An Intelligent Fault Diagnosis Scheme Based On PCA-BP Neural Network for the Marine Diesel Engine

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Abstract. Using AVL-BOOST to simulate the thermal fault of diesel engine, the principal component analysis method is used to analyze the thermal fault of diesel engine, and the three principal components are selected that can reflect the original variable 99.589% information as the input of BP neural network. The failure mode of the diesel engine is used as an output to construct a three-layer neural network prediction model. The results show that the PCA-BP neural network model can well diagnose the failure mode of diesel engines.

1. Introduction

As the core equipment of marine power plant, marine diesel engine is widely used in the field of ships. However, due to its poor working conditions, it is prone to failure, which will affect the operation of the ship and may cause huge economic losses and even cause damage to key equipment and endanger personal safety [1]. If the fault can be detected and repaired according to the relevant operating data of the diesel engine, the accident can be avoided and the economic loss can be reduced.

The various thermal parameters of the diesel engine can directly reflect the state of the diesel engine working process, and these data are easy to collect and can be used for fault diagnosis of diesel engines. Therefore, the AVL-BOOST software [2] is used to simulate the turbocharger fault and fuel injection fault of MAN B&W L16/24 diesel engine in this paper. The diesel engine simulation model can produce the actual thermal parameters, and the principal component analysis (PCA) is adopted to carry out the dimension reduction of thermal parameters, finally, the processed data is input into the BP neural network to achieve the goal of intelligent diagnosis.

2. Principal component analysis and BP neural network

2.1. Principal component analysis

Principal component analysis (PCA) is a commonly used dimensionality reduction method in multivariate statistics [3]. PCA selects fewer unrelated new variables to replace the original more associated variables, and the new variables are linear combinations of the original variables. Due to the large number of variables in the research object, a lot of data needs to be processed during the analysis, which leads to a complicated calculation process and an increase in computational workload.
Principal component analysis can reduce the dimension of the data, and the selected variables after dimension reduction contain enough original variable features, which can significantly reduce the workload.

The PCA is to collect enough sample data of diesel engine running under normal conditions, establish the principal component statistical model of normal data. In the process of calculation, first, the data of the diesel engine operating under normal conditions is standardized according to the formula (1), this is mainly to avoid the impact of different dimensions of different index variables of diesel engine on the calculation. The standardized formula is:

$$\bar{X} = \frac{X - \mu}{D \sigma}$$  \hspace{1cm} (1)

Where $X$ is a sample row vector of $X = [x_1, x_2, \cdots, x_m]$, $\mu$ is the mean value of the sample, $D \sigma$ is the sample variance, the standardized sample data set is still marked as $X_{train}$.

The data $X_{train}$ obtained by standardized calculation can be regarded as a matrix $R_{m \times n}$, it can be decomposed into the sum of external product of $n$ vectors, the formula is as follow:

$$X_{train} = t_1 p_1^T + t_2 p_2^T + \cdots + t_n p_n^T$$  \hspace{1cm} (2)

Where $t_i \in R_n$ is the score vector, $p_i \in R_m$ is the load vector. The score vector is also called the principal element. The above formula can be simplified as follows:

$$X_{train} = TP^T$$

Where $T = [t_1, t_2, t_3, \cdots, t_n]$ is the score matrix, $P = [p_1, p_2, p_3, \cdots, p_m]$ is the load matrix. And there is:

$$\begin{cases}
P_i^T P_j = 0(i \neq j) \\
P_i^T P_j = 1(i = j)
\end{cases}$$  \hspace{1cm} (3)

Multiply the left and right sides of formula (3) by $P_i$ at the same time, the following formula is obtained:

$$X_{train} p_i = t_1 p_1^T p_i + t_2 p_2^T p_i + \cdots + t_n p_n^T p_i$$  \hspace{1cm} (4)

Substitute formula (3) into formula (4), can get:

$$t_i = X_{train} p_i$$  \hspace{1cm} (5)

Formula (5) shows that each score vector is actually the projection of data matrix $X_{train}$ in the direction of load vector corresponding to this score vector. Among them, the projection of the original data changes in the first several load vector directions is large, the first few principal components are enough to reflect the main information of the process. Therefore, matrix $X_{train}$ can be decomposed as follows:

$$X_{train} = \tilde{X} + \bar{X} = t_1 p_1^T + t_2 p_2^T + \cdots + t_k p_k^T + E$$  \hspace{1cm} (6)
Where $E$ is the residual matrix. Can decompose $X_{train}$ into principal component subspace (Principal Component Subspace, PCS) and residual subspace (Residual Subspace, RS). As shown in Figure 1.

![Figure 1. Data projection of principal component analysis](image)

As shown in Figure 1, the decomposed PCS and RS are orthogonal subspaces. The two subspaces have different meanings, PCS mainly reflects the change of normal data, RS mainly reflects the change of abnormal data. When the fault occurs, the projection of $X_{train}$ on RS will increase significantly, so the fault detection of diesel engine is carried out by this principle.

In the process of establishing the principal component model, it is very important to determine the number of principal components, it directly determines the quality of the established principal component model. This is because when the number of principal components is less, the ability of data interpretation will decrease; when the number of principal components is large, in the data, too much noise will be introduced into the principal component model, so as to increase the deviation of the principal component model. The method of principal component selection is usually based on the cumulative contribution rate, the principle is shown below.

The maximum eigenvalue of the sample covariance matrix corresponds to the variance of the first principal element, and so on. The ratio of the variance of each principal component to the total variance is the corresponding contribution rate of the principal component, the eigenvalues of variance are arranged in the order of large to small, find the cumulative contribution rate, the formula is as follows:

$$
\frac{1}{n} \sum_{i=1}^{k} \lambda_i \geq 0.85
$$

When the cumulative contribution rate reaches 85%, the first $k$ principal components can be selected to replace the original $m$ principal components. Because there is a strong linear relationship between the first $k$ principal components and the later data, it can well replace the data characteristics of the sample population, reduce dimensions, at the same time, it can also reduce the workload.

The steps of PCA are as follows:
1) Standardization of raw data;
2) Calculation of the correlation coefficient matrix;
3) Find the eigenvalues and eigenvectors of the correlation matrix $R$.
4) Calculate the cumulative contribution rate of the principal component and determine the number of principal components [4];
5) Calculate the principal component and calculate the principal component value as the input of BP neural network.
2.2. **BP neural network**

The neural network is a multi-level forward neural network [5], which consists of input layer, hidden layer and output layer. Its core is to continuously adjust the parameters of network by transmitting errors backwards and correcting errors, which can achieve the goal of desired input and output mapping relationships. Currently, BP neural network is widely used in the field of information processing and pattern recognition.

BP neural network is a multilayer forward network, as shown in Figure 2, it is mainly divided into three layers: Input layer, hidden layer and output layer, each layer is composed of several simple neurons with parallel operation. The neurons of each layer are connected to each other, there was no connection between neurons in the same layer. According to the network model structure, the input signal first enters the input layer node, then go to the hidden layer, and finally to the output layer. In the whole process of signal transmission, the weight of the network remains unchanged, the upper neurons only affect the lower neurons. When the error between the output of the network and the expectation is large, it will enter the back propagation process, Correct the weight of each layer of neurons according to the negative gradient direction of the error function, make the error meet the set value requirements of the network model, finally complete the network learning.

![Figure 2. Three layer BP network structure chart](image)

As shown in Figure 2, the input vector of the network is \( X = (x_1, x_2, \cdots, x_m)^T \), the output vector of the hidden layer is \( Y = (y_1, y_2, \cdots, y_{n-1})^T \), the output vector of the output layer is \( O = (o_1, o_2, \cdots, o_{l})^T \), The expected output vector is \( d = (d_1, d_2, \cdots, d_l)^T \). The weight matrix from input layer to hidden layer is \( V = (v_1, v_2, \cdots, v_{n-1})^T \), The weight matrix from the hidden layer to the output layer is \( W = (w_1, w_2, \cdots, w_{l})^T \). The structure of each layer is described as follows:

For the output layer, there are:

\[
o_k = f(net_k) \quad k = 1, 2, \cdots, l
\]  

\[
net_k = \sum_{j=0}^{m} a_{jk} y_j \quad k = 1, 2, \cdots, l
\]
For the hidden layer, there are:

\[ y_j = f(\text{net}_j) \quad j = 1, 2, \ldots, m \]  

\[ \text{net}_j = \sum_{i=0}^{n} v_{ji} x_i \quad j = 1, 2, \ldots, m \]

In the above two formulas, The transfer function \( f(x) \) adopts the unipolar S-type function, the formula is:

\[ f(x) = \frac{1}{1 + e^{-x}} \]  

For the derivation of \( f(x) \) in (12), there are:

\[ f'(x) = f(x)[1 - f(x)] \]

When solving some problems, the transfer function can also adopt bipolar S-type function, and its formula is as follows:

\[ f(x) = \frac{1 - e^{-x}}{1 + e^{-x}} \]

In the structure of BP neural network, it is very important to determine the number of neurons in the hidden layer, too many or too few of them can determine whether the performance of the network model is in an ideal state. Therefore, the number of them can be determined according to the previous experience, the empirical formula is:

\[ n = \sqrt{m + l} + a \]

\[ n = \log_2 m \]

\[ n = 2m + l \]

Where \( m \), \( n \) and \( l \) are the number of nodes in input layer, hidden layer and output layer respectively, constant of \( a \in [1, 10] \).

In the process of actually solving problems, there is a deviation between the number of hidden layers and the number calculated by the above formula. In order to determine the optimal number of neurons in the hidden layer, we need to debug it according to the actual situation.

The application of three-layer network structure of BP algorithm in artificial neural network is classic, next, the relationship between the transfer process of BP learning algorithm is deduced, this can better grasp the principle of BP neural network.

The output error \( E \) of the network is the difference between the real output and the expected output, The calculation formula is:
Expand formula (19) to obtain the hidden layer as follows:

\[
E = \frac{1}{2} \sum_{k=1}^{l} \left[ d_k - f(\text{net}_k) \right]^2 = \frac{1}{2} \sum_{k=1}^{l} \left[ d_k - f(\sum_{j=0}^{m} \omega_{jk} y_j) \right]^2
\]  

(19)

In the same way, expand to get the input layer as follows:

\[
E = \frac{1}{2} \sum_{k=1}^{l} \left[ d_k - f(\sum_{j=0}^{m} \omega_{jk} f(\sum_{i=0}^{n} v_{ij} x_i)) \right]^2
\]  

(20)

In formula (21), \( \omega_{jk} \) and \( V_{ij} \) are the weight functions of each layer of network error. In order to train the network in the direction of convergence, the error \( E \) needs to be changed by constantly adjusting the weight. Therefore, the purpose of adjusting the weight is to make the network error converge to the decreasing trend, the adjustment amount of weight should be in direct proportion to the decrease of network error gradient, namely:

\[
\Delta w_{jk} = -\eta \frac{\partial E}{\partial \omega_{jk}} \quad j = 0, 1, 2, \ldots; m; k = 0, 1, 2, \ldots, l
\]  

(21)

\[
\Delta v_{ij} = -\eta \frac{\partial E}{\partial V_{ij}} \quad i = 0, 1, 2, \ldots, n; j = 0, 1, 2, \ldots, m
\]  

(22)

In formula (22), negative sign indicates a gradient decrease, constant \( \eta \in (0, 1) \) is the rate of learning. This formula only gives the basic direction of weight adjustment, the specific weight adjustment calculation formula is derived below.

Formula (22) can be rewritten as:

\[
\Delta w_{jk} = -\eta \frac{\partial E}{\partial w_{jk}} = -\eta \frac{\partial E}{\partial \text{net}_k} \frac{\partial \text{net}_k}{\partial w_{jk}} = \eta \delta_k^o y_j
\]  

(23)

\[
\Delta v_{ij} = -\eta \frac{\partial E}{\partial v_{ij}} = -\eta \frac{\partial E}{\partial \text{net}_j} \frac{\partial \text{net}_j}{\partial v_{ij}} = \eta \delta_j^y x_i
\]  

(24)

It can be seen from formula (23) As long as \( \delta_k^o \) and \( \delta_j^y \) are obtained, the calculation formula of the weight adjustment amount can be derived.

For output layer, \( \delta_k^o \) can be expanded to obtain:

\[
\delta_k^o = -\frac{\partial E}{\partial \text{net}_k} = -\frac{\partial E}{\partial \sigma_k} \frac{\partial \sigma_k}{\partial \text{net}_k} = -\frac{\partial E}{\partial \sigma_k} f'(\text{net}_k)
\]  

(25)
For hidden layer, $\delta_j^y$ can be expanded to obtain:

$$\delta_j^y = -\frac{\partial E}{\partial \text{net}_j} = -\frac{\partial E}{\partial y_j} \frac{\partial y_j}{\partial \text{net}_j} = -\frac{\partial E}{\partial y_j} f'(\text{net}_j)$$  \hspace{1cm} (26)

For the output layer, according to formula (20), the derivation can be obtained:

$$\frac{\partial E}{\partial o_k} = -(d_k - o_k)$$  \hspace{1cm} (27)

For the hidden layer, according to formula (21), the derivation can be obtained as follows:

$$\frac{\partial E}{\partial y_j} = - \sum_{k=1}^{l} (d_k - o_k) f'(\text{net}_k) w_{jk}$$  \hspace{1cm} (28)

Substituting formula (27) and formula (28) into formula (25) and formula (26), we get:

$$\delta_k^o = (d_k - o_k) o_k (1-o_k)$$  \hspace{1cm} (29)

$$\delta_j^y = \left[ \sum_{k=1}^{l} (d_k - o_k) f'(\text{net}_k) w_{jk} \right] f'(\text{net}_k)$$

$$= \left[ \sum_{k=1}^{l} \delta_k^o w_{jk} \right] y_j (1-y_j)$$  \hspace{1cm} (30)

Substituting equation (29) and (30) into equation (24), the weight adjustment calculation formula is obtained:

$$\Delta w_{jk} = \eta \delta_j^y y_j = \eta (d_k - o_k) o_k (1-o_k) y_j$$  \hspace{1cm} (31)

$$\Delta v_y = \eta \delta_j^y x_i = \eta \left[ \sum_{k=1}^{l} \delta_k^o w_{jk} \right] y_j (1-y_j) x_i$$  \hspace{1cm} (32)

In this paper, the combination of PCA and BP neural network [6,7] makes the information processing capability of neural network stronger. The principal component analysis method is used to analyze the thermal fault of diesel engine, and the main component is used as the learning sample data of neural network, and the fault diagnosis model of neural network is built. Therefore, using the PCA-BP neural network combined analysis method, the advantages of both can be fully utilized, and the model algorithm has the learning ability and robustness of the neural network, which not only meets the accuracy requirements, but also reduces the neural network, and the complexity of the input layer neurons improves the learning rate of the BP network.
3. Simulation results

3.1. Simulation models
In this paper, the AVL-BOOST is used to simulate the diesel engine model. According to the module provided by the software, the configuration interface built with the actual situation of the simulation object is shown in Figure 3.

![Man B&W L16/24 Diesel Engine Simulation Model](image)

**Figure 3.** MAN B&W L16/24 diesel engine simulation model

The simulated diesel engine model is MAN B&W L16/24 diesel engine, which is a high-pressure 4-stroke diesel engine. The main parameters are shown as Table 1.

| Technical indicators                  | Values     |
|---------------------------------------|------------|
| Bore diameter (mm)                    | 160        |
| Stroke length (mm)                    | 240        |
| Link length (mm)                      | 480        |
| Compression ratio                     | 15.2: 1    |
| Linkage mass (kg)                     | 14.3       |
| Piston mass (kg)                      | 21.1       |
| Average effective pressure (Pa)       | 2.24×10⁶   |
| Rated speed (r/min)                   | 1 000      |
| Single cylinder power (kW)            | 90         |
| Maximum combustion pressure (Pa)      | 1.7×10⁷    |
| Fuel consumption (g/(kW·h))           | 189(+5%)   |
| Fire order                            | 1-2-4-6-5-3|

3.2. The verification of simulation model
In order to verify the effectiveness of the model, the validation of model is required. The simulated diesel engine model is MAN B&W L16/24 diesel engine, which is a high-pressure 4-stroke diesel engine. The main parameters are shown as Table 1. Since the model is mainly used for the research of thermal fault diagnosis methods for diesel engines, the final need is to extract the key thermal parameters and then use these parameters to generate sample data. Therefore, only the key thermal parameters of the model are compared in the Table 2. If the performance of the thermal parameters of the simulation model is consistent with the experimental results, then the rationality and correctness of
the model can be verified. The working condition under the 1000 r/min and the load of 100% is simulated, and the simulation results are as shown in the Table 2.

Table 2. The comparison of test results with calculated results

| Thermal parameters       | Experimental value | Simulation value | Error       |
|--------------------------|--------------------|------------------|-------------|
| PowerkW                  | 540                | 540.4            | 0.07%       |
| Fuel consumption g/(kW·h)| 192                | 189              | -1.56%      |
| Boost pressure Pa        | 3.67×10⁵           | 3.699            | 0.54%       |
| Temperature after cooler°C | 50.6               | 49.9             | -1.38%      |
| Maximum combustion pressure Pa | 18.6×10⁶          | 18.8             | 1.08%       |
| Turbine front exhaust temperature °C | 510               | 512              | 0.39%       |
| Turbine exhaust temperature °C | 330               | 334              | 1.21%       |

It can be seen from Table 2 that the calculation results are consistent with the data of the test results, which verifies the rationality and correctness of the model. Therefore, the model can be selected for the simulation analysis of thermal faults of diesel engines.

3.3. The process of fault diagnosis

In this paper, several typical thermal faults are selected for simulation. The selected faults are turbocharger faults and fuel injection faults. These two conditions have the most significant impact on diesel engine performance, and the fault probability is also the largest, which is very representative. Two different levels of failure are set for each type of fault, which are mild and severe. If the fault simulation involves in-cylinder parameters, the 3# cylinder is targeted. The parameter selection and settings are shown in Table 3.

Table 3. The fault simulation scheme

| Fault mode | Fault name               | Fault parameter setting                                                |
|------------|--------------------------|------------------------------------------------------------------------|
| I          | Single cylinder oil stop |                         | Parameter | Unit      | Normal value | Failure degree 1 | Failure degree 2 |
| II         | Compressor blockage      | Compressor efficiency — 0.65 0.6 0.55                                  |
| III        | Injection timing lag     | Burning start time(Top dead center) CA 5 4 3                            |
| IV         | Fuel injection timing in advance | Burning start time (Bottom dead center) CA 5 6 7                        |
| V          | Injector blockage        | Single cylinder cycle injection quantity mg 576 526 476                |

In this paper, considering the unit of different thermal parameters and the difference of the order of magnitude, the simulation data is dimensionlessly processed, that is, the offset rate of the thermal parameters is used to represent the current state of the thermal parameters, so that all the thermal parameters are in the same Under the condition of reference, it is convenient for pattern recognition of neural networks. The results are shown in Table 4.
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Table 4. Thermal parameter shift rate corresponding to different thermal faults of diesel engine

| $P_{oi}$ | $T_{oi}$ | $P_{co}$ | $T_{co}$ | $P_{ao}$ | $T_{ao}$ | $P_{ni}$ | $T_{ni}$ | $P_{max}$ | $T_{max}$ | $P_{co}$ | $T_{co}$ | $P_{ni}$ | $T_{ni}$ | $N_e$ | $P_e$ | Mode |
|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|-------|------|------|
| 0.6     | 0.2     | 0.1     | 0.0     | 0.0     | 0.0     | 0.0     | 0.0     | 0.0     | 0.0     | 0.0     | 0.0     | 0.0     | 0.0     | 0.0   | 0.0  | I    |
| 0.0     | 0.5     | 3.2     | 0.0     | 0.0     | 0.0     | 0.0     | 0.0     | 0.0     | 0.0     | 0.0     | 0.0     | 0.0     | 0.0     | 0.0   | 0.0  | II   |
| 0.6     | 0.4     | 0.3     | 0.0     | 0.0     | 0.0     | 0.0     | 0.0     | 0.0     | 0.0     | 0.0     | 0.0     | 0.0     | 0.0     | 0.0   | 0.0  | III  |
| 0.1     | 0.5     | 0.0     | 0.3     | 0.0     | 0.0     | 0.0     | 0.0     | 0.0     | 0.0     | 0.0     | 0.0     | 0.0     | 0.0     | 0.0   | 0.0  | IV   |
| 0.1     | 0.5     | 0.0     | 0.0     | 0.0     | 0.0     | 0.0     | 0.0     | 0.0     | 0.0     | 0.0     | 0.0     | 0.0     | 0.0     | 0.0   | 0.0  | V    |

Principal component analysis was then performed on the data in Table 4, and the results are shown in Table 5.

Table 5. Contribution rate and cumulative contribution rate of principal components

| Serial number | Eigenvalues | Contribution rate | Cumulative contribution rate |
|---------------|-------------|-------------------|------------------------------|
| 1             | 11.589      | 72.432            | 72.432                       |
| 2             | 3.783       | 23.643            | 96.075                       |
| 3             | 0.562       | 3.514             | 99.589                       |
| 4             | 0.041       | 0.256             | 99.846                       |
| 5             | 0.015       | 0.094             | 99.940                       |

It can be seen from the calculation results in Table 5 that the eigenvalue of the first principal component is 11.589, which contains 72.432% of the information of the overall variable. The larger the eigenvalue, the more information is contained in the original data. Because the cumulative contribution rate of the first three principal components is 99.589%, which already contains enough information of the original variables, and the subsequent contribution rate is relatively small, the first,
second and third principal components are selected as the overall evaluation indicators. The degree reaches 99.589%, and it can be considered that the first three principal components of the extraction can contain most of the information of the original 16 variable indicators. Then, the principal component values of the first, second, and third are calculated, and the results are shown in Table 6.

Table 6. The Principal components of sample data

| Sample number | Principal component 1 | Principal component 2 | Principal component 3 |
|---------------|------------------------|------------------------|------------------------|
| 1             | -7.59                  | -2.67                  | -0.17                  |
| 2             | -0.47                  | 1.78                   | -0.21                  |
| 3             | 2.28                   | -0.33                  | -0.45                  |
| 4             | 2.09                   | -0.46                  | 0.70                   |
| 5             | 1.49                   | -0.71                  | 0.22                   |
| 6             | -3.32                  | 4.22                   | 0.14                   |
| 7             | 2.67                   | -0.31                  | -1.56                  |
| 8             | 2.11                   | -0.52                  | 1.07                   |
| 9             | 0.74                   | -1.00                  | 0.26                   |

The first six sets of data of the diesel engine thermal parameters after PCA processing were selected as the training test, and the last three groups were used as test samples. The BP neural network was created by Matlab software. The three principal components were used as input vectors, and the fault mode output matrix of the diesel engine was used as the target vector. The output matrix is expressed as: [1,0,0,0,0] is represented as single-cylinder oil stop, [0,1,0,0,0] is represented as compressor blockage, [0,0,1,0,0] is expressed as injection timing lag, [0,0,0,1,0] is indicated as injection timing advance, and [0,0,0,0,1] is indicated as injector clogging.

For this diagnostic system, the neural network is created using the newff.m function of Matlab's neural network toolbox. The structure of network is 3-12-5. The transfer function of implicit layer is tansig. The transfer function of output layer is logsig. The training function is trainlm. The number of iterations are 2000. The learning rate is 0.01. The target error is 0.00001. The network training error curve is shown in Figure 4.

![Figure 4. The network training error curve](image-url)
It can be seen from Fig. 2 when the calculation reaches 8 steps, the training error value reaches the target error requirement. The last three sets of data were used as test samples to test the trained network. The results are shown in Table 7.

| Sample number | Predicted result | Expected result | Prediction accuracy (%) | Fault mode          |
|---------------|-----------------|-----------------|-------------------------|---------------------|
| 7             | [0.0002, 0.0001, 1, 0.0002, 0.0003] | [0,0,1,0,0] | 100 | Injection timing lagged |
| 8             | [0.0001, 0.0001, 0, 0.9769, 0.0009] | [0,0,0,1,0] | 97.69 | Fuel injection timing advanced |
| 9             | [0.0002, 0, 0.0001, 0.0008, 0.9954] | [0,0,0,0,1] | 99.54 | Injector blockage |

It can be seen from Table 7 that the model has high diagnostic accuracy for the failure mode of the diesel engine, which is consistent with the actual situation, indicating that the method can correctly identify the failure mode of the diesel engine.

4. Conclusion

1) Using PCA to process the simulated data of the diesel engine, the dimension of parameters to be identified is reduced from 16 to 3, which greatly reduces the complexity of the model, and the diagnostic efficiency and accuracy are high.

2) Combining PCA with BP neural network, the diagnostic model of PCA-BP neural network is built. Through the example verification, the method can be well used for the diagnosis of marine diesel engine.

3) This diagnosis model can only diagnose the fault mode that has been set in this paper, and it cannot be identified when multiple faults occur or other fault occur, but the subsequent setting of the diesel engine’s fault simulation can be increased to improve the diagnostic capability of the fault mode.

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