Armored Cabin Air Conditioning System Fault Diagnosis Method Based On Back Propagation Neural Network And Probabilistic Neural Network

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***Abstract*— Fault diagnosis of armored cabin air conditioning systems based on regular maintenance is inaccurate, inefficient, and inadequate. This paper presents a fault diagnosis method based on a combination of back propagation neural network (BPNN) and probabilistic neural network (PNN). This method extracts fault features and fault locations while considering the large number of monitoring parameters for cabin air conditioning systems, the difficulty in extracting fault features, the strong correlation between fault locations, and the imprecise location of faults. The average diagnostic accuracy of the test samples reached 95% using BPNN to optimize the PNN, which is 29% higher than that of only conducting PNN method. A corresponding cabin air conditioning system fault diagnosis platform verifies the developed fault diagnosis method and shows that the method based on BPNN-PNN work very well, and the diagnostic accuracy reach 99%.**

Keywords—Air conditioning system, fault diagnosis, back propagation neural network, probabilistic neural network

I. INTRODUCTION

A healthy, comfortable, and safe working environment in armored vehicle cabins guarantees that the vehicle occupants will effectively operate the equipment. Due to the limited space in an armored passenger cabin, the heat source is large and the air convection is poor. The temperature and humidity are often high in the passenger compartment [1]. After an armored vehicle has been driven for 2 hours in the summer, the cabin temperature can reach 8.8 ℃ to 9.5℃ higher than the outside temperature, and the humidity can reach more than 98% [2].

In 2017, a key laboratory of China Ordnance Industry Group investigated and analyzed the impact of man-machine environment on occupant operations in armored vehicles. According to the survey and analysis of the results, 48.9% of the occupants think that excessive temperature and humidity are the main factors affecting their ability to operate the vehicle. Temperature and humidity ranks second in the factors affecting the operation of armored vehicles [3,4]. The temperature and humidity in the cabin are mainly controlled by the cabin air conditioning system. As the air conditioning system in the cabin is highly integrated and automated, the causes and symptoms of the fault are becoming more and more complicated, and fault diagnosis is becoming more and more important. Accurate and timely fault diagnosis of the air conditioning system is not only important for ensuring the safety and comfort of the vehicle occupants, but can also improve system reliability, maintainability, and effectiveness.

Fault diagnosis of equipment or systems for armored vehicles was developed in the early 1970s. For example, US Military Vehicle Command developed fault detection equipment for the M60A3 and M48A1 tanks [5]. In recent years, the vehicle health diagnosis system developed by the United States has been widely loaded in M1A1, M1A2 main battle tanks, "Bradley" infantry fighting vehicles as well as other third-generation armored equipment in the United States, and the British "Samurai" infantry fighting vehicles [6]. Researchers also developed expert systems for ordnance equipment fault diagnosis [7], tank stabilizers, and electrical fault diagnosis systems [8] for armored vehicles. These diagnostic equipment or systems are still not intelligent enough. The recent development of artificial intelligence technology provides a new solution to the problem of fault diagnosis. Artificial neural networks offer advantages such as fault tolerance, association, memory, speculation, self-learning, and parallel computing and processing [9,10], which have been gradually applied in the fault diagnosis of vehicle tank devices [11-13], transmission systems [14,15], and fire control systems [16] of armored vehicles.

Nowadays, more and more scholars have combined or improved various neural networks to conduct fault diagnosis research and have achieved good results. In [17], a method for fault diagnosis of engine pneumatic systems based on ReliefF-PNN was proposed. The ReliefF algorithm was used to determine the subset of optimal feature parameters that characterize the gas path system. Probabilistic neural network (PNN) was used to build the fault diagnosis model for the pneumatic system. This method effectively reduces the dimension of the characteristic parameters of the pneumatic

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system and improves the diagnostic accuracy. In [18], aiming at the non-stationary and non-periodic characteristics of compressor valve fault signals, a fault diagnosis method for compressor valves based on principal component analysis (PCA) and genetic algorithm and particle swarm optimization (GA-PSO) optimized back propagation neural network (BPNN) was proposed. The fault feature vector reduced the dimension through PCA, which reduced the scale and calculation time of the network, improved the training efficiency, and achieved a good diagnostic effect. In [19], a passenger cabin temperature model based on a BPNN algorithm was proposed. The model was integrated into the air conditioner controller. As an input value and temperature feedback value of the air conditioning system, the passenger compartment temperature could be adjusted more accurately and in a more timely manner. In [20], a transformer fault diagnosis based on improved Radial basis function (RBF) neural network optimized by PSO was proposed, which improves the premature phenomenon often found in RBF neural network diagnosis and realizes accurate diagnosis of transformer fault. Existing fault diagnosis of the cabin air-conditioning system is still based on regular maintenance, with poor diagnostic accuracy, low efficiency, insufficient maintenance or over-maintenance [21].

Back propagation neural network（BPNN）has strong adaptive and self-learning ability for complex nonlinear mapping relations [22,23], and probabilistic neural network (PNN) has strong classification recognition and fast training convergence ability[24,25], In order to advance the diagnostic accuracy and efficiency, this paper combines the BPNN with the PNN to propose a BPNN-PNN fault diagnosis method for cabin air conditioning system. BPNN is used to optimize PNN. Additionally, a corresponding fault diagnosis software of cabin air conditioning system is developed to verify the effectiveness of this BPNN-PNN diagnosis method.

II. THOUGHTS ON FAULT DIAGNOSIS METHOD OF CABIN AIR CONDITIONING BASED ON BPNN-PNN

The faults caused by different parts and types of cabin air conditioning systems change the monitoring parameters. It is inferred from the changes of these parameters that the fault location is the task of fault diagnosis of the cabin air conditioning system. How to use the artificial neural network to extract the fault feature parameters from the monitoring parameters, and determine the faults and the location from the known feature parameters is the target of the fault diagnosis. The diagnosis processes is shown in Fig. 1. Firstly, this paper analyzes the cabin air conditioning system based on the system principle and gives the monitoring parameters and status parameters related to the system. Secondly, this paper uses FMEA (failure mode and effects analysis) to determine the faults of each component and its impact characteristics. The parameters are then combined with BPNN and PNN for fault diagnosis and localization. BPNN is mainly used for fault feature extraction, and PNN is used for further location and isolation of faulty devices.

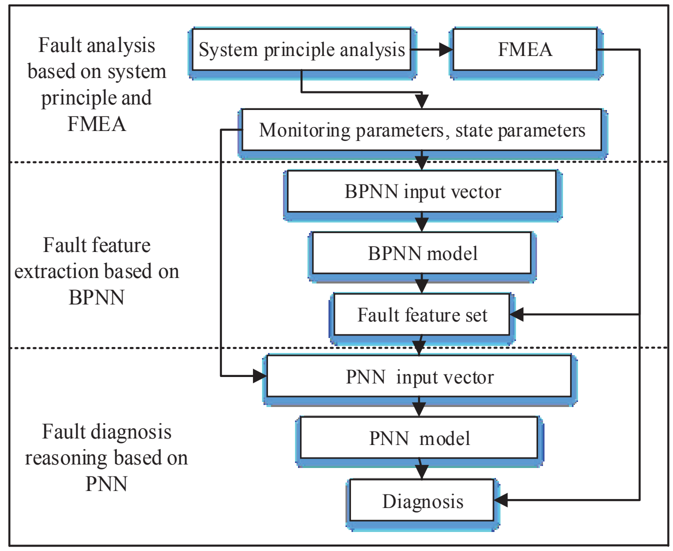

Figure1. Fault diagnosis based on BPNN-PNN neural network.

III. FAULT DIAGNOSIS ALGORITHM BASED ON BPNN-PNN

If there are n number of monitoring parameters and status parameters, m number of fault characteristics and v number of failure modes in the cabin air-conditioning system through FMEA analysis based on system principle. All these parameters, fault characteristic and failure modes are respectively expressed using the sets of A, S and F as followings

$$A = \{a_1, a_2, \dots, a_i, \dots, a_n\} \tag{1}$$

$$S = \{s_1, s_2, \dots, s_k, \dots, s_m\} \tag{2}$$

$$F = \{f_1, f_2, \dots, f_l, \dots, f_v\} \tag{3}$$

where a_i represents i^{th} monitoring or status parameters, s_k represents k^{th} fault feature, and f_l represents l^{th} fault mode.The process of fault diagnosis based on BPNN-PNN is to extract the fault feature from the monitoring parameters and state parameters, and then judge the fault mode according to the fault feature. In order to establish diagnosis algorithm based on BPNN-PNN, the value corresponding to parameters set A, fault feature set S and failure mode F are respectively set as the vector X, Q and P as followings.

$$X = [x_1, x_2, \dots, x_i, \dots, x_n]^T \tag{4}$$

$$Q = [q_1, q_2, \dots, q_k, \dots, q_m]^T \tag{5}$$

$$P = [p_1, p_2, \dots, p_l, \dots, p_v]^T \tag{6}$$

Here, x_i is the value of the parameter a_i, q_k is the value of the fault feature s_k, and p_l indicates whether the failure mode occurred or not. If p_l equals to 1, then the failure mode f_l occurs, and if p_l equals to 0, the failure mode f_l does not occur.

The fault diagnosis algorithm based on BPNN-PNN are as follows:

Step 1. Initialize each weight coefficient and the threshold of BPNN and PNN.

Step 2. Calculate the input of the BPNN input layer.

The parameters set $X = [x_1, x_2, \dots, x_i, \dots, x_n]^T$ of the cabin air conditioning system is used as the input of the BPNN.

Step 3. Calculate the input and output of the BPNN hidden layer.

The j^{th} node input of the hidden layer is calculated in

$$h_j = \sum_{i=1}^{i=n} W_{ij} \times x_i \tag{7}$$

and the output of the hidden layer is $d_j = g(h_j)$, where j is the number of the hidden layer nodes, W_{ij} is the connection weight between the input layer and the hidden layer.

Step 4. Calculate the input and output of the BPNN output layer.

The input of the k^{th} node output layer is calculated in

$$y_k = \sum_{j=1}^{j=u} W_{jk} \times d_j \tag{8}$$

where W_{jk} is the connection weight between hidden layer and output layer, and u is the number of hidden layer nodes.The output of the k^{th} node output layer is calculated in $q_k = g(y_k)$. Then the output result of the output layer is $Q = [q_1, q_2, \dots, q_k, \dots, q_m]^T$.

Step 5. Calculate the error between expected value and output value using

$$\delta = \frac{1}{2}(q_k^* - q_k) \tag{9}$$

q_k^* represents k^{th} expected value of fault feature .

Step 6. Adjust the weights W_{jk} and W_{ij}, and recalculate the output value of BP neural network until the error meets the requirements according to the error back propagation rules and gradient descent.

Step 7. The output value of BP neural network is taken as the input of PNN, and calculate the output vector of the PNN pattern layer using

$$f_{pq}(Q) = \exp\left(-\sum_{q=1}^{q} (Q_q - Q_{qp})^2 / 2\sigma^2 \right) \tag{10}$$

Where Q_q represents the central value of the number q feature, Q_{qp} is the q^{th} eigenvalue in the p^{th} failure mode, and σ is smoothing factor of the PNN network and $\sigma \in (0,1]$.

Step 8. Calculate the output of the PNN network summation layer using

$$f_p(Q) = \frac{1}{sum} \sum_{sum} W_{pq} f_{pq}(Q) \tag{11}$$

Wherein sum represents the total number of samples in the p^{th} failure mode, W_{pq} is the connection weight between the q^{th} node of the PNN pattern layer and the p^{th} node of the summation layer. The number of neurons in the summation layer is the number of failure modes, and the output result is the probability value of each failure mode.

Step 9. Calculate the output value of the PNN output layer using

$$C(Q) = \max_p f_p(Q) \tag{12}$$

The diagnostic results of the cabin air conditioning system is analyzed by the output value of output layer. Through comparing with the output value of the summation layer, the output value of PNN output layer of the fault mode with the highest probability is 1, and the rest output value is 0.

IV. Application

The developed fault diagnosis method based on BPNN-PNN is applied in a type of cabin air conditioning system fault diagnosis. Through analyzing based on the system principle and FMEA, cabin air conditioning system has 13 monitoring parameters, 6 status parameters and 5 failure mode, The types of monitoring parameters are the temperature, humidity, pressure inside and outside the cabin, oxygen concentration value, and the air volume at the air outlet of the air conditioner. The status parameters includes air conditioning switch signal, cooling mode, heating mode, dehumidification mode, internal circulation mode, external circulation mode. The failure modes, includes normal operating conditions, PTC ceramic chip failure, compressor failure, condenser failure, circulating fan failure, and which are sequentially encoded as $(1,0,0,0,0)^T$, $(0,1,0,0,0)^T$, $(0,0,1,0,0)^T$, $(0,0,0,1,0)^T$, $(0,0,0,0,1)^T$. Through carrying out FMEA analysis of the system, it is found that the final impact of each component failure of a certain type of cabin air conditioning system is often manifested by indicators such as temperature, humidity and air volume in the cabin. At the same time, the failure has an important relationship with the mission phase. Therefore the temperature, humidity, air volume, mission phase are all set as fault feature. The FMEA analysis results of a certain type of cabin air conditioning system are shown in Table 1.

This paper collected 300 sets of sample data, of which 220 sets of data were used as training samples, 40 sets of data were used as cross-test samples, and the remaining 40 sets of data were used as test samples for BPNN-PNN training. Set the maximum number of training for BPNN-PNN is m_{max}=1 000, learning rate of gradient descent L=0.01 and the convergence accuracy E=0.001. Some sample data are shown in Table 2.

TABLE I. FMEA RESULTS OF CABIN AIR CONDITIONING SYSTEM

No.	Component	Function	Fault cause	Mission phase	Local impact	High level impact	Final impact
1	PTC	Heating air	Component damage	Air conditioning heating	Unable to heat the air	Air conditioning cannot heat	In-cabin temperature is too low
			Maximum power limitation		Air temperature does not meet the requirements	Air conditioning cannot control temperature	
2	Compressor	Provide refrigerant circulation power	Internal component damage	Air conditioning refrigeration; air conditioning heating; dehumidification	Refrigerant cannot circulate	Air conditioning cannot be cooled	The cabin temperature is not low enough; the cabin humidity is too high
					Refrigerant cannot continuously circulate	Air conditioning refrigeration is not continuous	
					Insufficient refrigerant circulation	Air conditioning refrigeration temperature is not up to standard	
					Insufficient evaporator refrigeration		
3	Condenser	Refrigerant condensation releases heat	High ambient temperature	Air conditioning refrigeration	Refrigerant does not condense	Air conditioning cannot be cooled	The cabin temperature is not low enough
			Dirty block		Insufficient heat release from the condenser		
			Motor output is not enough		The air side of the condenser circulates too slowly		
4	Circulation fan	Powering the circulating wind inside the cabin	Impeller or motor damage	Full mission stage	Cabin air cannot circulate	Air conditioning or oxygen system does not get enough air	Ventilation volume becomes smaller

TABLE II. RAW DATA SETS OF CABIN AIR CONDITIONING SYSTEM (PARTIAL)

No.	**Expected output**	**Input parameters (partial)**								
		X1	***X2***	***X3***	***X4***	***X5***	***X6***	**...**	***X18***	***X19***
1	(1,0,0,0,0)T	24.12	27.89	18.43	1	103.57	78.43	...	15.52	6.35
2	(1,0,0,0,0)T	26.00	33.25	8.56	2	114.65	66.46	...	23.12	8.41
...	...	...	...	...	...	...	...	...	...	...
150	(0,1,0,0,0)T	25.23	27.26	41.65	3	125.16	42.31	...	17.29	2.27
151	(0,0,1,0,0)T	26.32	23.73	24.12	4	87.83	44.02	...	16.36	4.93
...	...	...	...	...	...	...	...	...	...	...
299	(0,0,0,1,0)T	27.26	43.37	32.28	3	72.60	65.57	...	22.27	7.21
300	(0,0,0,0,1)T	16.33	34.32	26.53	3	4.22	76.54	...	14.75	6.82

And this paper have used Matlab for programming to get the prediction effect of the BPNN-PNN test sample. After 1000 tests, the average diagnostic accuracy of the BPNN-PNN algorithm training samples reached 99%, and the average diagnostic accuracy of the test samples reached 95%. The diagnostic results of one of the tests are shown in Fig. 2. There are 5 failure modes. The test sample number is taken as the abscissa, and the diagnosis result is taken as ordinate. For comparison, the monitoring parameters and status parameters of the cabin air conditioning system were directly used as input to the PNN without the optimization of BPNN, and the average diagnostic accuracy of the training samples is only 80%, and the average diagnostic accuracy of the test samples is only 66%. The results show that the BPNN-PNN based cabin air conditioning system diagnostic method has higher diagnostic accuracy.

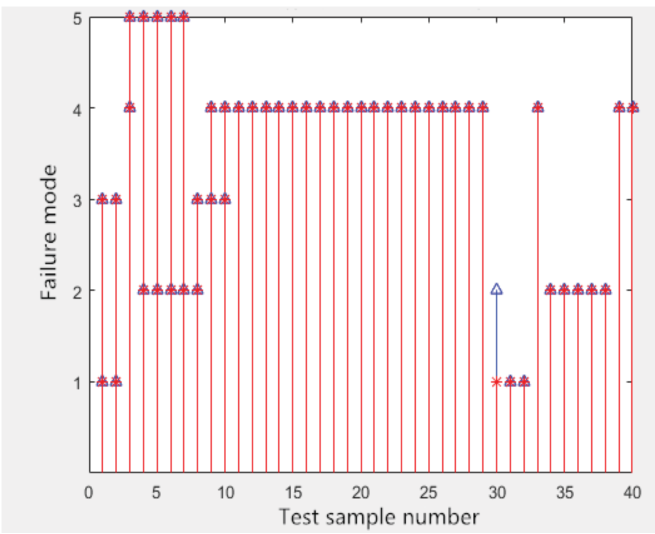

Figure2. BPNN-PNN model test sample diagnostic effect. ("*" indicates the expected output, and "△" the predicted output of the BPNN-PNN algorithm. If "*" and "△" coincide, then the diagnosis was successful.)

Taking BPNN-PNN fault diagnosis method as the core, we design and develop software system for cabin air conditioning system fault diagnosis. The platform can collects, processes and displays the real-time monitoring and status parameters of the cabin air conditioning system, as shown in Fig. 3. The proposed BPNN-PNN fault diagnosis algorithm is used to extract the key parameters which can characterize the fault characteristics from the monitoring parameters and status parameters, and perform fault reasoning and fault alarm if some fault modes exist. The platform can support online fault diagnosis, and display the information of fault modes, fault causes and maintenance suggestions, as shown in Fig. 4. The cabin air conditioning system fault diagnosis has connected to the control system of one prototype of cabin air conditioning system, and carried out prototype test. During prototype testing, the real-time fault diagnosis based on proposed BPNN-PNN fault diagnosis method work very well, and the diagnostic accuracy reach 99%.

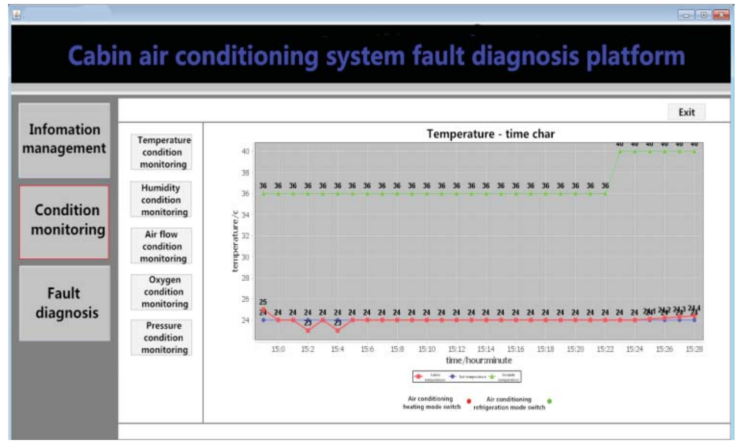

Figure3. In-cabin air conditioning system fault diagnosis platform status monitoring interface.

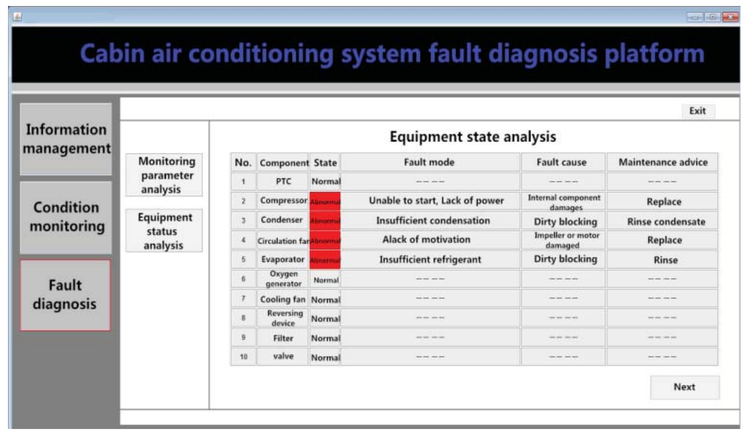

Figure4. Fault diagnosis interface of the cabin air conditioning system fault diagnosis platform.

V. CONCLUSION

This paper combines a back propagation neural network (BPNN) and a probabilistic neural network (PNN) to develop a fault diagnosis method for cabin air conditioning systems. Existing fault diagnosis methods for cabin air conditioning systems have difficulty extracting fault features and identifying the strong correlation between fault locations. In the developed fault diagnosis method, BPNN is used to extract fault characteristics because it has strong adaptive and self-learning ability for complex nonlinear mapping relations, and PNN is used to locate faults in the cabin air conditioning system because it has strong classification recognition and fast training. Application and calculation show that the developed BPNN-PNN algorithm has achieved good diagnostic results. The average diagnostic accuracy of the test samples reached 95% using BPNN to optimize the PNN, which is 29% higher than that of only conducting PNN method. In addition, we developed a cabin air conditioning system diagnostic platform to achieve real-time state monitoring, online diagnostics and other functions. The platform has tested well in a prototype of one new type of cabin air conditioning system.

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