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RESEARCH ON THE RISK CLASSIFICATION OF CRUISE SHIP FIRES BASED ON AN ATTENTION-BP NEURAL NETWORK

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ABSTRACT

Due to the relatively closed environment, complex internal structure, and difficult evacuation of personnel, it is more difficult to prevent ship fires than land fires. In this paper, taking the large cruise ship as the research object, the physical model of a cruise cabin fire is established through PyroSim software, and the safety indexes such as smoke temperature, CO concentration, and visibility are numerically simulated. An Attention-BP neural network model is designed for realizing the intelligent identification of a cabin fire and dividing the risk level, which integrates the diagnosis results of multiple neural network models through the self-Attention mechanism and adaptively distributes the weight of each BP neural network model. The proposed model can provide decision-making reference for subsequent fire-fighting measures and personnel evacuation. Experimental results show that the proposed Attention-BP neural network model can effectively realize the early warning of the fire risk level. Compared with other machine learning algorithms, it has the highest stability and accuracy and reduces the uncertainty of early cabin fire warning.

Keywords: Cruise Fire; Simulation Modeling; Ensemble Learning; BP Neural Network

INTRODUCTION

Cruise tourism is a form of tourism that involves onboard activities and shore leisure on large passenger ships, with sea cruises being the main form [1]. Due to the complex internal structure, large number of cabins, and large passenger capacity of the cruise ship, the property and safety of the passengers can be greatly threatened if a fire breaks out. Therefore, it is very important to identify and classify the risk level of a fire in the cabin of the cruise ship, which can provide suggestions for the later implementation of fire-fighting measures and personnel evacuation.

The cruise cabin fire has the characteristics of the high possibility of the fire, the heavy load of the fire, low fire resistance rating, serious fire losses, and low risk tolerance. Assessing the level of the fire is the key to implementing fire extinguishing measures and the evacuation of personnel in the later stage. The fire level is not accurately assessed according to certain information. It is necessary to monitor the parameters in the cabin and further judge the level of the cabin fire. Yoshidak et al. [1] built a three-story ship test channel to study and analyze the spread of flue gas in the channel during the fire and observed the change in the fire source, smoke exhaust, temperature, and pressure in the channel. Zhang [2] took a bulk carrier as an example, simulated the development process of the engine room fire, summarized the fire spread law by analyzing the simulation data, and used the Unity3D virtual reality engine to visualize the fire data, thereby strengthening the trainees' understanding

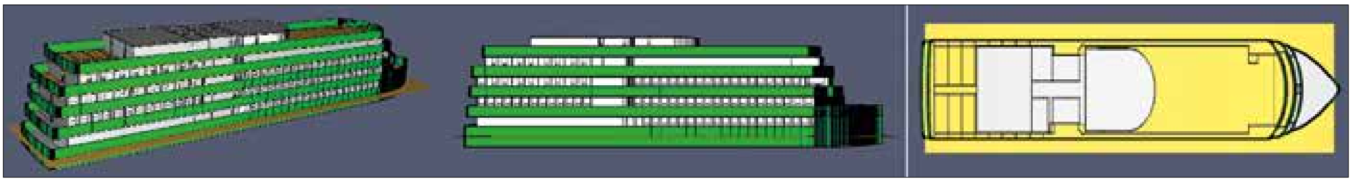


Fig. 1. Modeling diagram of the cruise cabin by using PyroSim

of the fire. Yang [3] studied a ship fire alarm system based on visual sensors that can detect flames and guide people to escape in the event of a fire. According to the monitoring of the cabin parameter information, how to determine the fire level is of great significance for the subsequent implementation of fire extinguishing measures and the evacuation of personnel.

The traditional fire model judgment level method is mainly based on the threshold set by the smoke, temperature, and other sensors to compare the values. The threshold judgment based on a single monitoring variable will be subject to errors caused by different factors such as the location of the ignition source, the combustion material, and the accuracy of the sensor. With the rapid development of machine learning technology, a fire class classification method based on multi-pass information fusion is proposed, which can extract features from cabin fire information in different scenarios and finally identify the fire class. Wu et al. [4] realized the monitoring of toxic and harmful gases in fire scenes based on machine learning. Wang [5] designed a ship fire secondary reasoning model based on a Back Propagation neural network (BP neural network) and Demspter Shafer evidence (D-s evidence) theory algorithm and built a ship fire intelligent alarm system based on the model. Wei et al. [6] proposed a rapid fire risk assessment method based on fuzzy mathematics and Support Vector Machine (SVM) algorithms. L. Jiang et al. [7] used multi-sensor information fusion methods to fuse at different levels to predict fire conditions. Xu et al. [8] established a BP neural network model to perform the real-time classification of fire hazard levels on ship compartments. Shi et al. [9] established a fuzzy comprehensive evaluation system to assess the level of fire risk.

Many parameters of fire change when a fire occurs, such as temperature, humidity, and gas concentration. It is difficult to accurately reflect the overall characteristics of the fire in a cruise cabin by the single fire characteristic information. Moreover, it is easy for the single fire information to be disturbed by the external environment, and the fire response is not sensitive enough, which might cause false alarms and missed alarms. In this paper, a novel Attention-BP neural network model based on the ensemble learning is proposed to classify the fire risk level of the cruise cabin. The proposed model integrates multiple BP neural network models to operate in parallel. The self-attention mechanism is introduced to adaptively calculate the weight of each individual model and fuse the diagnostic results of each model, which can improve the classification accuracy an reduce the uncertainty of the individual model. The proposed Attention-BP model can diagnose the fire risk level of the cruise cabin in real time and provide the basis for the subsequent fire-fighting measures and personnel evacuation.

THE SIMULATION OF THE FIRE PROCESS IN A CRUISE CABIN

Due to the high cost of cruise cabin fire experiments, it is difficult to conduct on-site experiments. In this paper, PyroSim software was used to simulate the development of cruise cabin fires [10]. By simulating the fire process with PyroSim software, the diffusion process of smoke during the whole fire process can be directly observed, and the curves of temperature, gas concentration, smoke, and personnel over time can be obtained.

CRUISE CABIN LAYOUT AND MODELING

In this paper, a cruise ship is selected as a simulation object. The total tonnage of the cruise ship is 4924 tons, the length is 135.20 m, and the width is 19.60 m. There are 5 decks in the passenger area, namely, the upper deck L1, walk deck L2, pilot deck L3, entertainment deck L4, and sun deck L5. The layout and structure of this real cruise shipc cabin are very complex. This paper introduces the PyroSim softare to simply model this ship canbin, and the three-dimensional view, front view and top view of this cruise ship are shown in Fig. 1.

All calculations in PyroSim must be calculated according to the grid. When using PyroSim to perform a numerical simulation of the fire in a cruise cabin, the cabin model needs to be meshed to determine the calculation area and the accuracy of the area grid. However, in the actual simulation work, as the mesh scheme becomes finer, the number of meshes will increase and the computing resources will cost more. The mesh setting will also lead to inaccurate simulation results. Therefore, the setting of the simulation grid size is the decisive factor in the accuracy and calculation time of the calculation simulation, and under the premise of ensuring the accuracy of the result, one must try to use thicker cells to save calculation resources and running time.

The determination of the grid size is related to the size of the fire source power, and the following formula is used to determine the size of the fire source feature diameter. Then, the range of the cell size is determined according to the relationship between the cell size and the fire source feature diameter.

$$D = \left(\frac{Q}{\rho C_p T g^{1/2}}\right)^{2/5} \tag{1}$$

where D is the characteristic diameter of the fire source (m), Q is the heat release rate of the fire source (kW), ρ is the air density (taken as 1.2 kg/m^3), Cp is the specific heat capacity of the air, (taken as 1.014 kJ/(kg.k)), T is the ambient temperature (293 K), and is the acceleration of gravity (taken as 9.8 m/s^2).

According to the calculation results of the formula, and then comprehensively considering the impact of the simulation calculation running time and calculation accuracy, the uniform meshing method is used to set the size of each unit grid 0.5 m * 0.5 m * 0.5 m, and the entire cabin model is divided into 4 large calculation areas with a total of 974848 unit grids. The complete cabin model meshing diagram is shown in Fig. 2.

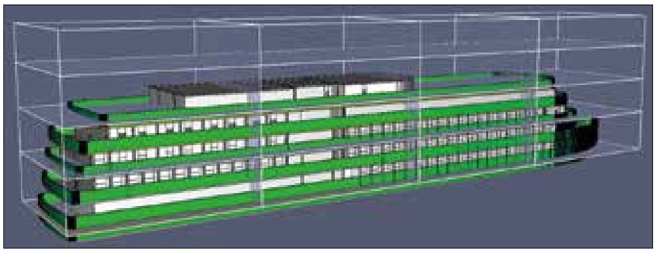


Fig. 2. Grid division of the cruise cabin model

SIMULATION OF FIRE SCENES

In this paper, the purpose of the fire simulation is to investigate the safe evacuation of personnel in a cabin fire, so the setting of the fire scene should be considered in terms of the safety of personnel evacuation. When designing a fire scene, it should be determined according to the principle of the most disadvantageous and the principle of the greatest probability. Combined with the internal structure and fire protection characteristics of the cruise cabin, four typical fire scenes are set, namely, the dining room on the 1st floor, a guest room on the 2nd floor, a business room on the 3rd floor, and the chess and card room on the 4th floor, as shown in Fig. 3.

In order to obtain more comprehensive simulation data during the occurrence of cabin fires, a total of 579 detectors were arranged in the model, which were divided into 4 groups for measuring temperature, visibility, and CO concentration located in L1, L2, L3, and L4, the detection points on each floor are mainly distributed near the burning room and on the ground of the main evacuation channel, and the distribution location of the detector is shown in Fig. 4.

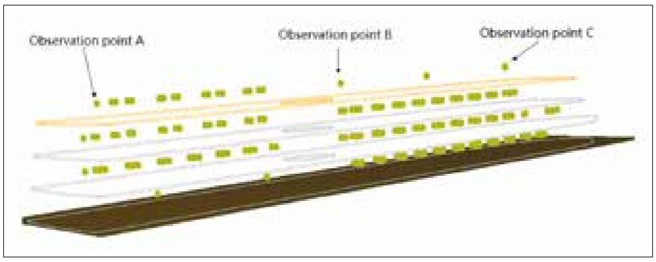


Fig. 4. Detector distribution diagram

In this paper, it is necessary to compare and analyze the visibility, the temperature, and the CO concentration at a 2.0 m height of the observation point in order to calculate the available safe evacuation time in different observation points. The limit time of human endurance for these three indicators is shown in Fig. 5. The minimum critical time of the three safety evaluation indicators is selected as the the available safe evacuation time of the observation point under each fire scenario.

CRUISE CABIN FIRE CLASSIFICATON MODEL

In this paper, the Attention-BP neural network based on the ensemble is proposed to realize the intelligent identification of the fire level in the cruise cabin, which can provide the basis for the subsequent fire-fighting measures and the personnel evacuation. The self-attention mechanism adopted in the Attention-BP neural network automatically learns the weights of the individual BP neural network model, which adaptively fuse multiple models and reduce the uncertainty of the individual model.

BP NEURAL NETWORK MODEL

The BP neural network is a multilayer feed-forward neural network trained according to an error inverse propagation algorithm. Fig. 6 shows a schematic diagram of a simple BP neural network with one input layer, implicit layer, and an output layer.

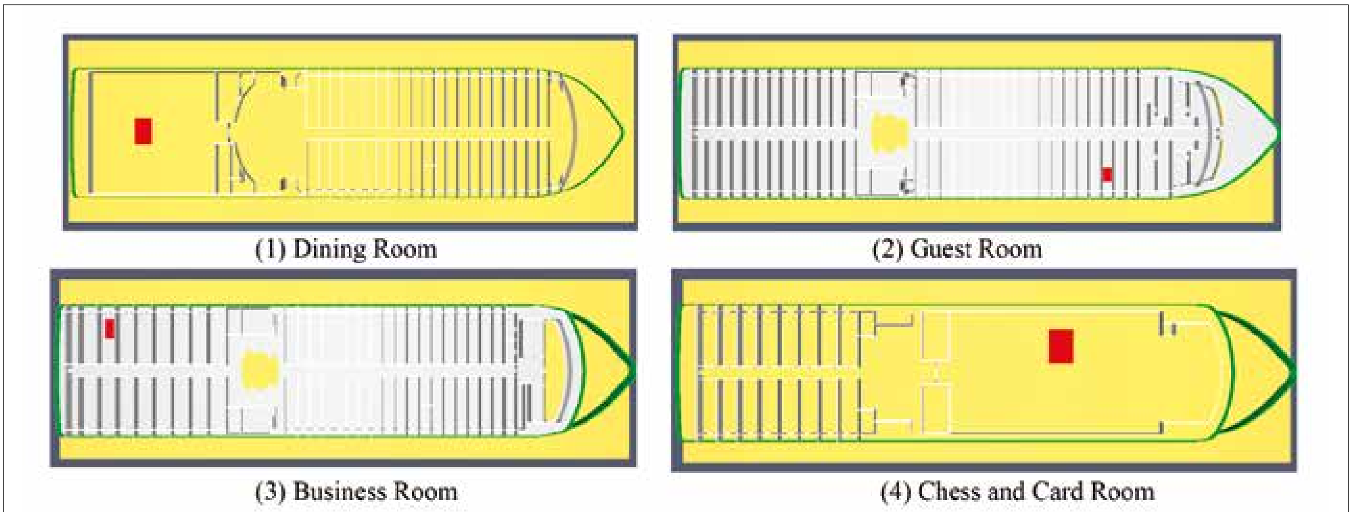
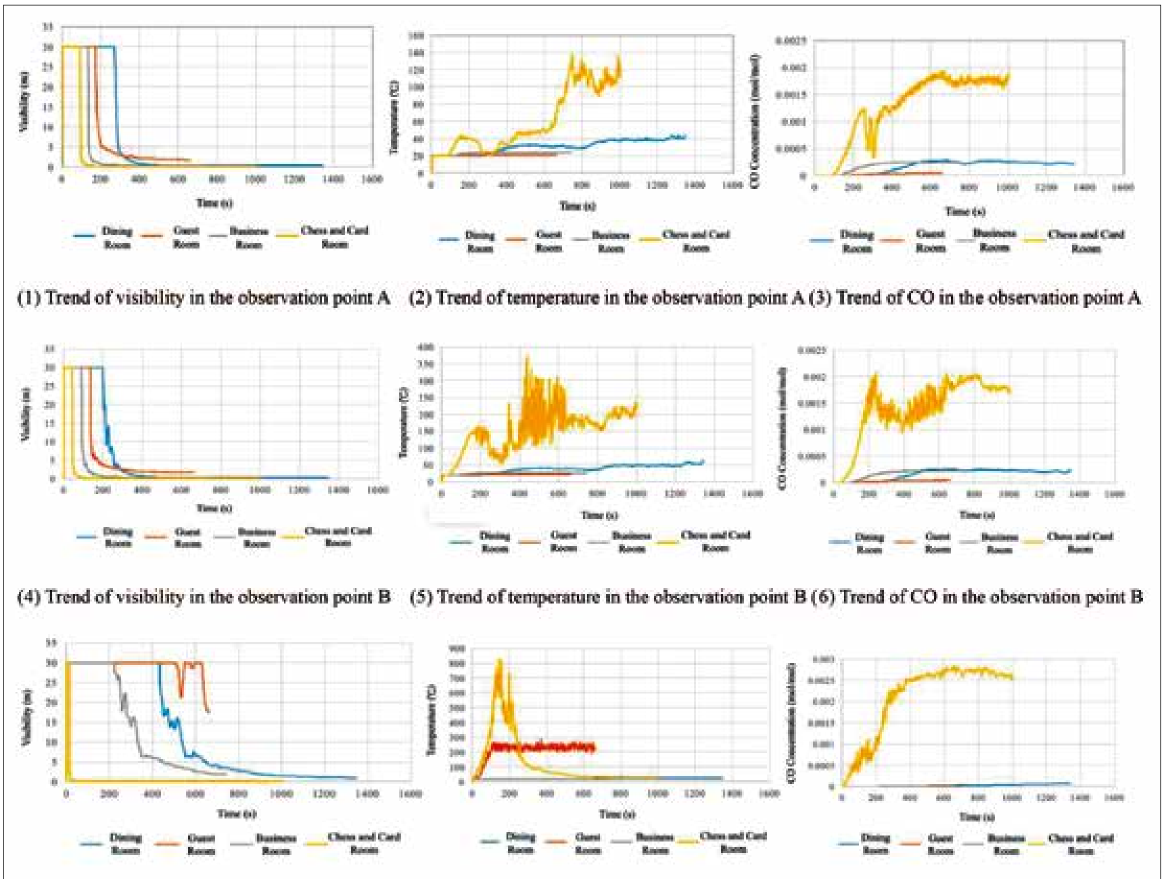


Fig. 3. Four fire points in the fire scene


(1) Trend of visibility in the observation point A (2) Trend of temperature in the observation point A (3) Trend of CO in the observation point A

(4) Trend of visibility in the observation point B (5) Trend of temperature in the observation point B (6) Trend of CO in the observation point B

(4) Trend of visibility in the observation point C (8) Trend of temperature in the observation point C (9) Trend of CO in the observation point C

Fig. 5. Comparision of the trend of three safety indicators

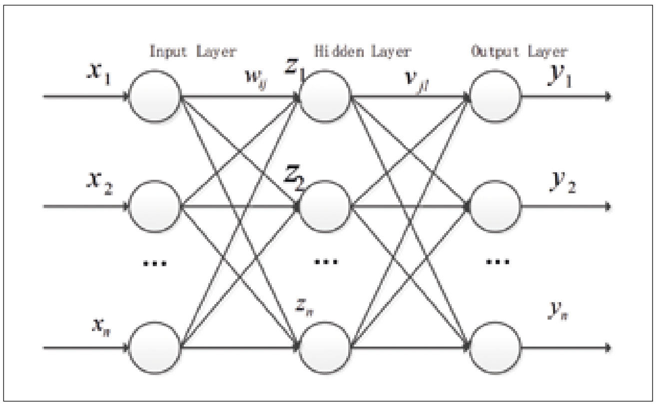


Fig. 6. BP neural network structure

The BP neural network has n inputs. The inputs are connected to the next layer by weights, and the output can be expressed as:

$$Z_j = f\left(\sum_i w_{ij} x_i - b_j\right) \quad (2)$$

where x_i is the input of the neuron, w_{ij} is the connection weight, b_j is the threshold of the neuron, z_j is the output of the neuron, and f represents a mapping function that maps the characteristics of the input node to another multidimensional space.

The mapping function is an activation function that extracts the characteristics of the input data nonlinearly through the activation function and finally realizes the mining of nonlinear relationships in the data. Commonly used activation functions are divided into Sigmoid, Tanh, RuLU, etc. These activation functions perform nonlinear transformations of extracted features from each layer of neural networks.

The data are passed in by the input layer, and after being processed by the feature extraction and nonlinear transformation of the implicit layer, the result of the processing of the layer is the output. For the output, the error function is used to calculate the error of the output result and the expected value. The error function is:

$$E = \frac{1}{2}\sum_i (y_l - z_l)^2 = \frac{1}{2}\sum_l \left(y_l - f\left(\sum_j v_{jl} - b_l\right)\right)^2 \quad (3)$$

where y_l is the true label value and v_{jl} is the eigenvalue extracted after nonlinear treatment by the hidden layer of the neural network.

The BP neural network uses backpropagation to calculate the resulting error E. The neuron node weights of each layer are adjusted and repeatedly trained until the error value reaches the expected error or the number of iterations is reached. A threshold is set to classify the input features using the network parameters at this time. The purpose of adjusting the network parameters is to make the network error E continuously decrease, and the weights of netwok can be determined when the error E is minimum. The amount of adjustment is proportional to the decrease of the network error gradient, which is the process of finding the partial derivative. The formula is:

$$\frac{\partial E}{\partial \theta} = \frac{\partial}{\partial \theta}\sum_{k=1}^{n}\Big(y - f(z_{jl} - b_l)\Big) \tag{4}$$

where $\theta = (z, b)$ is the parameters of the network model and n is the number of neural elements. The update process of θ is:

$$\theta_i = \theta_i - l.\frac{\partial E(\theta)}{\partial \theta} \tag{5}$$

where l represents the school rate of the model, which is the model hyper parameter that is set manually.

SELF-ATTENTION MECHANISMS

In the Attention-BP neural network model, the features extracted by each BP neural network are z_i. The features extracted by the various BP neural networks are correlated through the attention mechanism [12]. The weights of each BP neural network are calculated to obtain the importance of each extracted feature z_i:

$$(\partial_1, \partial_2, \dots, \partial_i) = att(z_1, z_2, \dots, z_i) \tag{6}$$

where ∂_1 is the weights of each BP neural network model and $\partial_1 \in R^{n*1}$ is the attention value of n nodes that output z_i.

The output is transformed using a nonlinear activation function to multiply z_i by a shared attention vector q point to obtain the final attention value w_i:

$$w_i = q^T \cdot \tanh(W \cdot z_i^T + b) \tag{7}$$

where W is the weight matrix of the attention mechanism and b is the bias vector.

The attention value ∂_i can be standardized by the Softmax function, and the formula is as follows:

$$\alpha_i = \mathrm{so}ftmax(w_i) = \frac{\exp(w_i)}{\sum_{i=1}^{n}\exp(w_i)} \tag{8}$$

The model parameters z_i obtained by each BP neural network are fused through the attention value, ∂_i, and the final fusion feature value Z is obtained. Through the fusion of this characteristic parameter, the classification results can be made more accurate and reliable, and the formula is as follows:

$$Z = \alpha_1 \cdot z_1 + \alpha_2 \cdot z_2 \dots + \alpha_n \cdot z_n \tag{8}$$

FIRE CLASSIFICATION PROCESS BASED ON THE ATTENTION-BP NEURAL NETWORK

In this paper, a new type of Attention-BP neural network is designed for the classification of the risk level of a fire in a cruise cabin, and the structure of the network is shown in Fig. 7. The procedures can be summarized as follows:

(1) Data collection. The fire information data are collected through the smoke temperature sensor, CO concentration sensor, and the light transmittance sensor in the cabin.

(2) Data pre-processing. The acquired signals need to be standardized, and the datasets are divided into the training datasets and the testing datasets. The standardized data are fed into the BP neural network, and the standardized method selected in this paper is the Main-Max method. The collected data are normalized by the following formula:

$$x = \frac{x_{max} - \hat{x}}{x_{max} - x_{min}} \tag{10}$$

where $\hat{x}$ is the original sample data, x_{max} is the maximum value in the sample data, and x_{min} is the minimum value in the sample data.

(3) Model training. The Attention-BP neural network model is constructed by the attention mechanism, and the normalized data training set is input into the integrated BP neural network model. The network model is trained, and the optimal network parameters are obtained after multiple iterations.

(4) Testing and verification. The trained Attention-BP neural network model is classified into the test set and the final classification results are obtained. The results are compared to the actual labels to verify the performance of the model.

(5) Online fire classification. The temperature, CO concentration, and particle size collected in real time are processed and input into the trained Attention-BP neural network model to classify the fire risk level of the cruise cabin.

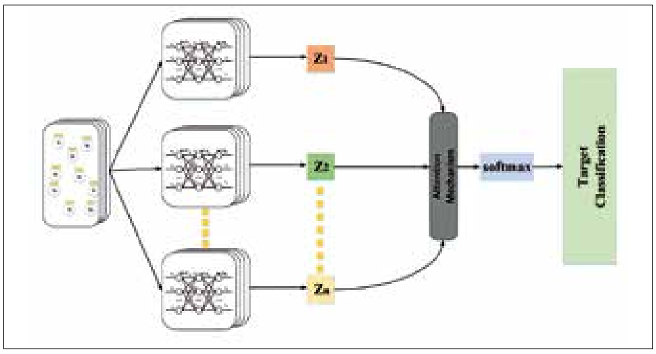


Fig. 7. Attention-BP neural network structure

EXPERIMENTAL VERIFICATION

CLASSIFICATION OF CRUISE CABIN FIRE CLASSES

Flue gas is a combustion product that is visibly suspended in the air due to pyrolysis and combustion, mainly including visible smoke particles and invisible combustion gases. The structure of the cruise ship cabin is complex, causing a wide variety of fire hazards. Once a fire occurs, it will quickly produce a large amount of smoke, which will pose a great threat to the safety of passengers. There are many factors affecting the safety of human life in the process of root fire development, and through the study of the characteristics of the fire spread and the analysis of the causes of death and injury due to the fire, the fire level can be classified. Considering the aspects of the temperature, visibility, and toxicity of the flue gas, the

Tab. 1. Classification of hazard classes in cruise cabins

	No impact (Hazard level 1)	Mild effects (Hazard level 2)	Moderate impact (Hazard level 3)	Serious impact (Hazard level 4)
Temperature	–40°C	40°C–60°C	60°C–90°C	90°C–
CO Concentration	–400 ppm	400–800 ppm	800–1200 ppm	1200 ppm–
Visibility	15 m or more	15–10 m	10–5 m	5 m or less
Physiological Symptoms	Less impact	The headache worsens and is dizziness, nausea life-threatening after 3 h	Within 30 min, dizziness, nausea, spasms; loss of consciousness within 2 h	Headache, dizziness, nausea within 20 min, death within 30 min

fire level is divided into 4 levels according to the physiological symptoms of the human body, as shown in Table 1.

NEURAL NETWORK STRUCTURE AND RESULTS ANALYSIS

The structure of the BP neural network will have an important impact on the classification results. The network structure parameters that affect the final classification results include the number of hidden layers, activation function, and the number of neurons. According to the characteristics of the fire data in this paper, the number of nodes entering the neural elements is 3, and the characteristics of the model input samples are temperature, CO concentration, and visibility. The number of nodes outputting neural elements is 4, which is the four fire hazard levels divided above. The number of hidden layers of the BP neural network and the number of neurons in the implicit layer are not guided by systematic theory, and their selection is mainly based on experience. In this paper, 8 kinds of network structures are designed for testing, and the designed network structure is shown in Table 2.

Tab. 2. BP neural network structure

Serial Number	Structure of the network and the number of neurons in the hidden layer
1	Input layer (3) + hidden layer 1 layer (15, Tanh) + hidden layer 2 layer (8, ReLU) + output layer (4, softmax)
2	Input layer (3) + hidden layer 1 layer (20, Tanh) + hidden layer 2 layer (10, ReLU) + output layer (4, softmax)
3	Input layer (3) + hidden layer 1 layer (15, ReLU) + hidden layer 2 layer (8, ReLU) + output layer (4, softmax)
4	Input layer (3) + hidden layer 1 layer (20, Sigmoid) + hidden layer 2 layer (10, Sigmoid) + output layer (4, softmax)
5	Input layer (3) + hidden layer 1 layer (20, Tanh) + hidden layer 2 layer (8, ReLU) + output layer (4, softmax)
6	Input layer (3) + hidden layer 1 layer (25, Tanh) + hidden layer 2 layer (15, Tanh) + hidden layer 3 (8, ReLU) + output layer (4, softmax)
7	Input layer (3) + hidden layer 1 layer (25, Sigmoid) + hidden layer 2 layer (15, Sigmoid) + hidden layer 3 layer (8, Sigmoid) + output layer (4, softmax)
8	Input layer (3) + hidden layer 1 (30, Tanh) + hidden layer 2 layer (15, ReLU) + hidden layer 3 (10, ReLU) + output layer (4, softmax)

Each network structure conducts 30 experiments and then takes the average of the 30 experimental results as the final accuracy of the network. The result is shown in Fig. 8. The BP neural network with the sequence number 3 has the highest accuracy rate and uses the shortest model training time. The network structure is 3-15-8-4 and the activation function is ReLU. After analysis, it can be seen that the Sigmoid activation function is the worst effect. When the activation function is Tanh and ReLU, the model accuracy has improved to a certain extent. When the model uses the ReLU activation function, the training speed of the model will be greatly improved. This is because the convergence speed is fast when using the ReLU function, there is no need to calculate the index, and the gradient will not be saturated. When the hidden layer is 3 layers, the classification accuracy of the BP neural network begins to decline, indicating that the increment of the number of hidden layer and neurons will not improve the performance of the model. Considering that the classification model is aimed at the data set of three characteristics of temperature, CO concentration, and visibility collected in the cruise cabin, the data scale is not large, so the hidden layer of the BP neural network used in this paper is 2 layers.

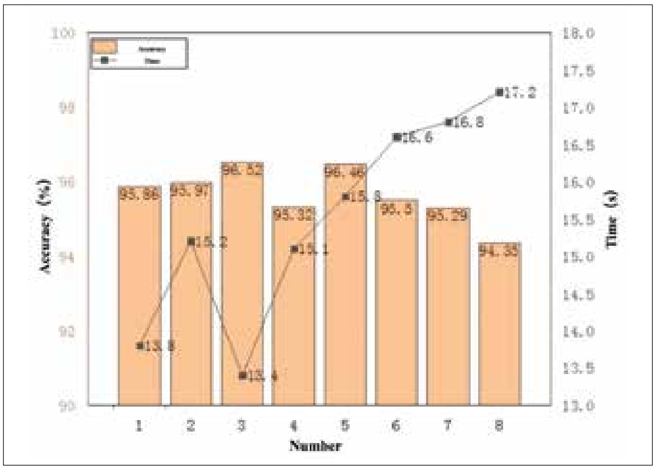


Fig. 8. Average accuracy and average training time under different network structures

In this paper, the BP neural network model uses the Adam optimizer. The initial iteration step is 1500 and the initial learning rate is 0.01. Fig. 9 shows the training and testing process of the BP neural network model. It can be concluded from Fig. 9(a) that during 250–600 iterations, the training process will fluctuate slightly, and then the training accuracy will continue to increase, while after 800 iterations, the test accuracy will not change significantly and even decrease

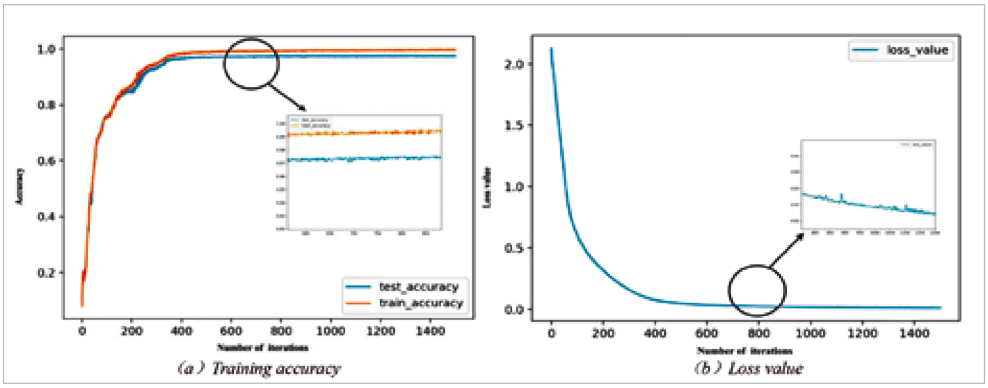


Fig. 9. Accuracy and loss in the training process

slightly. It can finally be determined that the number of iterations of this model is 800.

ALGORITHM COMPARISON

After determining the structure of an individual BP neural network in the previous section, it is of great significance to determine the number of a single BP neural network model in the integrated BP neural network model. The number of models can affect the quality of the final classification results. In this article, the number of BP neural network models is selected by searching {3,5,8,10}. The number of single models in the Attention-BP neural network can be determined from two aspects, the training time and classification accuracy. Table 3 shows the average classification accuracy and average training time under different model quantities. When the number of models increases, the classification accuracy of the integrated BP neural network also increases, but the calculation cost also increases gradually. When the number of models is 10, the training time of the Attention-BP neural network is up to 23.2 s. Through the average accuracy analysis, when the number of models is 5, 8, and 10, the classification accuracy of the Attention-BP neural network model is almost the same, which is about 1.5% higher than that when the number of models is 3. When the number of models is 8, the classification accuracy of the Attention-BP neural network model is the highest, but it is only 0.01% higher than that when the number of models is 5, but the training cost is greatly increased. Considering the two aspects of training time and accuracy, when the number of models is 5, the classification accuracy of the Attention-BP neural network model is higher (97.68%), and the training cost is relatively low. Therefore, the number of single models in the Attention-BP neural network model selected in this paper is 5.

Tab. 3. Accuracy rate and training time under different models

Number of BP neural network models	Average accuracy	Average training time
3	96.38%	19.1 s
5	97.68%	20.2 s
8	97.69%	21.4 s
10	96.55%	23.2 s

This paper compares the proposed model with other classification algorithms to verify the performance of the proposed Attention-BP neural network model. The comparison algorithms used are Support Vector Machine (SVM), Decision Tree (DT), K-Nearest Neighbor (KNN), Back Propagation Neural Network (BPNN), and Random Forest (RF). In order to quantify the classification performance of the different models, three performance indicators are introduced, including the recall rate (r), precision rate (p), and accuracy (a), which are defined as:

$$r = \frac{TP}{TP + FN} \tag{11}$$

$$p = \frac{TP}{TP + FP} \tag{12}$$

$$\alpha = \frac{TP + TN}{TP + TN + FP + FN} \tag{13}$$

where TP represents a positive sample that is correctly classified as a positive sample, FP is defined as the instance when a negative sample is misclassified as a positive sample, TN is when a positive sample is misclassified as a negative sample, and FN is a prediction that a negative sample is correctly classified as a negative sample.

Fig. 10 shows the performance of the different models. The proposed Attention-BP neural network model has the best performance in this paper. The average recall rate, precision rate, and accuracy of the proposed model can reach 97.83%, 97.54%, and 97.32%, respectively. Moreover, the stability is also higher than other algorithms. The RF model based on integrating multiple decision trees can achieve more generalized classification results and reduce the uncertainty of classification of a single model. Therefore, in this classification task of the fire risk, the performance of the RF model is higher than other simple classifiers, and its accuracy can reach 90.64%. The average recall rate, precision rate, and accuracy rate of a single BPNN model can reach 88.21%, 89.26%, and 88.51%, respectively, which are higher than classifiers such as SVM, KNN, and DT, but its performance is far lower than the Attention-BP neural network model. From the analysis of the classification performance and stability, it can be seen that the Attention-BP neural network model can provide high classification accuracy and stable diagnosis and is fully applicable to the classification of the cruise cabin fire risk level.

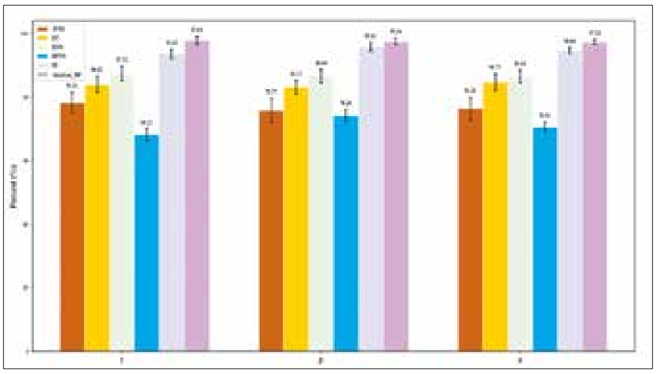


Fig. 10. Classification performance of different models

CONCLUSION

Based on the idea of integrated learning, this paper proposes an Attention-BP neural network structure for identifying the fire hazard level of cruise cabins. First of all, the cruise cabin fire development process was simulated by PyroSim software to achieve visibility, CO concentration, and temperature as three safety evaluation indicators. The fire hazard level is divided into four levels. The proposed Attention-BP neural network model is used to identify the fire level, which can realize the hazard level of the cabin in real time. After many experiments and comparison with other algorithms, it is proved that the recognition accuracy of the proposed model is high (reaching greater than 98%) and the classification stability is the best. Through the cruise cabin fire classification model, the operators on the cruise ship can understand the risk level of the fire, and then important guidance and suggestions can be provided for arranging fire extinguishing strategies and personnel evacuation measures.

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