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RESEARCH ON INTELLIGENT DIAGNOSIS METHOD FOR LARGE-SCALE SHIP ENGINE FAULT IN NON-DETERMINISTIC ENVIRONMENT

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ABSTRACT

Aiming at the problem of inaccurate and time-consuming of the fault diagnosis method for large-scale ship engine, an intelligent diagnosis method for large-scale ship engine fault in non-deterministic environment based on neural network is proposed. First, the possible fault of the engine was analyzed, and the downtime fault of large-scale ship engine and the main fault mode were identified. On this basis, the fault diagnosis model for large-scale ship engine based on neural network is established, and the intelligent diagnosis of engine fault is completed. The experiment proved that the proposed method has high diagnostic accuracy, engine fault diagnosis takes only about 3s, with a higher use value.

Keywords: Non-determinism, Large-scale ship engine, Fault intelligent diagnosis

INTRODUCTION

Large-scale ship is a transport with high cost, its safety has been a high degree of concern, large-scale ship engine fault intelligent diagnosis is an important method to ensure the safety of large-scale ship's navigation [1-2]. Through the intelligent diagnosis of faults, detect the large-scale ship engine problems timely, to ensure the safety of personnel on board [3-4]. As a typical reciprocating power machine [5], the complexity of the structure determines the efficiency of large-scale ship engine fault diagnosis [6-7]. the traditional intelligent diagnostic method based on the support vector machine, extracts the fault feature first and uses the principle of structural risk minimization to replace the principle of experience risk minimization in traditional machine learning method to identify the fault features of large-scale ship engine and realize the intelligent diagnosis of large-scale ship engine fault [8-9], but this method needs a long time to diagnose, cannot complete the fault diagnosis timely. To this end, an intelligent diagnosis method for large-scale ship engine fault in non-deterministic environment based on neural network is proposed in this paper.

ANALYSIS OF FAULT DIAGNOSIS PROCESS FOR LARGE-SCALE SHIP ENGINE IN NON-DETERMINISTIC ENVIRONMENT

There are a variety of complex factors in the whole process of design, manufacture, assembly, use and maintenance of the large-scale ship engine, the possible sources of fault are:

1) Design problems, large-scale ship engine design is a very complex work, small individual errors will inevitably appear in the design process.

2) Manufacturing problems, including defects in the entire manufacturing process, such as material defects, manufacturing errors;

3) Environment of the use, during the voyage process, some parts through the erosion of seawater, and bear long-term mechanical vibration, humidity, radiation and other harsh environments, resulting in large-scale ships fault;

4) Accidents, various papers reported large-scale ship engine faults occurred during the tsunami, storm and other accidents. In the above sources, due to the rapid development of modern industrial manufacturing level, the percentage of faults caused by manufacturing problems is declining in all sources of faults, while the proportion of environmental and human factors have increased.

The features of the ship engine fault are:

1) The faults of most ship engine parts are random. There is no inherent fault rate, since most of the fault comes from environmental and human factors, and these factors are random in their own, there is no definite intrinsic fault rate in the normal service life.

2) The overall fault rate of large-scale ship engines follows the "bathtub curve". In the early stage of the use, the performance parameters of the various parts of the engine are in the stage of commissioning and process running. The performance parameters changed greatly and worked unstably that the total fault rate is relatively high. With the increase of the voyage time of the large-scale ships, engine parts complete the commissioning and process running, its performance is gradually stable, and the total fault rate has declined. When the use of time is more than 75% of economic life, the effects of engine wear, corrosion and fault caused by environmental factors are becoming more and more serious, and the total failure rate is increasing again.

3) Fault mechanism is complex. Modern large-scale ship engine integrated application of mechanical, electronic, computer, automatic control, detection technology and other multi-disciplinary advanced technology, is a large-scale complex mechanical and electrical equipment, the diversity of the working principle of the system led to the complexity of its fault mechanism.

4) The possibility of concurrent fault occurs. The complexity of the large-scale ship engine system determines the comprehensive fault features, any of the occurrence of a primary fault has a number of potential trigger fault, which is a multi-fault concurrent system.

In the large-scale ship fault detection, the engine fault detection is the most important content, once the engine is faulty, may lead to other system faults, so the ship engine fault detection is conducive to ensuring the normal operation of the ship. Large-scale ship engine fault mode varied, as shown in Table 1 is the downtime fault analysis of large-scale ship engine, Table 2 is the main fault mode of large-scale ship engine.

Tab. 1. Large-scale Ship Downtime Fault Analysis

Fault classification	Fault probability /%
Fuel injection equipment and fuel supply system fault	27.0
Valve and valve seat fault	11.9
Bearing fault	7.0
Leakage fault	17.3
Oil spill and lubrication system fault	5.2
Piston component fault	6.6
Turbocharging system fault (Including the fault caused by foreign invasion)	4.4
Governor gear fault	3.9
Gear and drive fault	3.9
Leakage	3.2
Crankshaft fault	0.2
Fuel leakage	3.5
Other damage and rupture except special title	2.5
Other faults	2.5

Tab. 2. Main Fault Modes of the Large-scale Ship Engine

Fault modes	Cause of fault	Fault severity
Machine abnormal sound	Valve clearance or clear knock sound	Severe
Engine locking	Crankshaft locking	Severe
Engine stuck	The piston is stuck in the cylinder	Severe
Cylinder pressure improperly	Piston ring leaks	Severe
Gas channeling, power improper	Increased fuel consumption (severe cylinder wear)	Severe
Gas channeling	Piston ring broken	Severe
Pistons dead	Inhalation of foreign matter caused by piston damage	Severe
Engine overheating	Due to partial clogging of the watercourse or damage of the thermostat	General
Engine block is damaged	Piston broken or connecting rods broken, the cylinder broke by the connecting rod, engine scrapped	Fetal
Piston ring leaking	After leaking, the impact of oil low shell caused abnormal sound	Severe

Through the analysis of Table 1 and Table 2, we can see that because of the interaction between the subsystems of the engine, the relationship is complicated, the engine fault presents a complex diversity, mainly reflected in the following aspects:

1) The complexity of the fault

Engine structure is complex, which has many fault excitation source and thermal parameters. As a reciprocating machine, in the same working condition, the characteristic parameters are different in the working cycle at different times, some faults showed the same fault features, which requires people to use multiple thermal parameters to multi-level comprehensive diagnosis.

2) The ambiguity of the fault

There is ambiguity between the cause of the engine fault and the fault symptom, such as the degree of influence of a fault symptom on the fault phenomenon and the possibility of a fault phenomenon.

3) Fault correlation and relativity

Under different conditions and circumstances, the performance of the engine fault features is sometimes not the same; engine fault of a subsystem may cause other related system fault.

4) The coexistence of multiple faults

Multiple engine faults may occur in the work at the same time, and there exists interference between the feature information of different parts.

INTELLIGENT FAULT DIAGNOSIS METHOD FOR LARGE-SCALE SHIP ENGINE BASED ON NEURAL NETWORK IN NON-DETERMINISTIC ENVIRONMENT

Through the above discussion, the fault of large-scale ship engine is analyzed, and the main fault modes are expounded, which lays the foundation for the determination and implementation of intelligent fault diagnosis method for large-scale ship engine in non-deterministic environment.

The basic unit of artificial neural network is neuron, and the mathematical model of neuron corresponds to biological nerve cells. The classical neuron model is a non-linear structure with multiple input single output.

The mathematical description of the neural model to achieve large-scale ship engine fault diagnosis [10-12] can be expressed as:

$$u_k = \sum_{j=1}^{n} w_{kj} x_j \tag{1}$$

$$v_k = net_k = u_k - \theta_k \tag{2}$$

$$y_k = f(v_k) \tag{3}$$

In the above equation, $x_j \in \{x_1, x_2, \cdots, x_n\}$ represents the input signal of the large-scale ship engine fault diagnosis, w_{kj} and θ_k represent the weight and thresholds of the neuron k respectively, $f(\cdot)$ represents the fault transfer function, and y_k represents the output of the neuron k.

BP neural network is a multi-layer forward neural network, the network training uses the error back propagation algorithm, its feature is to use the error back propagation algorithm to adjust the weight of the neural network. BP network learning algorithm is through the reverse learning process so that the network output node error is minimal, the weight and threshold of the network correct along the negative gradient of error function. In the BP network, the nonlinear learning process is done by the interaction between the implicit layer and the output layer. When the output value does not match the expected value given in the sample, the error signal is returned from the output side, and the weight is continuously corrected until the desired output value is obtained at the output layer node as the training end of the samples. When the sample p completes the weight adjustment of the network, enter another batch of patterns to learn until N sample trainings are completed.

Set x_j as the input to the jth node of the large-scale ship engine in input layer based on the BP neural network. $j = 1, 2, \cdots, M$; w_{ij} represents the weight between the ith node of the input layer and the jth node of the implicit layer based on the BP neural network. θ_i represents the threshold of the ith node of the BP neural network implicit layer; $\phi(x)$ represents the implicit layer excitation function; w_{ki} represents the weight between the kth node of the output layer and the ith node of the implicit layer, $i \quad 1, 2, \quad , q$; $\psi(x)$ represents the output layer excitation function; a_k represents the kth node threshold of the output layer, $k = 1, 2, \cdots, L$; O_k represents the output of the kth node of the large-scale ship engine fault diagnosis output layer based on the BP neural network, the training step of the neural network can be expressed as: first input signal forward propagation process, then calculated the neuron output error from the output layer as the error gradient method to adjust the weight and thresholds of the basis, so that iterative adjustment of the network, the output error can eventually be close to the expected value. The specific process is described below.

Calculate the implicit Layer input of ith Node as net_i :

$$net_i = \sum_{j=1}^{M} w_{ij} x_j + \theta_i \tag{4}$$

Calculate the implicit layer output of the ith node as y_i :

$$y_i = \phi(net_i) = \phi(\sum_{j=1}^{M} w_{ij} x_j + \theta_i) \tag{5}$$

The input of the kth node in input layer as net_k :

$$net_k = \sum_{i=1}^{q} w_{ki} y_i + a_k = \sum_{i=1}^{q} w_{ki} \phi(\sum_{j=1}^{M} w_{ij} x_j + \theta_i) + a_k \tag{6}$$

The output of the kth node in input layer as O_k :

$$O_k = \psi(net_k) = \psi(\sum_{i=1}^{q} w_{ki} y_i + a_k) \\ = \psi\left(\sum_{i=1}^{q} w_{ki}\phi(\sum_{j=1}^{M} w_{ij}x_j + \theta_i) + a_k\right) \tag{7}$$

Set E_p as the quadratic error criterion function of each sample p, then:

$$E_p = \frac{1}{2}\sum_{k=1}^{L}(T_k - O_k)^2 \tag{8}$$

The total error criterion function of p training samples can be expressed as:

$$E = \frac{1}{2}\sum_{p=1}^{p}\sum_{k=1}^{L}(T_k^p - O_k^p)^2 \tag{9}$$

According to the error gradient descent method, the correction amount of the output layer weight Δw_{ki}, the correction amount of the output layer threshold Δa_k, the correction amount of the implicit layer weight Δw_{ij}, and the correction amount of implicit layer threshold $\Delta\theta_i$ are corrected.

$$\begin{cases} \Delta w_{ki} = -\eta \dfrac{\partial E}{\partial w_{ki}} \\ \Delta a_k = -\eta \dfrac{\partial E}{\partial a_k} \\ \Delta w_{ij} = -\eta \dfrac{\partial E}{\partial w_{ij}} \\ \Delta \theta_i = -\eta \dfrac{\partial E}{\partial \theta_i} \end{cases} \tag{10}$$

Output layer weight adjustment formula:

$$\Delta w_{ki} = -\eta\frac{\partial E}{\partial w_{ki}} = -\eta\frac{\partial E}{\partial net_k}\cdot\frac{\partial net_k}{\partial w_{ki}} \\ = -\eta\frac{\partial E}{\partial O_k}\cdot\frac{\partial O_k}{\partial net_k}\cdot\frac{\partial net_k}{\partial w_{ki}} \tag{11}$$

Output layer threshold adjustment formula:

$$\Delta a_k = -\eta\frac{\partial E}{\partial a_k} = -\eta\frac{\partial E}{\partial net_k}\cdot\frac{\partial net_k}{\partial a_k} \\ = -\eta\frac{\partial E}{\partial O_k}\cdot\frac{\partial O_k}{\partial net_k}\cdot\frac{\partial net_k}{\partial a_k} \tag{12}$$

Implicit layer weight adjustment formula

$$\Delta w_{ij} = -\eta\frac{\partial E}{\partial w_{ij}} = -\eta\frac{\partial E}{\partial net_i}\cdot\frac{\partial net_i}{\partial w_{ij}} \\ = -\eta\frac{\partial E}{\partial y_i}\cdot\frac{\partial y_i}{\partial net_i}\cdot\frac{\partial net_i}{\partial w_{ij}} \tag{13}$$

Implicit Layer Threshold Adjustment Formula:

$$\Delta\theta_i = -\eta\frac{\partial E}{\partial \theta_i} = -\eta\frac{\partial E}{\partial net_i}\cdot\frac{\partial net_i}{\partial \theta_i} \\ = -\eta\frac{\partial E}{\partial y_i}\cdot\frac{\partial y_i}{\partial net_i}\cdot\frac{\partial net_i}{\partial \theta_i} \tag{14}$$

Because:

$$\frac{\partial E}{\partial O_k} = -\sum_{p=1}^{p}\sum_{k=1}^{L}(T_k^p - O_k^p) \tag{15}$$

$$\frac{\partial net_i}{\partial w_{ki}} = y_i, \quad \frac{\partial net_i}{\partial a_k} = 1 \\ \frac{\partial net_i}{\partial w_{ij}} = x_j, \quad \frac{\partial net_i}{\partial \theta_i} = 1 \tag{16}$$

$$\frac{\partial y_i}{\partial net_i} = \phi'(net_i) \tag{17}$$

$$\frac{\partial O_k}{\partial net_k} = \psi'(net_k) \tag{18}$$

Get the formula:

$$\begin{cases} \Delta w_{ki} = \eta\sum_{p=1}^{p}\sum_{k=1}^{L}(T_k^p - O_k^p)\cdot\psi'(net_k)\cdot y_i \\ \Delta a_k = \eta\sum_{p=1}^{p}\sum_{k=1}^{L}(T_k^p - O_k^p)\cdot\psi'(net_k) \\ \Delta w_{ij} = \eta\sum_{p=1}^{p}\sum_{k=1}^{L}(T_k^p - O_k^p)\cdot\psi'(net_k)\cdot w_{ki}\cdot\phi'(net)\cdot x_j \\ \Delta\theta_i = \eta\sum_{p=1}^{p}\sum_{k=1}^{L}(T_k^p - O_k^p)\cdot\psi'(net_k)\cdot w_{ki}\cdot\phi'(net) \end{cases} \tag{19}$$

Through the above discussion, a large-scale ship engine fault diagnosis network model based on neural network is established. The process is divided into two steps. The first step is to acquire the appropriate number of training sample sets, and train the neural network to obtain the available fault diagnosis network model. The second step is to use the existing model to diagnose the unknown symptom data set, get the corresponding state and mode. The diagnosis process is the process of the neural network to compute the input vector and obtains the output. Before the learning and diagnosis of the network model, extract the original data and training sample data by summarizing the existing troubleshooting, diagnosis, maintenance experience and knowledge, and preprocessing the data smoothing, feature selection/extraction and so on. The purpose of building a sample space is to provide suitable training samples and diagnostic samples for the diagnostic network.

The purpose of the preliminary analysis of the fault model sample is to confirm whether the fault feature information contained in the fault sample space is sufficient, whether the fault features of the selected large-scale ship engine are reasonable, and evaluate whether the model can distinguish all large-scale ship engine fault modes. The space composition of large-scale ship engine fault samples is an important factor to determine the general performance of the established diagnostic system in practical diagnostic applications.

For the network fault diagnosis model, the correlation coefficient between the large-scale ship engine components can be expressed as:

$$\rho(f, x_j) = \frac{\sum_{i=1}^{N} (f_i - \bar{f})(x_{ij} - \bar{x}_j)}{\sqrt{\sum_{i=1}^{N} (f_i - \bar{f})^2 \sum_{i=1}^{N} (x_{ij} - \bar{x}_j)^2}} \quad \textbf{(20)}$$

Where f represents the target value and x_i represents the feature interval. Since the correlation coefficient $\rho(f, x_j)$ is between $(-1,1)$ and the absolute value is between $(0,1)$, the closer absolute value to 1, the similarity between the target and the feature is higher. In this way, the intelligent diagnosis method of large-scale ship engine fault based on neural network in non-deterministic environment is realized.

EXPERIMENTAL RESULTS AND ANALYSIS

To prove the validity and feasibility of intelligent fault diagnosis method for large-scale ship engine in non-deterministic environment based on neural network, an experiment is carried out under the operating system of Windows 7 Ultimate. The CPU model is 3.2Ghz Intel Core I3, running platform is Microsoft Visual Studio. NET 2010. Through the construction of large-scale ship engine fault intelligent diagnostic platform, using the signal processing board shown in Figure 1 to deal with the engine data, the proposed method and the methods proposed in literature [8] and [9] are used, respectively, compare the results and complete the experiment.

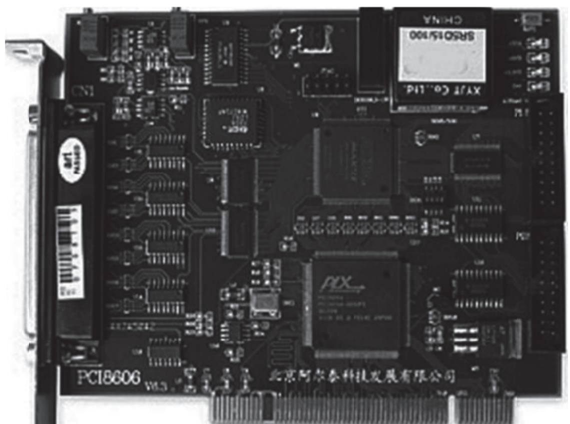

Fig. 1. Signal Processing Board

First, the experimental process of the proposed method is shown in Figure 2.

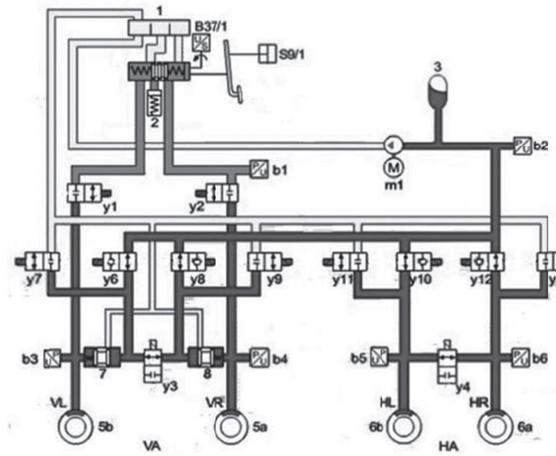

Fig. 2. Intelligent Diagnosis Process of Large-scale Ship Engine Fault Based on the Neural Network

Figure 2 showed that the proposed method can realize the intelligent diagnosis of large-scale ship engine fault, and effectively realize the real-time data monitoring and fault analysis, it can monitor the operating status of the components in the engine system which has a strong use value.

Then, the response time (s) and the time-consuming (s) of the proposed method are compared with that proposed in literature [8] and [9], which are shown in figure 3 and 4.

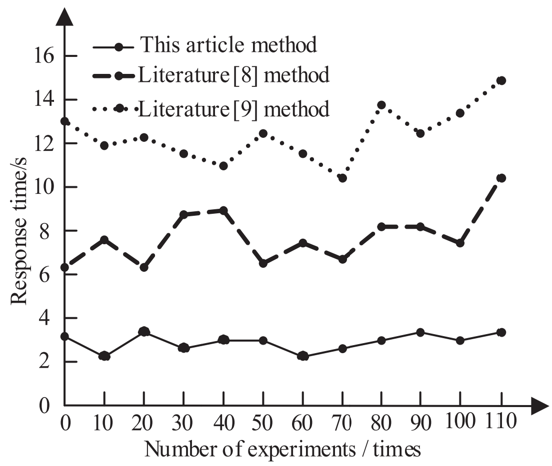

Fig. 3. Comparison of Response Time for Three Diagnosis Methods

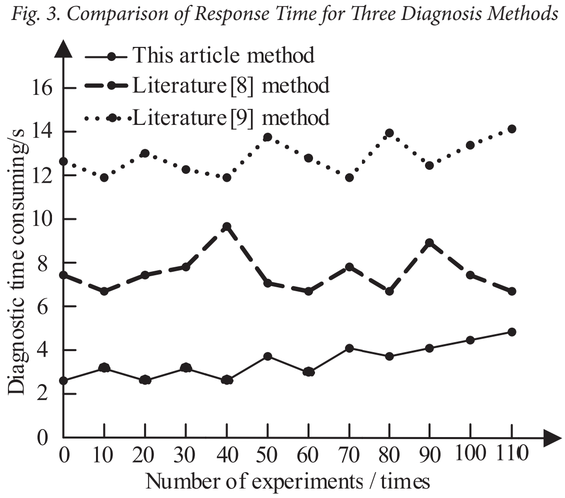

Fig. 4.Comparison of Time-consuming for Three Diagnosis Methods

The fault diagnosis delay is the time difference between the response time and the fault time of the ship engine fault. It can be seen from the above figure that the fault time of the proposed method is short, which can reflect the ship engine fault timely, reduce the engine fault caused by other ship system fault and reduce the difficulty of fault repair.

Finally, the efficiency of ship engine fault diagnosis is compared and the efficiency of ship engine fault diagnosis is set as (%). The calculation method is shown in equation (21). Through experiments, three methods are used to compare the efficiency of ship engine fault diagnosis. The comparison results shown in Figure 5.

$$\text{Diagnostic Efficiency} = \text{Diagnostic Accuracy} \times \frac{\text{Diagnostic Time Consuming}}{\text{Diagnostic Delay}} \quad (21)$$

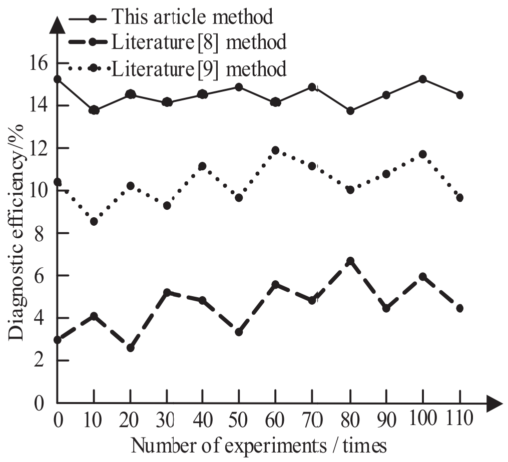

Fig. 5.Comparison of the Diagnostic Efficiency for Three Diagnosis Methods

Figure 5 showed that the diagnostic efficiency of the proposed method is higher which has a better diagnostic effect. Because of the fault diagnosis model is established before the fault diagnosis, the diagnostic accuracy is improved, which also improved the diagnostic efficiency [13-16].

In this paper, the proposed method is concerned with the fault diagnosis of ship engine, which has a less diagnostic response time, a faster diagnostic speed and a higher efficiency [17]. The diagnostic content of the proposed method is more comprehensive, which promote the research development in this field[18].

CONCLUSION

1. In this paper, a fault diagnosis method for large-scale ship engine fault in non-deterministic environment based on neural network is proposed. Firstly, the fault source and fault features of large-scale ship engine are analyzed to determine the fault of large-scale ship engine and the main fault mode. Based on this, the neural network is used to construct the fault diagnosis model, and completed the intelligent diagnosis method through the establishment of ship engine fault sample space and the selection of diagnosis model.
2. The experimental results showed that the proposed method has a higher reliability, and the real-time diagnosis is more real-time compared with the method proposed in literature [8] and [9], which can effectively diagnose the fault of large-scale ship engine in non-deterministic environment.

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