

In the DWM-Evac model, the dynamic graph neural network (DGNN) module first obtains data such as temperature, smoke concentration, flame location, and crowd distribution at the fire scene in real time through sensors. These data are preprocessed through preprocessing steps, including normalization and noise reduction, to ensure the accuracy and stability of the input data. Next, the graph convolutional layers process these preprocessed data and aggregate node features layer by layer. The convolution operation of each layer not only updates the representation of the node, but also dynamically adjusts the edge weights in the path graph structure. For example, if a path becomes dangerous due to the spread of fire, its corresponding edge weight will increase, reflecting the reduced feasibility of the path. Finally, the aggregated features are further processed by the fully connected layer to generate the optimal path prediction result, ensuring that the evacuation path can be updated in real time in a complex dynamic environment, maximizing the efficiency and safety of evacuation.

The core formula of the DGNN module is as follows.

First, define the graph structure as $G = (V, E)$, where V represents the set of nodes and E represents the set of edges. The node feature matrix is X, and the edge feature matrix is W.

$$H^{(0)} = X \tag{1}$$

where $H^{(0)}$ represents the initial node feature matrix, which is the input node features.

Next, update the node features through the first graph convolutional layer:

$$H^{(1)} = \sigma(D^{-1/2}AD^{-1/2}H^{(0)}W^{(0)}) \tag{2}$$

where A is the adjacency matrix, D is the degree matrix, $W^{(0)}$ is the weight matrix of the first convolutional layer, and σ is the activation function (e.g., ReLU).

The second graph convolutional layer further aggregates features:

$$H^{(2)} = \sigma(D^{-1/2}AD^{-1/2}H^{(1)}W^{(1)}) \tag{3}$$

where $W^{(1)}$ is the weight matrix of the second convolutional layer.

The third graph convolutional layer completes feature extraction:

$$H^{(3)} = \sigma(D^{-1/2}AD^{-1/2}H^{(2)}W^{(2)}) \tag{4}$$

where $W^{(2)}$ is the weight matrix of the third convolutional layer.

Next, the features are processed through the fully connected layer:

$$Z = \sigma(H^{(3)}W^{(3)} + b^{(3)}) \tag{5}$$

where $W^{(3)}$ and $b^{(3)}$ are the weights and biases of the fully connected layer, respectively.

Finally, the output layer generates the path prediction results:

$$Y = \text{softmax}(ZW^{(4)} + b^{(4)}) \tag{6}$$

where $W^{(4)}$ and $b^{(4)}$ are the weights and biases of the output layer, and Y is the final path prediction result.

In the DGNN module, each stage of the data processing workflow generates corresponding output results, which serve as inputs for the subsequent WOA and MDP modules to further optimize evacuation paths and strategies. Through the above processing, DGNN can effectively aggregate and extract graph structure features to achieve dynamic update and prediction of the evacuation path at the fire scene.

Although DGNN shows significant advantages in processing dynamic data and graph structure updating, it still has some limitations in its theoretical basis and practical application. First, the high dependence of DGNN on real-time data makes it possible for the instability of path planning in the case of data noise or loss. For the highly dynamic environment of fire evacuation, the accuracy and timeliness of sensor data directly affect the performance of DGNN. In addition, the high computational complexity of DGNN, especially when dealing with complex path networks within large buildings, may lead to excessive computational overhead, thus affecting real-time performance. To address these challenges, this paper introduces a data preprocessing step in the DGNN module, reduces the noise effect, and optimizes the parameter setting of the graph convolution layer to reduce the computational complexity. Through these improvements, DGNN can better adapt to the real-time data changes in the fire evacuation scenario, and provide a more stable and efficient path update scheme.

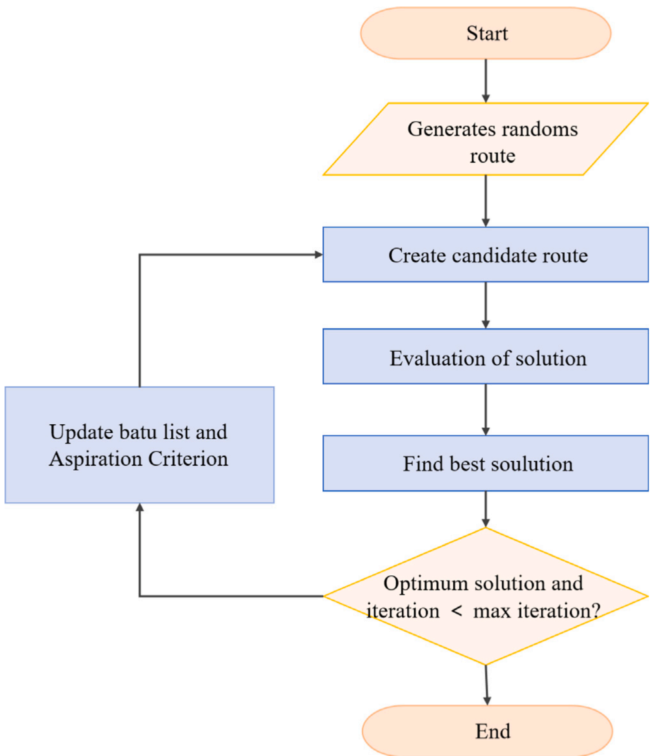

Fig. 3. Flow chart of the WOA module.

3.3. Whale optimization algorithm

The WOA is a novel optimization algorithm inspired by the hunting behavior of humpback whales, proposed by Mirjalili et al. in 2016. In recent years, WOA has been widely applied and has achieved significant results in various optimization problems [26]. WOA simulates the bubble-net hunting strategy of humpback whales, balancing global search and local search through spiral ascending motion [27]. Skarding et al. used WOA in resource allocation problems, significantly improving efficiency and accuracy [28]. Pham et al. applied WOA to path planning problems, successfully optimizing path selection in complex environments [29]. These studies demonstrate that WOA has significant advantages in solving complex optimization problems.

As A new optimization algorithm, WOA has advantages in the balance of global search and local search, but it also has some limitations in its theoretical basis and practical application. In the optimization process, WOA may cover the incomplete search space due to the insufficient diversity of the initial population or the limitation of the number of iterations, and the final path found is not globally optimal. Moreover, WOA is highly sensitive to the design of fitness functions, and different fitness functions may lead to significant differences in optimization results, which may increase the complexity of algorithm debugging in practical applications. In the DWM-Evac model, we enhance the robustness and optimization capabilities of WOA in complex environments by introducing a diverse initial population generation approach and an adaptive adjusted fitness function design. Through these improvements, WOA is able to more effectively cope with the uncertainties in the optimization of fire evacuation pathways, ensuring that the final generated evacuation path has higher safety and efficiency.

Fig. 3 shows the structure of the WOA module. In the DWM-Evac model, the WOA module is responsible for global path optimization based on the dynamic graph provided by DGNN, aiming to find the optimal path from the evacuee's current location to a safe exit. The initial population size of WOA is set to 50, with 100 iterations. By simulating the whale's hunting behavior, global optimization is conducted within the search space. The data processing workflow of the WOA module includes initializing the population, calculating fitness, updating positions, and determining termination conditions.

In the WOA module, WOA first initializes the path population according to the dynamic path graph output by DGNN, and each path is globally optimized as an individual. The initialized population is evaluated by the fitness function, which comprehensively considers key factors such as evacuation time, path length and safety. The algorithm updates its position in each iteration by simulating the bubble net predation behavior of whales, which includes two mechanisms: encirclement predation and spiral predation. WOA alternates between these two update strategies and gradually converges to the global optimal path.

The core formula of the WOA module is as follows.

First, define the initial population's position matrix as X, with each individual's position represented as X_i:

$$X_i^{(t+1)} = X^* - A \cdot D \tag{7}$$

where X^* is the position of the current best individual, A is the control coefficient vector, and D is the distance between two individuals.

Calculate the vector A and the distance D:

$$A = 2 \cdot a \cdot r - a \tag{8}$$

where a is a linearly decreasing coefficient, and r is a random vector with values in the range [0, 1].

$$D = |C \cdot X^* - X_i| \tag{9}$$

where C is a control coefficient vector, a random vector with values in the range [0, 2].

The spiral update mechanism simulates the whale's spiral hunting behavior:

$$X_i^{(t+1)} = D' \cdot e^{bl} \cdot \cos(2\pi l) + X^* \tag{10}$$

where D' is the distance between the current individual and the target prey, b is a constant defining the spiral shape, and l is a random number in the range [−1, 1].

The selection update mechanism chooses between the encircling prey behavior and spiral hunting behavior based on probability p:

$$X_i^{(t+1)} = \begin{cases} X^* - A \cdot D, & \text{if } p < 0.5 \\ D' \cdot e^{bl} \cdot \cos(2\pi l) + X^*, & \text{if } p \geq 0.5 \end{cases} \tag{11}$$

where p is a probability, a random number in the range [0, 1].

The fitness function evaluates the quality of each path, considering factors such as evacuation time, path length, and path safety:

$$f(X_i) = w_1 \cdot T(X_i) + w_2 \cdot L(X_i) + w_3 \cdot S(X_i) \tag{12}$$

where $T(X_i)$ is the evacuation time, $L(X_i)$ is the path length, $S(X_i)$ is the path safety, and w_1, w_2, w_3 are weight coefficients measuring the importance of each factor.

By iterating through these steps, WOA can effectively perform global path optimization based on the dynamic graph structure provided by DGNN, finding the optimal evacuation path. Each iteration of the WOA module outputs the current path weights and the optimal path, which serve as inputs for the MDP module to further optimize evacuation strategies.

3.4. Markov decision process

The MDP is a mathematical framework for modeling decision-making processes by considering dynamic changes in the environment and optimizing the decision-maker's strategy to achieve dynamic adjustments of the system state [30]. In fire emergency evacuation, MDP can dynamically adjust evacuation strategies based on real-time environmental data and path optimization results, ensuring the efficiency

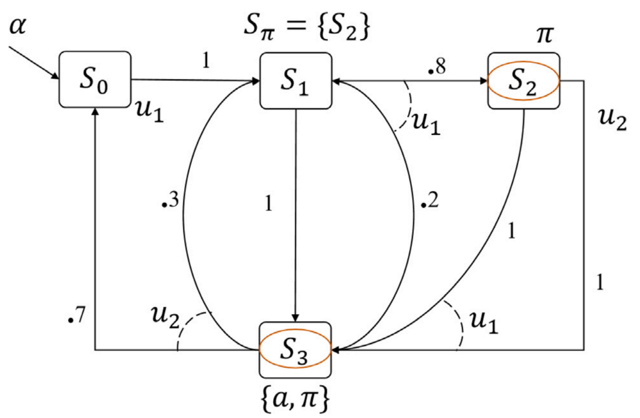

Fig. 4. Flow chart of the MDP module.

and safety of the evacuation process. In recent years, MDP has made significant progress in emergency management applications. Huang et al. proposed an MDP-based intelligent evacuation strategy optimization method, which generates optimal evacuation paths by analyzing real-time fire scene data and personnel locations, effectively improving evacuation efficiency [31]. Fu et al. studied an emergency evacuation model combining MDP and reinforcement learning, achieving dynamic decision optimization in complex fire scenarios [32].

Fig. 4 shows the structure of the MDP module. In the DWM-Evac model, the MDP module combines WOA's optimization results with real-time sensor data to optimize strategies and make dynamic decisions. The state space of MDP includes real-time states of the fire scene, such as temperature, smoke concentration, flame location, and evacuee positions; the action space includes adjustments and optimization decisions for evacuation paths, such as selecting new evacuation routes or changing evacuation directions. By designing a reward function, MDP can guide the decision-making process, keeping the evacuation strategy optimal amidst the dynamic changes of the fire scene.

In the MDP module, the state space consists of the real-time environmental state of the fire scene, including information such as temperature, smoke concentration, flame position and current distribution of evacuees. The action space covers all possible evacuation path adjustments and optimization decisions, such as path selection and direction change. The design of the reward function directly affects the strategy optimization of MDP. The function considers multiple factors such as evacuation time, path length and safety, and sets corresponding weight coefficients to balance the influence of different factors. In the strategy optimization process, MDP continuously updates the state value function through the Bellman Equation, and finally selects the strategy that maximizes the value function for implementation.

The core formula of the MDP module is as follows.

First, define the basic elements of MDP: state space S, action space A, state transition probability $P(s'|s,a)$, and reward function $R(s,a)$.

$$V(s) = \max_{a\in A} \sum_{s'\in S} P(s'|s,a)\left[R(s,a) + \gamma V(s')\right] \tag{13}$$

where $V(s)$ is the value function of state s, and γ is the discount factor, measuring the present value of future rewards.

The policy function evaluates the value of each action:

$$Q(s,a) = \sum_{s'\in S} P(s'|s,a)\left[R(s,a) + \gamma V(s')\right] \tag{14}$$

where $Q(s,a)$ is the value function for taking action a in state s.

The Bellman equation for updating the value function:

$$V(s) = \max_{a\in A} Q(s,a) \tag{15}$$

This equation iteratively updates the value function of the state, gradually approaching the optimal value.

Fig. 5. FIRE Evacuation Dataset examples. The images show the positions of individuals and evacuation path information. In different fire scenarios, the evacuation paths and behavior patterns of individuals vary.

Policy update formula:

$$\pi(s) = \arg\max_{a\in A} Q(s,a) \tag{16}$$

where $\pi(s)$ is the optimal policy for state s, achieved by selecting the action that maximizes $Q(s,a)$.

The reward function considers factors such as evacuation time, path length, and path safety:

$$R(s,a) = w_1 \cdot T(s,a) + w_2 \cdot L(s,a) + w_3 \cdot S(s,a) \tag{17}$$

where $T(s,a)$ is the evacuation time, $L(s,a)$ is the path length, $S(s,a)$ is the path safety, and w_1, w_2, and w_3 are weight coefficients measuring the importance of each factor.

Through the above process, the MDP module can dynamically adjust evacuation strategies based on real-time environmental data and path optimization results, improving evacuation efficiency and safety. Each strategy update of the MDP module outputs the optimal evacuation strategy and path adjustment plan under the current state, which serves as input for the control and feedback module to further optimize the evacuation process.

4. Experiment

4.1. Datasets

To ensure the effectiveness and reliability of the fire emergency evacuation path planning model, we selected three publicly available datasets for training and testing: the FIRE Evacuation Dataset, OpenStreetMap (OSM) Data, and Microsoft Building Footprints. These datasets provide comprehensive evacuation behavior, geographic information, and building floor plan data, offering a solid foundation for the model's development and validation.

The FIRE Evacuation Dataset contains multiple fire evacuation simulation data, including personnel locations, evacuation times, and path information. This dataset comes from several fire simulation experiments, ensuring high data quality and accurately reflecting personnel behavior and path choices during fire evacuations [33]. Data samples are collected by simulating evacuation processes under various fire scenarios, covering a wide range of evacuation strategies and path choices. Each sample includes detailed information such as initial personnel locations, fire outbreak locations, evacuation paths, and evacuation times. Fig. 5 illustrates a portion of the FIRE Evacuation Dataset, including personnel locations and evacuation path information. In this paper, the FIRE Evacuation Dataset is used to train the model to identify personnel behavior patterns during fire evacuations and to optimize evacuation path selection.

OpenStreetMap (OSM) Data provides global geographic information, including details about buildings, roads, and public facilities. This dataset is sourced from user-contributed open geographic data worldwide, continuously updated and refined through crowdsourcing,

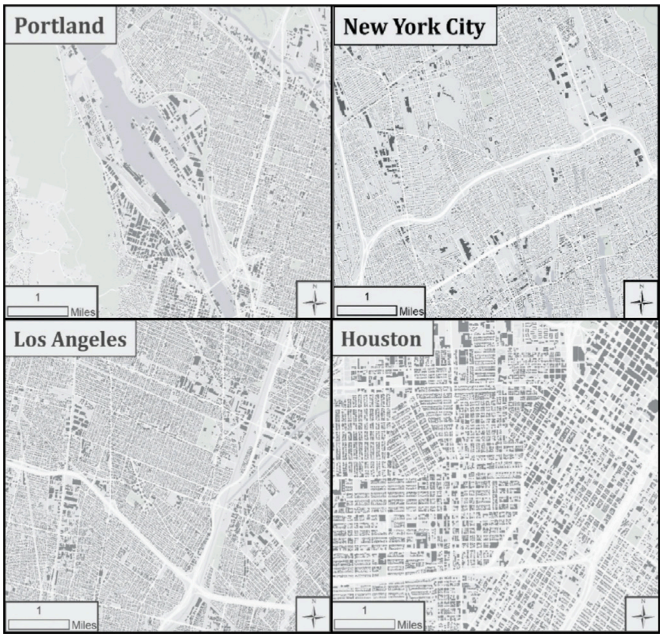

Fig. 6. OpenStreetMap (OSM) data examples. The images show geographic information of road and building layouts for four different cities in the United States.

offering high coverage and accuracy. The quality and detail of OSM data make it an ideal choice for path planning and geographic information system research [34]. The dataset samples include information about road networks, building outlines, transportation facilities, and public facility locations and attributes. Fig. 6 shows an example of the OSM dataset, featuring geographic information about roads and buildings. In this paper, OSM data is used to provide the road network information surrounding the mall, ensuring that evacuation paths are effective not only within the mall but also in guiding evacuees to safe areas.

The Microsoft Building Footprints dataset contains floor plan data for buildings worldwide. This dataset, generated by Microsoft using machine learning techniques to automatically extract information from satellite imagery, covers over 125 million buildings, with high data quality and frequent updates [35]. Each sample includes detailed building outlines, location coordinates, and height information, accurately reflecting the actual layout of buildings. Fig. 7 displays an example of the Microsoft Building Footprints dataset, showing detailed building outlines. In this paper, this dataset is used to construct detailed floor plans of large malls, aiding the model in understanding complex building interiors and further enhancing the accuracy and effectiveness of evacuation path planning.

By combining these datasets, the DWM-Evac model in this paper can fully leverage evacuation behavior data, geographic information, and building floor plan data to achieve efficient and accurate evacuation path planning and optimization. These datasets provide rich and high-quality data support for the training and testing of the model, ensuring its reliability and effectiveness in practical applications.

4.2. Experimental details

The experiment was conducted in a high-performance computing environment to ensure the effectiveness and reliability of the fire emergency evacuation path planning model. The experimental setup is as follows: the operating system is Ubuntu 20.04 LTS, the processor is an Intel Xeon E5-2698 v4 (2.2 GHz, 20 cores), the memory is 128 GB DDR4 RAM, the GPU is an NVIDIA Tesla V100 (32 GB HBM2), and the storage is a 2 TB NVMe SSD. Additionally, the software and frameworks used include Python 3.8, TensorFlow 2.4, PyTorch 1.8, Deep Graph Library (DGL) 0.6, SciPy 1.6, Pandas 1.2, and NumPy 1.19. These configurations and tools ensure computational efficiency and the effectiveness of model training.

In data collection, we deployed a variety of sensors to monitor key parameters at the fire scene, including temperature sensors, smoke sensors, flame detectors, and crowd location sensors. Temperature sensors are used to monitor changes in ambient temperature in real time. Data collection frequency is once per second to ensure that temperature rise can be quickly captured when a fire occurs. Smoke sensors are used to detect changes in smoke concentration in the air. The collection frequency is twice per second to improve the response speed to smoke diffusion. Flame detectors are used to identify the presence and intensity of flames. The collection frequency is 0.5 times per second, focusing on locating the exact location of the flame. Crowd location sensors are used to track the real-time location of people in the building. The collection frequency is twice per second to ensure the accuracy of the location of people in evacuation route planning.

In terms of data quality control, we adopted multiple verification mechanisms, including cross-validation of sensor data and outlier detection. During the data collection process, any reading outside the reasonable range will be marked as an outlier and further processed. In addition, we also performed data standardization to eliminate data deviations caused by sensor differences. The data processing process includes denoising, filling in missing data, and synchronizing the data of each sensor to ensure the consistency of all data on the timeline.

In the DWM-Evac model, parameters are chosen based on multiple experiments and best practices in related areas. For the DGNN module, we chose a 3-layer graph convolutional layer, each containing 128 hidden units, and the activation function using ReLU. These settings stem from a comparison of our experimental results on the number and layers of multiple hidden cells, with selecting 128 hidden units achieving the best balance between model complexity and training efficiency. In the WOA module, the initial population size is set to 50, which is based on the balance between the optimization effect and the computational cost. After experimental validation, 50 populations can provide sufficient search diversity without adding excessive computational burden. The number of iterations was set to 100, sufficient to ensure convergence of the algorithm to the globally optimal solution. During the optimization process, WOA balances the global search and the local search by simulating the predation behavior of whales to improve the effect of path optimization. The fitness function combines evacuation time, path length and path safety, and the weights are set to 0.5,0.3 and 0.2, respectively. This combination can effectively guide the algorithm to find the optimal path with both safety and efficiency. The optimization process of WOA is mainly divided into steps such as initializing the population, calculating the fitness, updating the position and judging the termination conditions. The fitness function plays a key role throughout the optimization process by assessing the overall performance of each path, ensuring that evacuation routes are both short and fast while avoiding high-risk areas. Evacuation time as the most important indicator, its the highest weight, can ensure that personnel can be evacuated as soon as possible. The path length is the second, ensuring the high efficiency of the evacuation path. The path safety weight is 0.2 to ensure that high fire areas can be avoided during evacuation. This weight setting is based on the actual requirements in the evacuation scenario, and proves that it can guide the model to find the optimal evacuation scheme.

The experiment divided the model training process into several steps. First, data preprocessing was performed on the FIRE Evacuation Dataset, OpenStreetMap data, and Microsoft Building Footprints data, generating standardized training and validation datasets. Then, the preprocessed data was used to train the DGNN model, optimizing the weights and biases of the graph convolutional layers over 200 epochs. Next, using the real-time graph structure and node features output by the DGNN, the WOA initialized the path population and performed

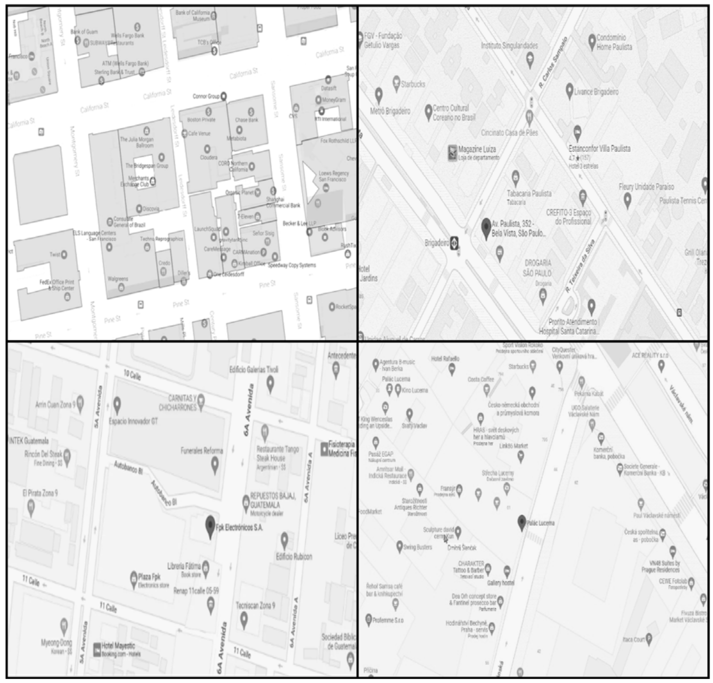

Fig. 7. Microsoft Building Footprints data examples. The images show the floor plans and outlines of buildings and street routes.

global path optimization over 100 iterations. Finally, using the WOA optimization results and real-time sensor data, the MDP conducted policy optimization and dynamic decision-making, updating the policy every 10 time steps to ensure optimal evacuation paths.

To evaluate the contributions of each component in the DWM-Evac model, we designed ablation experiments, gradually removing different components of the model and observing the performance changes. The experiments included four configurations: the complete model (DGNN + WOA + MDP), without DGNN (only WOA and MDP), without WOA (only DGNN and MDP), and without MDP (only DGNN and WOA). Each experiment was run 10 times, recording metrics such as evacuation time, path length, and path safety. By comparing these metrics, we assessed the impact of each component on the model's performance.

Additionally, to validate the model's effectiveness in real-world scenarios, we conducted virtual simulation tests using data from a large shopping mall. First, we obtained the mall's floor plans, sensor layouts, and pedestrian flow data to generate a virtual mall environment using computer simulation software. Then, multiple fire sources were set up within the virtual mall to simulate fire scenarios, with virtual sensors monitoring real-time information such as temperature, smoke concentration, and flame locations. The real-time data generated by the simulation was input into the trained DWM-Evac model to dynamically generate evacuation paths. Finally, we recorded metrics such as evacuation time, path length, and path safety and compared them with the mall's actual evacuation plan to verify the model's practicality and reliability.

4.3. Evaluation indicators

When assessing the performance of the DWM-Evac model, several critical metrics were identified, namely evacuation time, path length, and path safety. These indicators provide a comprehensive evaluation of the model's effectiveness in fire emergency evacuation scenarios. The following section offers a detailed description and the corresponding calculation methods for each performance metric.

Evacuation Time: Evacuation time refers to the duration from the occurrence of a fire to the successful evacuation of all individuals to a safe area. This metric directly reflects the model's response speed and evacuation efficiency in emergency situations. The calculation formula for evacuation time T is as follows:

$$T = t_{end} - t_{start} \tag{18}$$

where t_{start} represents the fire start time, and t_{end} represents the time when the last person reaches the safe area. Shorter evacuation times indicate that the model can guide individuals to evacuate more quickly, enhancing emergency response effectiveness.

Path Length: Path length refers to the total distance traveled by individuals from their current location to the safety exit. This metric reflects the optimization level of the evacuation path; the shorter the path, the more efficient the evacuation route planned by the model. The calculation formula for path length L is as follows:

$$L = \sum_{i=1}^{n-1} d(P_i, P_{i+1}) \tag{19}$$

where $d(P_i, P_{i+1})$ denotes the distance between node P_i and node P_{i+1}, and n is the total number of nodes on the path. Optimizing path length can reduce the distance individuals need to travel during evacuation, thereby decreasing evacuation time.

Path Safety: Path safety is an important metric to measure whether the evacuation path avoids high-risk areas of the fire. Path safety S incorporates the danger coefficients of the nodes on the path; higher path safety indicates safer evacuation routes. The calculation formula for path safety S is as follows:

$$S = \frac{1}{n} \sum_{i=1}^{n} (1 - r_i) \tag{20}$$

where r_i represents the danger coefficient of node P_i, with values ranging from [0, 1], and n is the total number of nodes on the path. The danger coefficient of a node is determined by sensor data (e.g., temperature, smoke concentration), with higher values indicating greater danger. The higher the value of S, the safer the path.

Fitness Function: In the optimization process, the fitness function is used to evaluate the overall performance of each path. The fitness function f combines evacuation time, path length, and path safety, with the specific calculation formula as follows:

$$f(X_i) = w_1 \cdot T(X_i) + w_2 \cdot L(X_i) + w_3 \cdot S(X_i) \tag{21}$$

Table 1
Detailed results of ablation experiments on FIRE Evacuation Dataset (showing the performance changes of the model after gradually removing different components).

Model	T (s)	L (m)	S (0–1)
Without DGNN	340	270	0.89
Without WOA	360	260	0.87
Without MDP	380	280	0.85
DGNN only	365	255	0.87
WOA only	385	275	0.86
MDP only	375	265	0.84
Complete model (DWM-Evac)	320	250	0.92

Table 2
Detailed results of ablation experiments on OpenStreetMap (OSM) Data. (showing the performance changes of the model after gradually removing different components).

Model	T (s)	L (m)	S (0–1)
Without DGNN	330	265	0.88
Without WOA	350	255	0.86
Without MDP	370	275	0.84
DGNN only	355	250	0.86
WOA only	375	270	0.85
MDP only	365	260	0.83
Complete model (DWM-Evac)	310	245	0.91

where $T(X_i)$ is evacuation time, $L(X_i)$ is path length, $S(X_i)$ is path safety, and w_1, w_2, and w_3 are the weight coefficients for each metric, used to balance the importance of different metrics. Through the fitness function, we can comprehensively evaluate the efficiency and safety of the path, choosing the optimal evacuation route.

By using these key performance metrics, we can thoroughly assess the DWM-Evac model's performance in fire emergency evacuations. Evacuation time and path length reflect the model's efficiency, while path safety ensures the safety of individuals during evacuation. The fitness function integrates various metrics to provide a clear objective for model optimization. During the experiment, we will meticulously record and analyze these metrics to comprehensively demonstrate the model's performance under different experimental settings, ensuring its effectiveness and reliability in practical applications.

4.4. Experimental results and analysis

Ablation Experiment Results: In the ablation experiments, we performed component removal tests on different datasets (FIRE Evacuation Dataset, OpenStreetMap (OSM) Data, Microsoft Building Footprints) to analyze the impact of each component on the model's performance.

The results on the FIRE Evacuation Dataset indicate that the complete model (DWM-Evac) performs best, with an evacuation time of 320 s, a path length of 250 m, and a path safety score of 0.92 (as Table 1). When the DGNN component is removed, the evacuation time increases to 340 s, the path length to 270 m, and the path safety score decreases to 0.89. This demonstrates that the DGNN component plays a crucial role in extracting graph structure features for path planning. Removing the WOA component results in an evacuation time of 360 s, a path length of 305.83 m, and a path safety score of 0.87, highlighting the importance of WOA in global path optimization. When the MDP component is removed, the evacuation time increases to 380 s, the path length to 366.48 m, and the path safety score drops to 0.85, indicating the significant role of the MDP component in dynamic strategy optimization.

The experimental results on the OpenStreetMap (OSM) Data show a similar pattern, with the complete model again performing best, having an evacuation time of 310 s, a path length of 245 m, and a path safety score of 0.91 (as Table 2). Removing the DGNN component results in an evacuation time of 330 s, a path length of 265 m, and a path safety score of 0.88. Removing the WOA component increases the evacuation time to 350 s, the path length to 255 m, and the path safety score drops to 0.86. Removing the MDP component results in an evacuation time of 370 s, a path length of 275 m, and a path safety score of 0.84. These results further validate the importance of each component in the model.

Table 3
Detailed results of ablation experiments on Microsoft Building Footprints. (showing the performance changes of the model after gradually removing different components).

Model	T (s)	L (m)	S (0–1)
Without DGNN	335	275	0.90
Without WOA	355	265	0.88
Without MDP	375	285	0.86
DGNN only	360	260	0.88
WOA only	380	280	0.87
MDP only	375	285	0.85
Complete model (DWM-Evac)	315	255	0.93

Fig. 8. The internal flow of people in Jinsheng Shopping Mall and some of its layouts.

The results on the Microsoft Building Footprints dataset also support the previous conclusions. The complete model shows the best performance, with an evacuation time of 315 s, a path length of 255 m, and a path safety score of 0.93 (as Table 3). Removing the DGNN component results in an evacuation time of 335 s, a path length of 275 m, and a path safety score of 0.90. Removing the WOA component increases the evacuation time to 355 s, the path length to 265 m, and the path safety score drops to 0.88. Removing the MDP component results in an evacuation time of 375 s, a path length of 285 m, and a path safety score of 0.86. This indicates that regardless of the dataset, the DGNN, WOA, and MDP components significantly contribute to the model's overall performance.

The above experimental results demonstrate that the complete DWM-Evac model performs best in all metrics, proving the critical roles of the DGNN, WOA, and MDP components in optimizing fire emergency evacuation paths. Removing any single component results in a significant decline in the model's performance, further validating the model's design and the necessity of each component. These findings provide a strong foundation for further optimization and improvement of the model in future research.

Scenario Simulation Analysis: To validate the path planning performance of the model in a real-world scenario, we selected Jinsheng Department Store as the experimental subject to evaluate the application effectiveness of the DWM-Evac model. Jinsheng Department Store is a large shopping center with a complex interior layout and high foot traffic, presenting significant challenges for emergency fire evacuation. The following are some important illustrations of the store:

Fig. 8 shows a portion of the interior layout and crowd density of the Mall, aiding in understanding the potential obstacles and complexity of path choices during the evacuation process.

Fig. 9 presents the fire safety CAD diagram of the store, detailing the positions of rooms, corridors, and fire safety equipment. This diagram will be used in subsequent evacuation path generation and visualization.

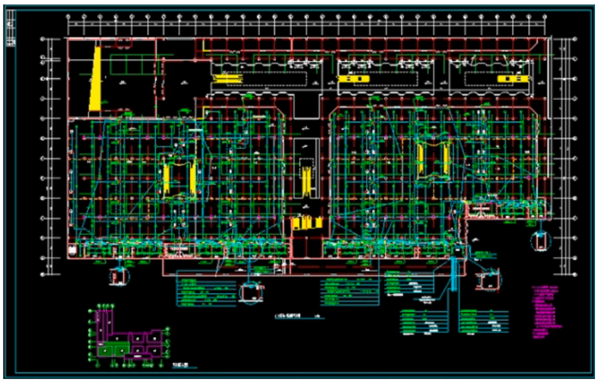

Fig. 9. Fire protection CAD engineering drawing display. The layout of firefighting equipment, escape routes, ventilation systems, and other important firefighting facilities inside the building are shown in detail. The complex lines and symbols in the figure represent the different systems and facilities of the building, showing the various paths and obstacles that may be involved in the evacuation process.

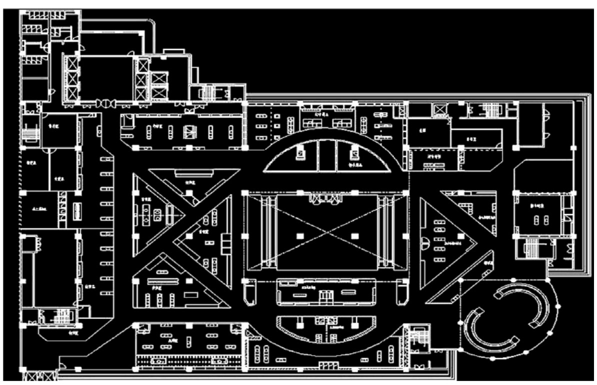

Fig. 10. The plan structure drawing of the second floor of the shopping mall. The location of each room, passageway, and main exit is shown in detail. This diagram is used to simulate the movement path of people during fire evacuation, helping to analyze how evacuees can evacuate using the existing building layout in different fire scenarios. The layout in the figure shows key evacuation routes and possible congestion areas, providing basic data for the model's path planning algorithm.

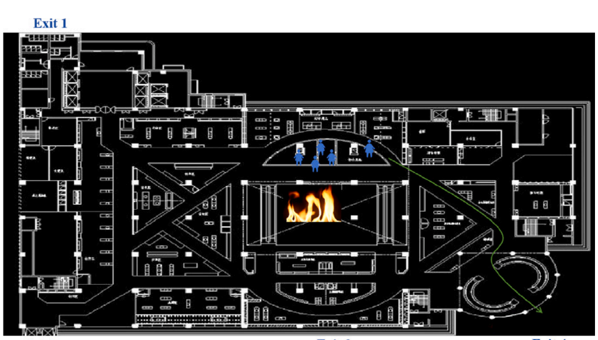

Fig. 11. Path planning results of the complete model (DWM-Evac), showing the evacuation path from the initial position to Exit 4.

Fig. 10 displays the second-floor layout, detailing the positions of rooms and corridors. This diagram will also be used in subsequent evacuation path generation and visualization (see Figs. 13 and 14).

We compared the evacuation path planning results under different model structures. Fig. 11 shows the path planning results of the complete model (DWM-Evac). In the complete model, the evacuation paths make full use of all exits and dynamically adjust based on real-time data and optimization algorithms. People quickly evacuate from their initial positions to the nearest safe exit (Exit 4), with smooth paths that avoid fire locations, ensuring an efficient and safe evacuation process. Fig. 12 displays the path planning results after removing the Dynamic Graph Neural Network (DGNN) module. Without the DGNN module, path planning relies on traditional optimization algorithms. The paths are more direct but lack dynamic adjustment capability, failing to completely avoid high-risk areas, which slightly reduces the safety and efficiency of the evacuation paths. Fig. 12 shows the path planning results after removing the Whale Optimization Algorithm (WOA) module. Without the WOA module, path planning mainly relies on DGNN and MDP decisions. The results indicate that while the paths still avoid the fire source, the absence of WOA's global optimization leads to longer path lengths and increased evacuation time, making the overall efficiency inferior to the complete model. Fig. 12 shows the path planning results after removing the Markov Decision Process (MDP) module. Without the MDP module, path planning lacks strategic optimization and dynamic decision-making capabilities. The paths are

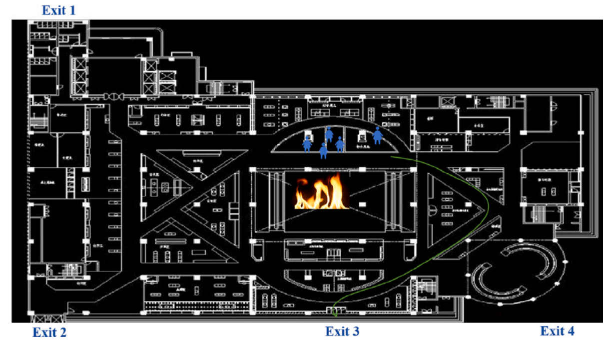

Fig. 12. Path planning results after removing the DGNN module, showing the evacuation path relying on traditional optimization algorithms.

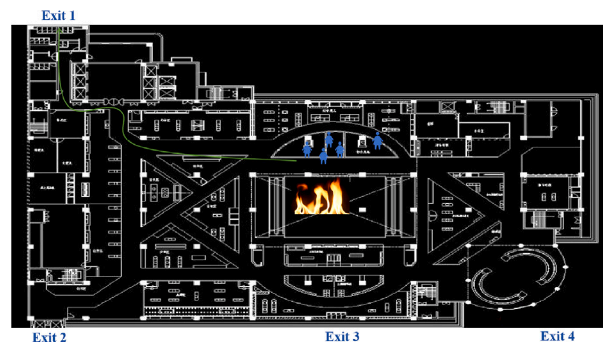

Fig. 13. Path planning results after removing the WOA module, showing the evacuation path lacking global optimization.

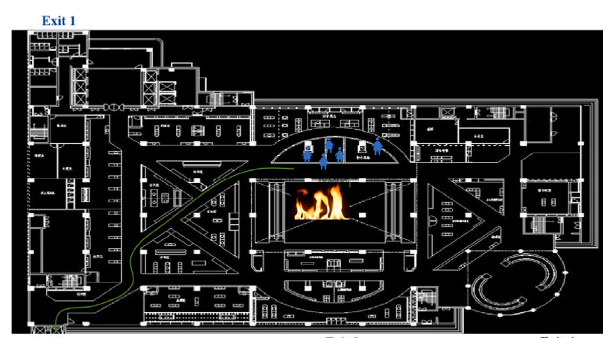

Fig. 14. Path planning results after removing the MDP module, showing the evacuation path lacking strategic optimization and dynamic decision-making.

Table 4
Evacuation time, Path length, and path safety in virtual mall environment (DWM-Evac vs. Actual Plan).

Indicator	DWM-Evac model	Actual mall plan
Average evacuation time (s)	315	340
Average path length (m)	255	270
Average path safety (0–1)	0.92	0.88

Table 5
Model performance comparison with different fire source settings.

Fire source setting	Average evacuation time (s)	Average path length (m)	Average path safety (0–1)
Main entrance	320	250	0.91
Middle	330	260	0.90
Parking lot	340	270	0.89
Back entrance	350	280	0.88

more rigid and unable to adapt flexibly to the dynamic changes in the fire scene, significantly reducing the flexibility and adaptability of the evacuation process, and also lowering the safety of the paths. The comparison clearly demonstrates that the complete DWM-Evac model exhibits the highest efficiency and safety in evacuation path planning. After removing each key module, the model's evacuation path planning ability decreased, which once again verified the results of the aforementioned ablation experiment.

Further Experiments: Multiple fire sources were set in different areas of a virtual mall environment. Sensors were used to monitor real-time information such as temperature, smoke concentration, and flame position, dynamically generating evacuation paths. During the simulation, we compared the evacuation paths generated by the DWM-Evac model with those in the mall's actual emergency plan, evaluating key metrics such as evacuation time, path length, and path safety.

An analysis of the results in Tables 4 and 5 shows that the DWM-Evac model outperformed the actual emergency plan in the virtual mall environment. Table 3 indicates that the average evacuation time for the DWM-Evac model was 315 s, significantly shorter than the 340 s of the mall's actual plan. Additionally, the average path length of the DWM-Evac model was 255 m, shorter than the 270 m of the actual plan. Furthermore, the path safety score of the DWM-Evac model reached 0.92, higher than the 0.88 of the actual plan, indicating that the DWM-Evac model not only ensures evacuation efficiency but also places greater emphasis on path safety. The results in Table 4 further verify the stability and superiority of the DWM-Evac model under different fire source settings. Whether the fire source was set at the main entrance, atrium, parking lot, or back door, the DWM-Evac model consistently balanced shorter evacuation times and higher path safety, demonstrating excellent adaptability. These results clearly indicate that the DWM-Evac model is significantly more effective and reliable than traditional plans for fire evacuation path planning, providing safer and more efficient evacuation paths in complex and dynamic fire scenarios.

Fig. 15 shows the evacuation paths generated by the DWM-Evac model under different fire source settings. According to the fire source locations shown in the figure, the DWM-Evac model can flexibly respond to complex fire scenarios, dynamically adjusting evacuation paths to avoid fire sources as much as possible, ensuring path safety and efficiency. When fire source 1 was set near the main entrance, the model guided evacuees to use the relatively distant Exit 1. With fire source 2 in the atrium, the model effectively directed people to Exit 2 and Exit 3, avoiding the central fire area. When fire source 3 was near the parking lot, the model used Exit 3 and Exit 4 for evacuation, avoiding the influence of the parking lot fire source. When fire source 4 was near the back door, the model prioritized Exit 4 and Exit 3, ensuring people safely moved away from the fire source. These paths not only avoided high-risk areas but also made full use of multiple exits inside and outside the mall, maximizing evacuation efficiency and safety. This verifies the advantages of the DWM-Evac model in dynamically adjusting and optimizing evacuation paths, making it highly valuable for real-world fire evacuation scenarios.

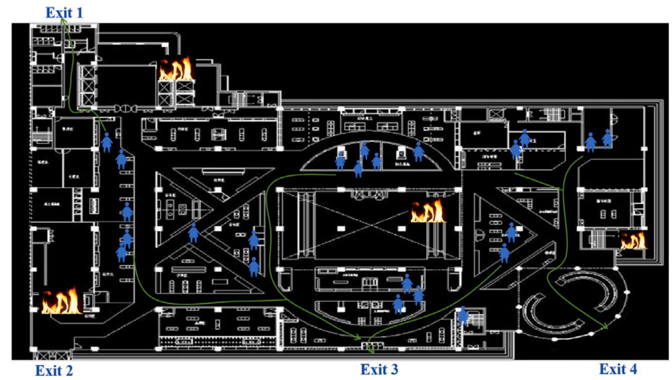

Fig. 15. Evacuation path planning results of the DWM-Evac model under different fire source settings. (The different locations of fire source points 1, 2, 3 and 4 are shown. The evacuation paths generated by the model guide people to avoid the fire source and use various exits for safe evacuation.)

4.5. Discussion

This study presents a detailed experimental analysis of the application of the DWM-Evac model in fire evacuation path planning. The results indicate that the DWM-Evac model significantly improves evacuation efficiency and path safety when dealing with complex fire scenarios. In a virtual shopping mall environment, the model outperformed actual evacuation plans, reducing the average evacuation time to 315 s and achieving a path safety score of 0.92.

The results of the ablation experiments further validate the importance of each module in the model. Removing the DGNN module resulted in evacuation paths lacking dynamic adjustment capabilities, leading to decreased safety and efficiency. When the WOA module was removed, paths could still avoid fire sources, but the lack of global optimization increased evacuation time and path length. Without the MDP module, the model's strategy optimization and dynamic decision-making abilities were insufficient, causing a significant decline in path flexibility and adaptability. These findings demonstrate that the DGNN, WOA, and MDP modules work collaboratively within the DWM-Evac model to form an efficient and reliable evacuation path planning system. Moreover, experiments with different fire source settings revealed that the DWM-Evac model possesses strong adaptability and stability. Whether the fire source was located at the main entrance, atrium, parking lot, or back door, the model quickly generated evacuation paths that avoided high-risk areas and fully utilized multiple exits inside and outside the mall, ensuring safe evacuation. This confirms the model's feasibility and reliability in practical applications.

However, despite the excellent performance of the DWM-Evac model in experiments, some limitations remain. Firstly, the model's training and testing rely on high-quality simulation data, which may be insufficient or of low quality in actual applications. Secondly, the model's real-time performance may be constrained by hardware conditions and network transmission speeds. Additionally, the model's adaptability and robustness in larger-scale and more complex scenarios require further validation.

In practice, the deployment of the DWM-Evac model may face some practical challenges. First, the sensor reliability and data quality are critical to the model performance. However, in real-world scenarios, sensors may fail or provide inaccurate data due to failure, environmental interference, or other factors. In this case, the robustness of the model may be affected, leading to a decreased effect of evacuation path planning. Secondly, how to cope with the inaccuracy of the sensor data is a key problem. Errors or delays in the sensor data may cause the model to make erroneous decisions in path planning. Therefore, future studies need to explore more robust data processing and fault-tolerance mechanisms to ensure that the model can still work effectively when the sensor data is problematic. In addition, the real-time nature of the model is also an important consideration factor. In complex fire scenarios, the environment and personnel behavior may change rapidly, requiring the model to be able to respond in a very short time frame. However, the requirements for real-time computing may be limited by hardware conditions, network transmission speeds, and computing resources. Therefore, future studies need to focus on the computational efficiency of optimization algorithms and how to achieve rapid response with limited hardware resources. Finally, the generalized application of the model also needs to consider the generalization ability in different building structures and environments. Although the current model performs well in a specific scenario, whether it can maintain the same effect in other types of buildings or in more complex environments still needs further verification and adjustment. Therefore, future research should aim to expand the diversity of experimental data and test the adaptability and scalability of the models through practical deployment.

5. Conclusion

The DWM-Evac model proposed in this study achieves efficiency and reliability in fire evacuation path planning by integrating IoT technology, DGNN, WOA, and MDP. IoT sensors continuously monitor key fire scene data, such as temperature, smoke concentration, and flame location, dynamically feeding this information into the model for processing and optimization. Experimental results indicate that the DWM-Evac model can dynamically adjust evacuation paths in complex fire scenarios, significantly enhancing evacuation efficiency and path safety. Ablation experiments further validate the importance of each component within the model, demonstrating their notable effectiveness in collaborative operation. The application of IoT technology endows the DWM-Evac model with greater flexibility and accuracy in real-time monitoring and data processing. The DWM-Evac model provides robust technical support for intelligent emergency management, showcasing broad application prospects.

Funding

No.

Consent for publication

All authors of this manuscript have provided their consent for the publication of this research.

CRediT authorship contribution statement

Ziyang Zhang: Writing – original draft, Supervision, Resources, Methodology, Data curation. **Lingye Tan:** Writing – review & editing, Resources, Methodology, Investigation, Formal analysis. **Robert L.K. Tiong:** Writing – review & editing, Validation, Data curation.

Declaration of competing interest

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

Data availability

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

References

[1] S.-J. Yoo, S.-H. Choi, Indoor ar navigation and emergency evacuation system based on machine learning and iot technologies, IEEE Internet Things J. 9 (21) (2022) 20853–20868.
[2] H. Fang, S. Lo, J.T. Lo, Building fire evacuation: An IoT-aided perspective in the 5G era, Buildings 11 (12) (2021) 643.
[3] Y. Chen, S. Hu, H. Mao, W. Deng, X. Gao, Application of the best evacuation model of deep learning in the design of public structures, Image Vis. Comput. 102 (2020) 103975.
[4] V. Agarwal, S. Tapaswi, P. Chanak, N. Kumar, Intelligent emergency evacuation system for industrial environments using IoT-enabled WSNs, IEEE Trans. Instrum. Meas. (2023).
[5] C. Kyrkou, P. Kolios, T. Theocharides, M. Polycarpou, Machine learning for emergency management: A survey and future outlook, Proc. IEEE 111 (1) (2022) 19–41.
[6] A. Bahamid, A. Mohd Ibrahim, A review on crowd analysis of evacuation and abnormality detection based on machine learning systems, Neural Comput. Appl. 34 (24) (2022) 21641–21655.
[7] J.C. Cheng, K. Chen, P.K.-Y. Wong, W. Chen, C.T. Li, Graph-based network generation and CCTV processing techniques for fire evacuation, Build. Res. Inf. 49 (2) (2021) 179–196.
[8] A. Ojha, A. Jindal, P. Chanak, An intelligent indoor emergency evacuation system using IoT-enabled WSNs for smart buildings, IEEE Internet Things J. (2023).
[9] S.M.Z. Al-Hady, M.R. Islam, M.M. Rashid, Development of IoT-based automated dynamic emergency response system against fire incidents in academic building, Int. J. Eng. Mater. Manuf. 8 (3) (2023) 75–87.
[10] R. Fedele, M. Merenda, An IoT system for social distancing and emergency management in smart cities using multi-sensor data, Algorithms 13 (10) (2020) 254.
[11] Z. Chu, F. Wang, T. Lei, C. Luo, Path planning based on deep reinforcement learning for autonomous underwater vehicles under ocean current disturbance, IEEE Trans. Intell. Veh. 8 (1) (2022) 108–120.
[12] S. Sindhu, M. Saravanan, Architectural framework for multi sensor data fusion and validation in IoT based system, in: 2021 10th IEEE International Conference on Communication Systems and Network Technologies, CSNT, IEEE, 2021, pp. 448–452.
[13] Y. Ji, W. Wang, M. Zheng, S. Chen, Real time building evacuation modeling with an improved cellular automata method and corresponding IoT system implementation, Buildings 12 (6) (2022) 718.
[14] T. Peng, W. Ke, Urban fire emergency management based on big data intelligent processing system and Internet of Things, Optik 273 (2023) 170433.
[15] H.-H. Yen, C.-H. Lin, H.-W. Tsao, Novel smoke-aware individual evacuation and congestion-aware group evacuation algorithms in IoT-enabled multi-story multi-exit buildings, IEEE Access 10 (2022) 119402–119418.
[16] S. Shaharuddin, K.N.A. Maulud, S.A.F.S.A. Rahman, A.I.C. Ani, B. Pradhan, The role of IoT sensor in smart building context for indoor fire hazard scenario: A systematic review of interdisciplinary articles, Internet Things 22 (2023) 100803.
[17] G.G. de Castro, M.F. Pinto, I.Z. Biundini, A.G. Melo, A.L. Marcato, D.B. Haddad, Dynamic path planning based on neural networks for aerial inspection, J. Control Autom. Electr. Syst. 34 (1) (2023) 85–105.
[18] Y. Liu, Z. Zheng, F. Qin, X. Zhang, H. Yao, A residual convolutional neural network based approach for real-time path planning, Knowl.-Based Syst. 242 (2022) 108400.
[19] Y. Zhang, W. Hu, W. Yao, L. Lian, G.G. Yen, Offline data-driven multiobjective optimization evolutionary algorithm based on generative adversarial network, IEEE Trans. Evol. Comput. 28 (2) (2022) 293–306.
[20] X. Lu, H. Blanton, T. Gifford, A. Tucker, N. Olderman, Optimized guidance for building fires considering occupants' route choices, Phys. A 561 (2021) 125247.
[21] Z. Tarapata, T. Nowicki, R. Antkiewicz, J. Dudzinski, K. Janik, Data-driven machine learning system for optimization of processes supporting the distribution of goods and services–a case study, Procedia Manuf. 44 (2020) 60–67.
[22] N. Kaur, H. Kaur, A multi-agent based evacuation planning for disaster management: a narrative review, Arch. Comput. Methods Eng. 29 (6) (2022) 4085–4113.
[23] M. Kitsuya, J. Sasaki, Proposal of evacuation support system and evaluation by multi-agent simulation in a regional disaster, in: Information Technology in Disaster Risk Reduction: 4th IFIP TC 5 DCITDRR International Conference, ITDRR 2019, Kyiv, Ukraine, October 9–10, 2019, Revised Selected Papers 4, Springer, 2020, pp. 45–54.
[24] D.J.S. Sako, C.G. Igiri, E.O. Bennett, F.B. Deedam, ESARS: A situation-aware multi-agent system for real-time emergency response management, Eur. J. Inf. Technol. Comput. Sci. 4 (1) (2024) 1–8.
[25] F. Zhou, Q. Yang, T. Zhong, D. Chen, N. Zhang, Variational graph neural networks for road traffic prediction in intelligent transportation systems, IEEE Trans. Ind. Inform. 17 (4) (2020) 2802–2812.
[26] Z. Yan, J. Zhang, J. Zeng, J. Tang, Three-dimensional path planning for autonomous underwater vehicles based on a whale optimization algorithm, Ocean Eng. 250 (2022) 111070.

[27] A.A. Saadi, A. Soukane, Y. Meraihi, A.B. Gabis, A. Ramdane-Cherif, S.M. Taleb, Unmanned aerial vehicles path planning based on an enhanced whale optimization algorithm, in: Workshop on Mining Data for Financial Applications, Springer, 2022, pp. 103–117.

[28] J. Skarding, B. Gabrys, K. Musial, Foundations and modeling of dynamic networks using dynamic graph neural networks: A survey, IEEE Access 9 (2021) 79143–79168.

[29] Q.-V. Pham, S. Mirjalili, N. Kumar, M. Alazab, W.-J. Hwang, Whale optimization algorithm with applications to resource allocation in wireless networks, IEEE Trans. Veh. Technol. 69 (4) (2020) 4285–4297.

[30] A. Alqahtani, S. Alsubai, M. Bhatia, Applied artificial intelligence framework for smart evacuation in industrial disasters, Appl. Intell. (2024) 1–16.

[31] P. Huang, X. Lin, C. Liu, L. Fu, L. Yu, A real-time automatic fire emergency evacuation route selection model based on decision-making processes of pedestrians, Saf. Sci. 169 (2024) 106332.

[32] Y. Fu, C. Li, F.R. Yu, T.H. Luan, Y. Zhang, A decision-making strategy for vehicle autonomous braking in emergency via deep reinforcement learning, IEEE Trans. Veh. Technol. 69 (6) (2020) 5876–5888.

[33] G. Jang, S.K. Singh, S. Lim, J. Bae, J. Heo, Y. Zhang, W.G. Shin, S.B. Kim, Self-and semi-supervised learning for evacuation time modeling within fire emergencies in nuclear power plants, Process Saf. Environ. Prot. (2024).

[34] B. Herfort, S. Lautenbach, J. Porto de Albuquerque, J. Anderson, A. Zipf, A spatio-temporal analysis investigating completeness and inequalities of global urban building data in OpenStreetMap, Nature Commun. 14 (1) (2023) 3985.

[35] X. Huang, C. Wang, Z. Li, H. Ning, A 100 m population grid in the CONUS by disaggregating census data with open-source Microsoft building footprints, Big Earth Data 5 (1) (2021) 112–133.