Design of diesel engine fault prediction system based on MATLAB

Wei Liu¹, Yu Gan¹, Ning Chen¹ and Zhimin Wang²

¹Energy and Power School, Jiangsu University of Science and Technology, Zhenjiang, Jiangsu, 212003, China
²Research and Development Department, SaierNico, Zhenjiang, Jiangsu, 212000, China
*Corresponding author’s e-mail: liu_just@163.com

Abstract: For the fault of main bearing wear of diesel engine, this paper puts forward the idea of combing artificial neural network and bearing wear warning system together. Selecting RBF neural network calculating fast as a research tool, diesel cross-head slide block working as the research object, we make the related systems. When the position of the slider changes due to wear, the sensor which monitors the position can immediately transmit the fault data to neural networks, after calculation, the neural network put the fault type out, to search the place of the failure. This method is of high accuracy, fast speed, and the results suggest clear.

1. Introduction
In recent years, with the fast development of the mechanical fault diagnosis technology, intelligent fault prediction system has become an important target of research and development. Jing Yao (Shanghai Jiao Tong University, 2015) proposes that the three-stage learning method to construct the running curve of diesel engine bearing [1]. Jigang Jia (Automotive Engineering, 2018) proposes that the vibration signal is used to judge the diesel engine fault [2]. Jun Zhu (Diesel Engine, 2017) proposes that the wear state of bearing was measured by thermoelectric method [3]. Although the method proposed above can partly solve the monitoring problem of main bearing wear of diesel engine, we can not use smart algorithms for lack of mass of data. Radial Basis Function Neural Network is proposed in this paper as a research carrier, which is easy to compile, with fast convergence, has effectively improved the accuracy of diesel engine fault diagnosis.

2. Basic Theory of RBF Neural Network
The structure of the regularized RBF network is shown in Figure 1. Features are: the model has N input points, P hidden neurons, L output points [4]. The number of hidden neurons of the model is equal to the number of input samples. Hidden neurons are trained by the Gaussian function, and all the input data is set as the center of the function.
3. Test Method for Bearing Wear of Two Low-Speed Two Stroke Diesel Engine

Some reasons may lead to the change of the lower stop (BDC) position of one or more cross-heads. The monitoring system of bearing wear studied in this paper is based on a distance measured by a sensing system. The function of the sensor is to measure the real-time position of the stop point under the cross-head, which can be installed on the guide plate inside the diesel engine frame. Based on the research object of six-cylinder low-speed two-stroke diesel engine, two eddy current displacement sensors are installed in each cylinder to monitor the position of the stop point under the cross-head of the diesel engine[5]. A diesel engine bearing detection system based on RBF neural network is established.

4. Construction of Neural Network for Bearing Failure Prediction

4.1. Description of the diagnostic problem

The diagnosis background of this simulation is the working state of the main bearing of a marine diesel engine. The six-cylinder marine diesel engine is selected as the research object for the fault diagnosis of the main bearing of the diesel engine. Put 12 sensors (two for each cylinder) in six cylinders (numbered sequentially: 1, 2, 3, 4, 5, 6) and number sequentially: 1.1, 1.2, 2.1, 2.2, 3.1, 3.2, 4.1, 4.2, 5.1, 5.2, 6.1, 6.2. So there are a total of 12 input vectors. At the same time, each cylinder corresponds to an alarm light, and the sensors continuously receive the real-time data from the diesel engine. When the data exceeds the previously set safety range, the alarm light of the corresponding cylinder will flash and alarm, and the position of the fault will be judged according to the serial number of the light.

4.2. Establishment and Simulation of Neural Network Model

According to the characteristics of the radial basis function[6], the data of this experiment has 12 sets of feature vectors. Each set of feature vectors corresponds to 560 sets of samples, and there is also an evaluation reference of 560 sets to judge the fault type. Therefore, the structure of the designed RBF neural network is: the input layer has 12 neurons, the output layer has 1 neuron, the middle layer
neurons use Gaussian function as the training function, and the transfer function of the output layer is a linear function. Randomly scramble each group of samples, select 480 groups of samples as training set (P-train, T-train), and the remaining 80 groups as test samples (P-test, T-test). After a series of calculations, a neural network is created.

Next, we need to determine the value of spread. In the RBF diagnosis process, the diagnostic accuracy is mainly affected by the expansion coefficient of spread, and also affected by the training samples. The more samples, the higher the accuracy. The value of spread is also the key to the accuracy rate. Therefore, under the premise of a fixed number of training samples, spread is selected many times, and then many simulation experiments have been completed to judge the effect of the expansion coefficient on the experimental accuracy, and choose the most suitable expansion coefficient. The following are two typical coefficients: the experimental results obtained by 0.01, 0.06.

![Figure 3. Accuracy spread 0.01.](image)

![Figure 4. Accuracy spread 0.06.](image)

From the analysis of the simulation results, it can be seen that as the value of spread continues to change, the accuracy of the experiment also fluctuates. When the value of spread reaches 0.06, the accuracy of the system is the highest, so 0.06 is selected as the final spread value.

After all the values are determined, perform the neural network test. The following are the test sample data and output results.

| Serial number | Sample testing | Simulation results | Error | Serial number | Sample testing | Simulation results | Error |
|---------------|----------------|--------------------|-------|---------------|----------------|--------------------|-------|
| 1             | 2              | 3.44285704         | 0.72142852 | 22            | 7              | 6.63462434         | 0.05219652 |
| 2             | 3              | 3.97233426         | 0.32411142 | 23            | 2              | 2                  | 2.09E-14     |
| 3             | 5              | 6.00007011         | 0.20001402 | 24            | 2              | 2                  | 1.07E-14     |
| 4             | 3              | 3.98025237         | 0.32675079 | 25            | 2              | 2                  | 1.95E-14     |
| 5             | 4              | 4.50171051         | 0.12542763 | 26            | 7              | 6.51974438         | 0.06860795  |
| 6             | 6              | 6.15367532         | 0.02561255 | 27            | 2              | 3.83579783         | 0.91789891  |

Table 1. Outputs.
7 2 2.03168466 0.01584233 28 4 4.44280078 0.11070019
8 6 6.001198 0.00019967 29 3 3 3.55E-15
9 3 3 1.42E-14 30 5 5.35181186 0.07036237
10 6 6.00001648 2.75E-06 31 7 7 5.58E-15
11 1 1 1.78E-14 32 3 3 1.42E-14
12 4 4.24921463 0.06230366 33 5 5.34530046 0.06906009
13 1 1 7.46E-14 34 6 6.00001127 1.88E-06
14 5 4.45504055 0.10899189 35 1 1 3.55E-15
15 6 6.00001715 2.86E-06 36 7 6.57058439 0.06134509
16 3 6.00007011 1.00002337 37 4 4.28306356 0.07076589
17 2 2 2.13E-14 38 4 4.72267360 0.1806684
18 2 4.11976921 1.05988461 39 6 4.58418788 0.23596869
19 2 2.72274312 0.36137156 40 7 6.3667005 0.09047136
20 1 1 3.55E-15 41 1 1 1.07E-14
21 4 4.26984521 0.0674613 42 1 1 1.07E-14

Network test results and analysis: In order to detect the ability of network diagnosis, the following simulation experiment was carried out, and 560 sets of data were divided into 7 categories. The first category of 42 sets of data of each feature vector is accurate, and the corresponding fault type is 0; The second type of 42 sets of data gets errors in the feature vectors of No. 1 and No. 2 subject to the No. 1 cylinder, and the corresponding fault type is 1, the third type of 42 sets of data gets errors in the feature vectors of No. 3 and No. 4 subject to the No. 2 cylinder, and the corresponding fault type is 2, and so on, there are 7 fault types in total. Through 42 randomly generated test samples, compared with 42 sets of simulation results, the final accuracy rate reached 0.94163.

4.3. Six-cylinder simultaneous failure experiment test
Corresponding to a six-cylinder diesel engine, a failure during operation does not necessarily mean that the corresponding single cylinder is damaged. Sometimes two or more errors occur at the same time. At this time, the above-mentioned neural network cannot be used to determine the location of the errors. Therefore, for the above problems, We make improvements for the neural network. The dimension of the feature vector extracted in this paper is 12, so the number of nodes in the input layer is also 12. The output layer is changed, because there are a total of 12 sensors in this experiment. The number of nodes in the output layer is changed from the previous 7 to 12. That is to say that the output
result is represented by 12 digits. For the convenience of observation, we change the output result into binary representation. The corresponding matrix of fault types is shown in Table 2.

Table 2. Fault type correspondence matrix.

| Serial number | Fault Type Matrix T       | Type of fault                  |
|---------------|--------------------------|--------------------------------|
| 1             | [101000000000]           | Damage to cylinder 1.2         |
| 2             | [101000000000]           | Damage to cylinder 1.3         |
| 3             | [101010000000]           | Damage to cylinder 1.2, 3      |
| 4             | [101000100000]           | Damage to cylinder 1.2, 4      |
| 5             | [101010100000]           | Damage to cylinders 1.2, 3 and 4 |
| 6             | [101010001000]           | Damage to cylinders 1.2, 3 and 5 |
| ...           | ...                      | ...                            |
| ...           | ...                      | ...                            |
| 11            | [111111111111]           | Damage to cylinders 1.2, 3, 4, 5 and 6 |

A large number of experimental data that meet the conditions are selected from the database and brought into the neural network for testing. The output results are shown in Table 3.

Table 3: Outputs

| Serial number | Sample testing | Simulation results | Error     |
|---------------|----------------|--------------------|-----------|
| 1             | 0              | 0.25843264         | 0         |
| 2             | 0              | -1.53268543        | 0         |
| 3             | 0              | 0.28563576         | 0         |
| 4             | 576            | 573.2474723        | -0.00478  |
| 5             | 1280           | 1265.863264        | -0.01104  |
| 6             | 33             | 41.26475215        | 0.250447  |
| 7             | 2368           | 2367.127336        | -0.00037  |
| 8             | 2192           | 2230.642164        | 0.017629  |
| 9             | 37             | 21.002532          | -0.43236  |
| 10            | 2384           | 2380.632144        | -0.00141  |
| 11            | 344            | 321.1256334        | -0.0665   |
| 12            | 1275           | 1210.613948        | -0.0505   |
| 13            | 1636           | 1630.153032        | 0.000609  |
| 14            | 682            | 677.2715337        | -0.00693  |
| 15            | 2470           | 2520.108533        | 0.020287  |
| 16            | 1365           | 1410.198533        | 0.033112  |

After the neural network test, the accuracy of the result is 0.91712, which shows that it can be used as a reference standard. The results are shown in Figure 5. The neural network can more accurately infer the location of each fault, the experimental accuracy is high, and can realize the application.
5. Conclusions
Based on the above introduction, the mechanical fault diagnosis can be solved by neural network, and the RBF neural network used in this paper successfully diagnose the main bearing fault of diesel engine. The results show that the RBF neural network is a kind of good feed-forward network, which can be applied to the diagnosis method of the main bearing fault of marine diesel engine.

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