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A Substation Fire Early Warning Scheme Based on Multi-Information Fusion

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Abstract: In view of the substation fire early warning using a single information sensor monitoring, it is easy to make mistakes and omissions. Taking the cable in substation as the research object, a multi-information fusion fire prediction model based on back propagation neural network (BPNN) and fuzzy set theory is proposed. Firstly, the BPNN model is trained by using the existing data. Secondly, the artificial fish swarm algorithm (AFSA) is used to optimize the BPNN, which speeds up convergence speed of the model and improves the accuracy of prediction. The fuzzy set theory is applied to fuse the predicted fire probability to obtain the optimal fire prevention and control decision. Finally, the fire protection measures are taken according to the fire decision. The experimental show that the average absolute errors of no fire, smoldering and open fire decreased by 26.06%, 38.5% and 43.13% respectively. The model has higher prediction accuracy, can reasonably output different levels of fire alarm signals, establish substation fire warning and prevention and control system, and provide reference for future substation fire and other disasters warning and prevention and control.

Keywords: artificial fish swarm algorithm; back propagation neural network; multi-information fusion; substation fire warning

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1. Introduction

Substation which is important part of the power system is responsible for voltage transformation, power distribution, and voltage regulation through current control. The alternating current (AC) power supply system offers assure for the safety and stable operation of the substation, which is the premise for stable operation of the entire substation [1–3]. However, in actual situation, this part of the power supply system is prone to fire, which causes the substation to not operate normally [4]. Station AC power supply provides reliable power supply for station load. The cables that transmit energy are spread in substation cable ditches and cable shafts. If there is no effective means to monitor the operation status of the cables, the fire caused by the cable failure will cause serious accidents in the substation [5,6]. Thus, studying the fire warning technology of the cables in the substation to raise the safety of AC power supply system for the station become more and more significant.

At present, the main way of fire alarm for substation AC power system is monitored by smoke sensor or temperature sensor [7]. Monitoring with a single sensor may cause false alarm, or delay alarm, resulting in more serious fire. For the above problems, multi-information fusion technology has been applied to load forecasting, industrial safety monitoring system, and substation fire monitoring system [8,9]. The literature [10] uses a fusion of multiple information such as weather, holidays, and historical loads to forecast transit compliance. It has better prediction results compared to single information. Reference [11] applied multi-information fusion technology to chemical plant safety warning and improved the performance of the warning system by monitoring dust concentration, temperature, and flue gas concentration. In ref. [12], an early warning system based on multi-information fusion was developed for the fire protection of energy storage systems. The linkage with the fire protection system was realized. In this paper, the multi-information fusion technology is applied to the fire probability prediction of substations. For the early warning technology of fire, different information is selected to determine whether a fire will occur or not [13]. In ref. [14], an accurate prediction model was constructed by analyzing the factors affecting hydrogen pipeline leakage fires and selecting the main factors. Ref. [15] uses temperature, smoke, and carbon monoxide as input signals for electrical fire warning systems. Ref. [16] applied a combination of smoke and gas sensors for aircraft fire detection with shorter alarm times than smoke sensors operating alone. Ref. [17] uses the characteristic parameter residual current of power equipment as a characteristic signal for predicting electrical fires, which effectively reduces the false alarm rate. Based on the above analysis, this paper proposes to use residual current, operating voltage and operating current as input signals for predicting fires according to the working characteristics of substations, and combine them with temperature to further improve the accuracy rate.

With the development of artificial intelligence in various fields, the combination of multi-information fusion technology and artificial intelligence algorithms is gradually applied to fire early warning. [18–21]. Ref. [22] applied fuzzy logic to substation fire detection and combined it with multi-information fusion technology to improve the performance of substation fire detection. Ref. [23] selected temperature, smoke concentration, and CO concentration and applied BP neural network to predict the probability of fire. In ref. [24], gray-fuzzy neural networks were proposed to predict fires and determine the fire probability by predicting the smoke concentration and density. In ref. [25] uses dynamic Bayesian networks combined with fuzzy set theory for evaluating the reliability of fire alarm systems.

Therefore, based on the working characteristics of the substation, this paper selects residual current, working voltage, working current and the inherent characteristic temperature when the fire occurs as the input of the prediction model. Artificial fish swarm algorithm is used to optimize BP neural network to predict fire probability, and the prediction results are divided into open fire probability, smoldering probability and no fire probability. The three fire probabilities are output through the decision-making of fuzzy theory to judge whether a fire occurs. Finally, the fire protection system is linked to ensure the safety of the substation. The main innovations of this study are as follows:

1. Residual current, working voltage, working current and temperature are used as input signals to judge the probability of fire. It can predict whether a fire will occur in advance through the change of current before the fire.
2. BP neural network is used to predict open fire probability, smoldering probability and no fire probability, and artificial fish swarm algorithm is used to optimize BP neural network to improve prediction accuracy.
3. The three fire probabilities are combined with the fire duration for decision output, and the final fire output is divided into four levels: no fire, alert, alarm and serious alarm. Combined with fire fighting system to ensure substation safety.

2. Multi-Sensor Information Fusion Technology

The technology contains information layer, feature layer and decision layer [26,27]. The structure of the text shown in the Figure 1:

The decision-making layer makes judgment based on fire probability, and combines fire probability value with other decision-making factors. When fire probability is exactly 0.5, it is impossible to judge whether there is a fire. Therefore, the fuzzy theory is introduced and the duration of fire signal is added as decision-making factor to improve the decision-making level. The output of decision-making level is divided into four levels: no fire, warning, alarm and serious alarm. The step of fuzzy reasoning firstly fuzzifies the input signals and output signals, then establishes the fuzzy rules [28]. Equations (1) and (2) establish fuzzy implication relations. Rule i correspond to the fuzzy implication relationship R_i. Finally, the table of input and output rules is generated.

$$R_i = (Y_1(i) \text{ and } Y_2(i) \text{ and } T_I) \tag{1}$$

$$R(x, y, z, u) = U_{i=1}^{n} R_i \tag{2}$$

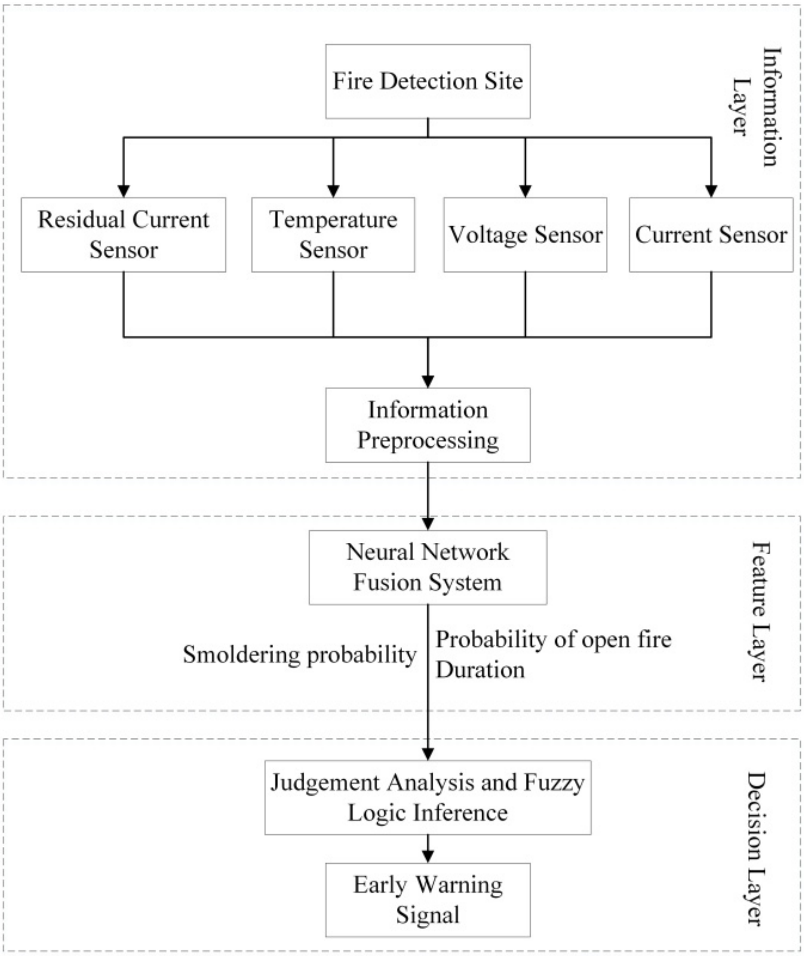

Figure 1. Multi-information fusion structure.

Figure 2 shows the output surface of the established fuzzy inference system.

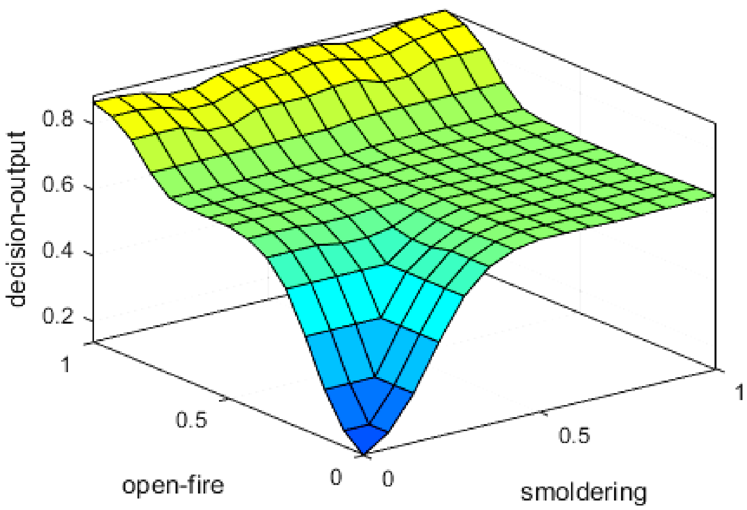

Figure 2. Fuzzy inference output surface.

The occurrence of fire can be clearly judged from the output surface of fuzzy inference. The x axis is the probability of open fire, the y axis is the probability of smoldering fire, the z axis is the decision output value u, and the fluctuation of color represents the early warning situation. The dark blue situation is relatively light, and the yellow situation is serious. Specifically, when $u < 0.25$, it is normal, $0.25 \leq u < 0.5$, it is abnormal, $0.5 \leq u < 0.75$, it is critical alarm, and $u \geq 0.75$, it is extremely urgent alarm.

3. Establishment of Substation Fire Warning Model

3.1. The Relationship between Input Signal and Output Signal

In the text, where $i = 1,2, \ldots, n$ is set to input signal. $j = 1,2, \ldots, m$ is set to output signal. The relationship between them is as follows:

$$S_k = \sum_{i=1}^{n} v_{ki} X_i + v_{k0}, 1 \leq k \leq h \tag{3}$$

$$Z_k = \sigma(S_k), 1 \leq k \leq h \tag{4}$$

$$Y_j = \sum_{k=1}^{h} \omega_{jk} Z_k + \omega_{j0}, 1 \leq j \leq m \tag{5}$$

The hidden layer input is S_k, the hidden layer output is Z_k, v_{ki} is the connection weight between input layer and hidden layer, v_{k0} is the hidden layer threshold, ω_{jk} is connection weight from hidden layer to the output layer, ω_{j0} is the output layer threshold [15].

The error is calculated by simulating the output of the training samples and is propagated backwards to continuously adjust the weights and thresholds to meet error requirements. The error function is:

$$E = \frac{1}{2} \sum_{a=1}^{t} \sum_{k=1}^{m} (q_k^a - p_k^a)^2 \tag{6}$$

where q_k^a is actual output, p_k^a is expected output.

3.2. Optimized Prediction Model of AFSA Based on BPNN

Owing to random selection of thresholds and weights of the BPNN, resulting in different convergence times, even the standard error cannot be reached within the specified number of times, this paper uses AFSA to optimize the BPNN [29–31].

3.2.1. Description of AFSA

An individual's state in an artificial fish population in a D-dimensional space is $X_i = (X_{i1}, X_{i2}, \ldots, X_{iD}), i = 1, 2, 3, \ldots, N$. Y represents the fitness of current position of artificial fish. The fitness of current position X_i, Y_i is used to evaluate the fitness of the current position X. The distance between individuals is $d_{ij} = ||X_i - X_j||$. The optimal solution is found by foraging, clustering and tailing behaviour.

1. Foraging Behavior

$$X_v = X_i + random \times visual \tag{7}$$

$$X_{i|next} = X_i + random \times step \times \frac{X_v - X_i}{||X_v - X_i||} \tag{8}$$

$$X_{i|next} = X_i + random \times step \tag{9}$$

If $Y_v > Y_i$, the food concentration at the location is high and the artificial fish moves to D in that direction. If it is not satisfied and the maximum number of attempts is reached, it moves randomly.

2. Cluster Behavior

Set a time t, artificial fish state X_i, number of partners N_f within the field of view to form a set S_i, if $S_i = \varnothing$, artificial fish perform foraging behavior, if there are other partners, partner population center location X_c, and $\frac{Y_c}{N_f} > \delta Y_i$, artificial fish move to that location.

3. Tailing Behavior

The optimal position with inartificial fish field of view is X_m, and the corresponding Y_m is the maximum fitness value. If $\frac{Y_m}{N_f} > \delta Y_i$ indicates that the food concentration in this location is high and not crowded, it moves in this direction.

3.2.2. Optimization Process of AFSA

The variables to be optimized in this paper are v_{ki}, ω_{jk}, b_k, b_j of the BPNN. Each artificial fish represents a set of weights and thresholds of the BPNN [32]. Use the reciprocal of E as the Y value to find the maximum of the fitness Y.

$$Y = \frac{1}{E} = 1/\left[\frac{1}{2}\sum_{a=1}^{t}\sum_{k=1}^{m}(q_k^a - p_k^a)^2\right] \tag{10}$$

Figure 3 shows the optimization process.

3.3. Assessment Indicators

In the text, the accuracy of substation fire warning model is evaluated by means of two error indexes, mean absolute percentage error (MAPE) y_{MAPE} and root mean square error (RMSE). MAPE and RMSE determine the accuracy of the model. Equation (11) is MAPE, and Equation (12) is RMSE.

$$y_{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_a(i) - y_p(i)}{y_a(i)}\right| \tag{11}$$

$$y_{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}[y_a(i) - y_p(i)]^2}{n}} \tag{12}$$

$y_a(i)$ and $y_p(i)$ are the actual and predicted values of fire probability.

Figure 3 is the workflow diagram of the model based on the behaviour of the fish school. The specific steps are: (1) Build a BP network model, set the dimensions of the neural network weight threshold, and set the parameters to be optimized for the BP network structure to the initial position of the fish school individual; (2) Calculate the fitness value of the individual of the initial fish school, and determine the behaviour of the fish school according to the judgment conditions; (3) Judge whether the optimal solution is found or the maximum number of iterations is reached. If the conditions are met, the iteration is terminated, otherwise, the iterative optimization is continued; (4) Output the weights and thresholds assigned to the BP network by the optimal solution; (5) Calculate the output fire probability.

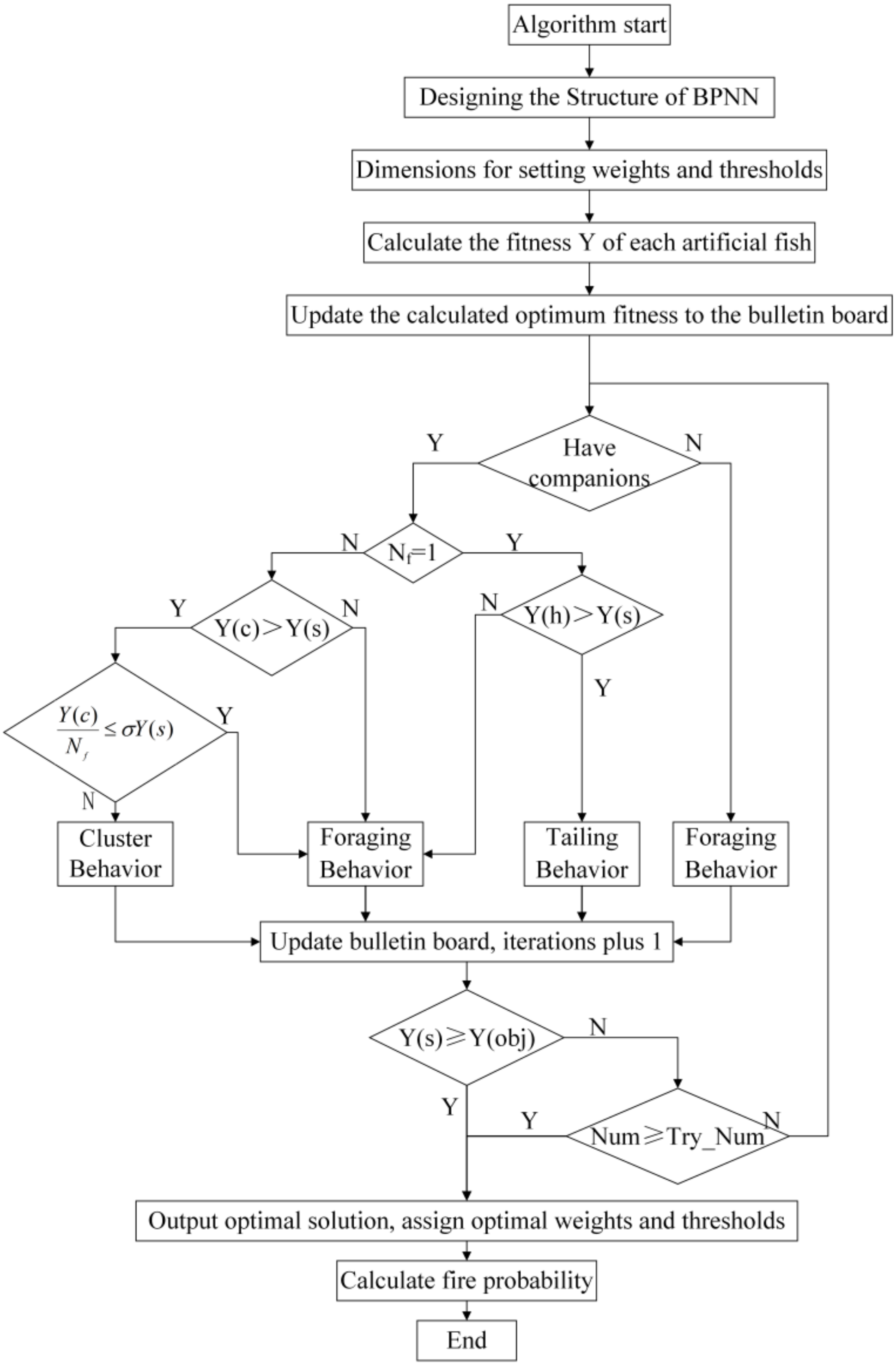

Figure 3. AFSA for optimizing flow chart of BPNN.

4. Forecast Results and Analysis

Select representative data samples from published papers and national standard fire test data. The model is trained and forecasted using the model. In the text, the parameters of BPNN are set to display the results once in 25 turns, the learning speed is 0.01, maximum training times are 5000, and mean square error is 0.0001.The size of artificial fish stocks is 20, is 0.6, step is 0.05. The number of iterations of the two algorithms is shown in Figure 4. The number of iterations of forecasting model optimized by the AFSA is significantly reduced.

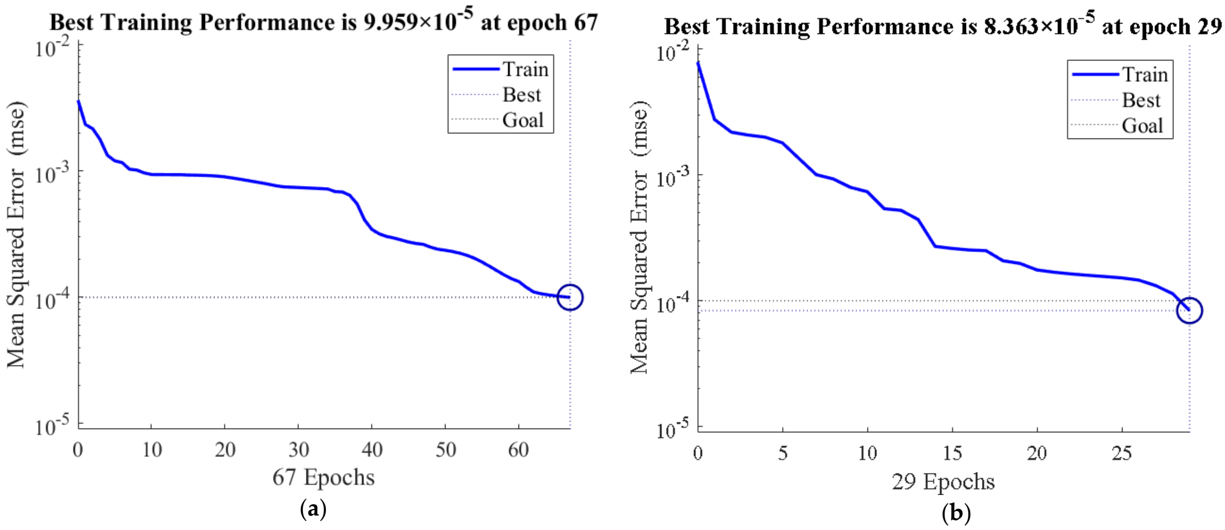

Figure 4. Comparison of BPNN and AFSA−BPNN algorithm iterations. (**a**) Iteration times of BPNN algorithm,(**b**) Iteration times of AFSA-BPNN algorithm.

The predicted values of BPNN optimized by AFSA and traditional BPNN for fire probability are shown in Figure 5.

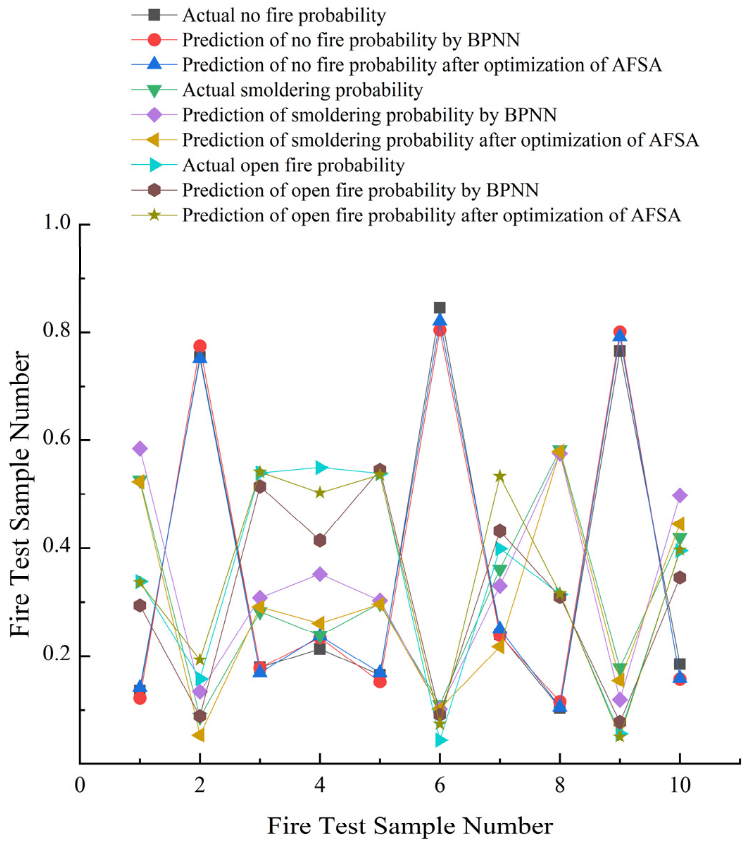

Figure 5. Forecast of fire probability.

The MAPE and RMSE of the predicted values optimized by BPNN and AFSA are shown in Figure 6.

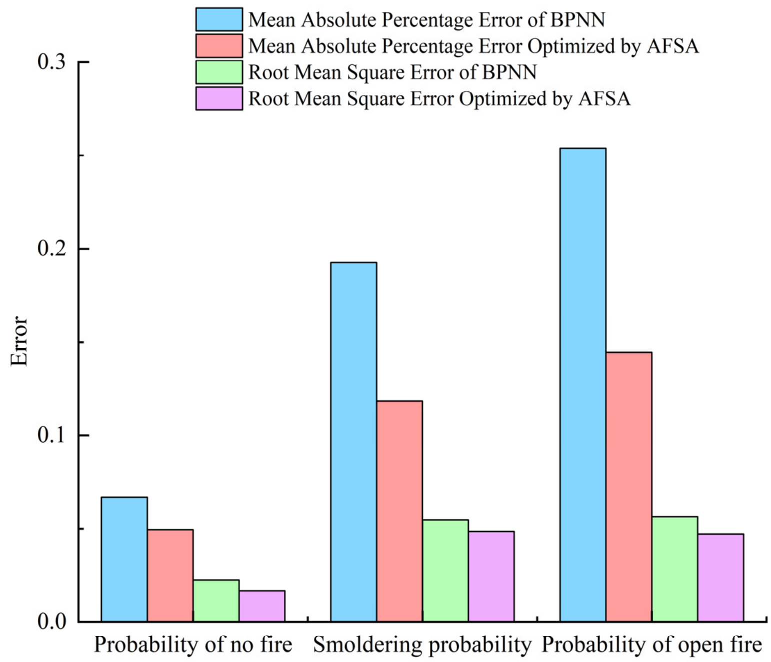

Figure 6. Error of BPNN and AFSA-BPNN algorithms in predicting fire probability.

From the graph analysis, the MAPE of no fire probability decreases by 26.06%, the RMSE decreases by 25.47%, the MAPE of smoldering probability decreases by 38.5%, the RMSE decreases by 11.18%, the MAPE of open fire probability decreases by 43.13%, the RMSE decreases by 16.23%, and the optimization of AFSA improve the accuracy of substation fire prediction model. After forecasting probability value of substation fire, output probability is judged by fuzzy strategy and different firefighting measures are taken by output decision signal. Table 1 is the decision-making judgment of fire probability value of forecast samples.

Table 1. Decision-making judgment of fire probability value of forecast samples.

	Smoldering Probability	Open Fire Probability	Decision Output	Decision-Making Judgment	Is the Decision Correct
1	0.5228	0.336	0.659	Alarm	correct
2	0.0534	0.192	0.381	Warning	correct
3	0.2906	0.5405	0.658	Alarm	correct
4	0.2604	0.5025	0.656	Alarm	correct
5	0.2957	0.5355	0.658	Alarm	correct
6	0.1021	0.074	0.222	No fire	correct
7	0.2176	0.5328	0.657	Alarm	correct
8	0.5788	0.3159	0.659	Alarm	correct
9	0.1548	0.0505	0.307	Warning	correct
10	0.446	0.3966	0.651	Alarm	correct

It can be seen from Table 1 that the decision and judgment on the fire probability values of ten prediction samples are correct, indicating the feasibility of this method.

5. Substation Fire Control Strategy

Based on the decision-making judgment of the predicted sample fire probability value, the fire alarm host interacts with the fire control equipment to take corresponding fire control measures. When the output decision is no fire, the substation operates safely; when the decision is warning, the fire extinguishing device is not started, and the substation personnel always observe the abnormal signal, and check the warning place if necessary;

when the decision is to alarm, the fire alarm host receives the signal to start the automatic fire extinguishing device immediately; when the decision is serious alarm, the automatic fire extinguishing device is started immediately, the power supply is cut off, and the substation personnel go to the alarm to handle the accident. The fire control system is shown in Figure 7. The black arrow indicates the direction of information interaction.

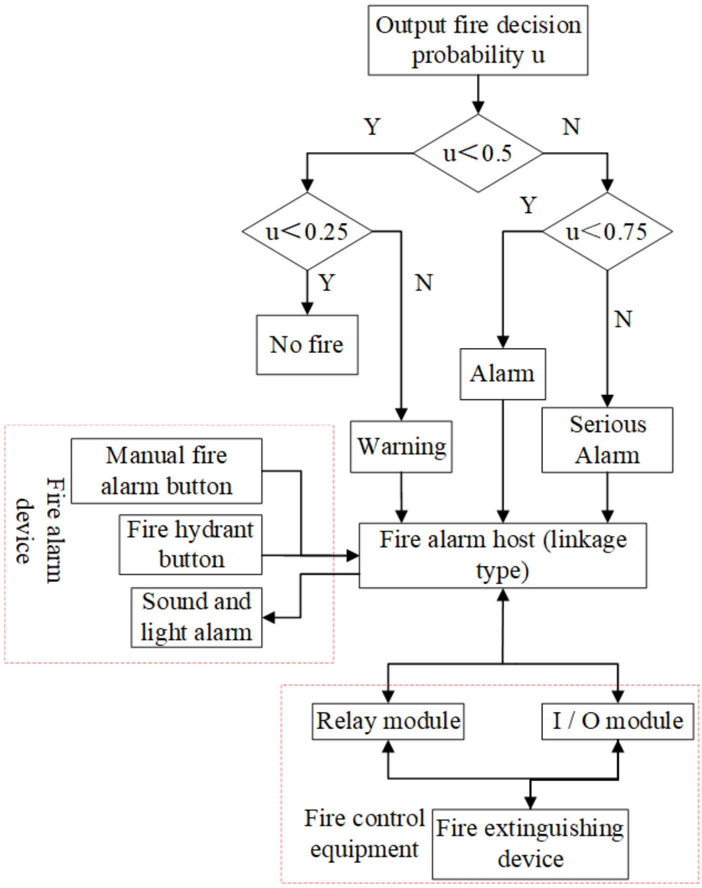

Figure 7. Flowchart of substation fire warning and fire control.

For cable trench, cable sandwich, cable shafts and other electrical equipment in substation, install automatic fire extinguishing devices to achieve active fire extinguishing in the event of a fire. The aerosol fire extinguishing system can be used for fire extinguishing devices in substations. When triggered by the aerosol fire extinguishing device, chemical agents filled inside generate fire extinguishing gases, mainly metal oxide particles and inert gases, to achieve full submerged fire extinguishing.

6. Conclusions

In this paper, aiming at the substation fire prevention problem, taking the substation AC power system cables as the research object, the multi-information fusion technology is proposed for the substation fire warning research, and the characteristics and decision-making layers of the multi-information fusion technology are deeply studied. The BPNN prediction model is optimized by AFSA optimization, which improves convergence speed and reduces error, making the fire probability more accurate. Through fuzzy set theory and decision-making factors, the accuracy of fire prediction in substation is further improved. The substation control center takes different fire control measures according to the output of decision-making. The model proposed in the text can not only be used in the fire prediction of substation, but also can provide reference for dealing with other disasters in Substation in the future.

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