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Design of a ship fault diagnosis system based on a radial basis neural network

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Abstract: Marine diesel engines in the operation process often exhibit single-cylinder oil stops, uneven single-cylinder oil supplies, excessively large exhaust valve gaps, injection timing lags, and other errors. Technicians with experience often cannot accurately determine the fault type. To improve the accuracy of the fault diagnosis, a simulation experiment was carried out in MATLAB, the initial evaluation was carried out using the sensor, and the fault type was determined based on the radial basis neural network during deep diagnosis. The results showed that the radial-based neural network ship fault diagnosis system can stabilize the assessment accuracy by more than 90%, which improves the accuracy of the fault assessment of technicians, thus reducing the incidence of ship accidents.

1. Introduction

With the development of the global economy, more than 90% of international trade is carried out by ships. Undoubtedly, to improve trade efficiency and cost savings, it is necessary to improve the development of ship technology, the key to improving the development of ship technology is to improve the diagnostic technology of ship diesel engines. With the development of information technology, an increasing number of scientists worldwide have begun studying diesel engine diagnostic technologies. Expert diagnosis is based on the technicians' experience at the beginning of diagnostic technology using an expert diagnosis algorithm. However, this type of technology relies heavily on human factors and the accuracy of diagnosis is not high [1]. With the development of artificial intelligence and machine learning, intelligent algorithms are being gradually applied to marine diesel engine diagnostic technologies [2]. By learning from a large amount of fault data, a fault-type recognition network was constructed to monitor diesel engine operations and identify fault types. Existing fault diagnosis techniques often require intelligent algorithms to identify and compare large amounts of data based on the type of fault, and have long running times, which can result in huge losses in the event of a ship failure when time is of the essence if the fault is not assessed and resolved in a timely manner. To solve this problem, this study pre-classifies diesel engine operating data using sensor evaluation and divides the operating parameter signals into three main categories: pressure, temperature, and energy signals. Through expert diagnosis for the initial judgment, the use of a radial basis neural network for the depth of judgment not only improves the algorithm operation cycle but also improves the accuracy of fault diagnosis[3].

2. Initial sensor diagnostics

Prior to the radial-based neural network fault diagnosis, sensors were used to make an initial determination, and the collected signals were collected and transmitted to a data-processing center for signal processing. Comparison with existing fault data: The signals were divided into three categories: pressure, temperature, and energy. A technician made the preliminary diagnosis, as shown in Fig. 1.

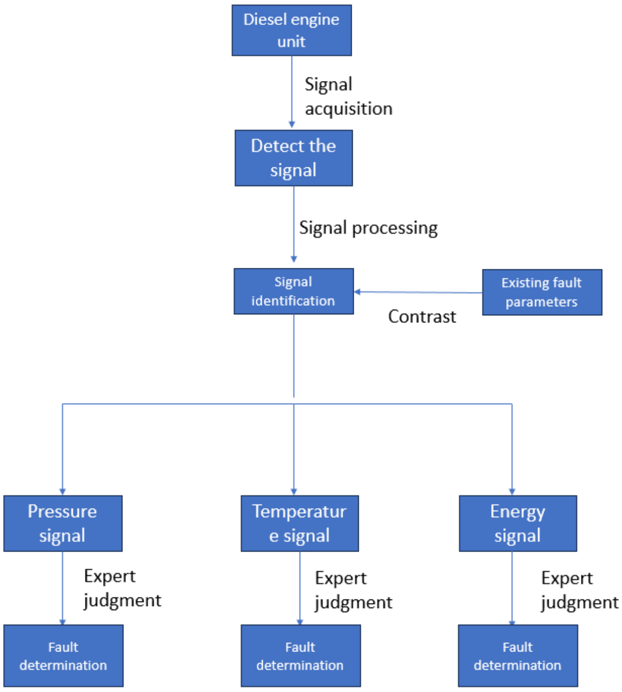

Figure 1: Sensor fault diagnosis procedure

3. Common operating faults of diesel engines

The ship diesel engines in the operation of a wide range of failures listed here are major types of failures that are introduced: single-cylinder oil stop, single-cylinder oil supply uneven, exhaust valve valve gap is too large, and injection timing delay. A single-cylinder oil stop refers to a ship sailing a marine diesel engine, because an insufficient oil supply leads to a decrease in the speed of the ship engine or even the phenomenon of stopping, leading to serious ship accidents. Uneven oil supply to a single cylinder refers to the uneven oil supply to diesel engine cylinders, which can lead to unbalanced operation of the diesel engine. An excessive oil supply can lead to cylinder explosions, and the black smoke and exhaust temperatures are too high. The exhaust valve clearance is extremely large. This is referred to as the exhaust-valve working environment. The exhaust valve is often subjected to high-temperature gas impact and is accompanied by a large mechanical load. The exhaust valve is in a harsh working environment. It is often subjected to high-temperature gas impact and is accompanied by a large mechanical load. Excessive clearance in the exhaust valve leads to interactions between the transmission parts and valve seats, which accelerates wear, shortens the valve opening time, and worsens the cylinder intake and exhaust. Injection timing lag refers to a situation in the operation of a diesel engine. In this process, the fuel supply is not timely. This can cause the diesel engine speed to drop, lead to a series of faults, or even result in diesel engine stopping.

To improve the effectiveness and credibility of the subsequent simulation, 12 types of marine diesel engine fault diagnosis indicators were selected as the basis for the fault evaluation. They are the net power, fuel consumption, average net power, maximum combustion pressure, maximum pressure rise ratio, compressor outlet pressure, intercooler inlet temperature, intercooler outlet temperature, cylinder exhaust temperature, intake manifold pressure, and exhaust manifold pressure.

4. Radial basis neural network

4.1 Introduction to Radial Basis Neural Networks

Most traditional PB neural network theories are based on learning algorithms for backpropagating multilayer feedforward networks. Most learning algorithms rely on nonlinear optimization techniques, which are computationally intensive and result in slow learning. However, the theory of radial basis function neural networks provides a novel and fast way to learn multilayer feedforward networks. Radial basis function neural networks not only have good generalization ability and require less computation, but also have faster learning speeds than other algorithms.

4.2 Principle of the radial basis neural network

A radial basis neural network is a three-layer neural network consisting of an input layer, hidden layer, and output layer, where the weights between the neurons in the input layer and those in the hidden layer are all 1. The transformation between the input and hidden layers was nonlinear. The weights between the hidden and output layers can be changed by training, and the transformation between the hidden and output layers is linear. The principle of a radial basis neural network is shown in Fig. 2.

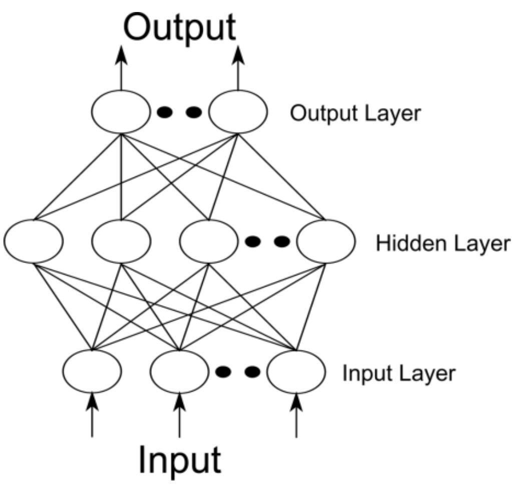

Figure 2: Schematic diagram of a radial basis neural network

The core idea of a radial basis neural network is to use a Gaussian kernel function, where no weights are set between the input and hidden layers, and the input vectors are mapped directly into the hidden space. Once the centroid of the radial neural network has been determined, the hidden layer is mapped directly to the output layer, and the weights between them change during execution.

Radial-based neural networks use Gaussian functions, so the activation function can be expressed as follows

$$R(x_p - c_i) = \exp\left(-\frac{1}{2\sigma^2}||x_p - c_i||^2\right) \quad (1)$$

The resulting expression for the output function of the radial basis neural network can be obtained as

$$y_j = \sum_{i=1}^{h} w_{ij} \exp\left(-\frac{1}{2\sigma^2}||x_p - c_i||^2\right) j = 1,2,\dots,n \quad (2)$$

The variance of the radial basis neural network can be expressed as

$$\sigma = \frac{1}{p}\sum_{j}^{m} ||d_j - y_i c||^2 \quad (3)$$

4.3 The Computational Flow of Radial Basis Neural Networks

The computational flow of the radial basis neural network is shown in Fig.3

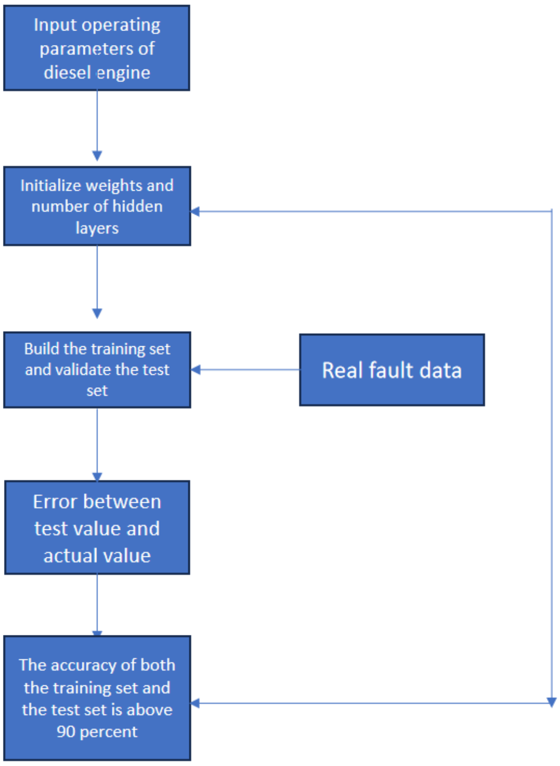

Figure 3: Flowchart of radial basis neural network computation

5. Radial basis neural network simulation experiment

5.1 Constructing the training set

By recording the operating parameters of a ship's diesel engine, collecting a series of parameters, such as pressure and temperature, and constructing a radial basis neural network in MATLAB, it was found that setting the training set to approximately 240 parameters provided the highest probability of diagnostic accuracy of 90% or more between the test set and the training set. Because of space limitations, the data for the first 15 parameters are given below [4], as shown in Figure 4.

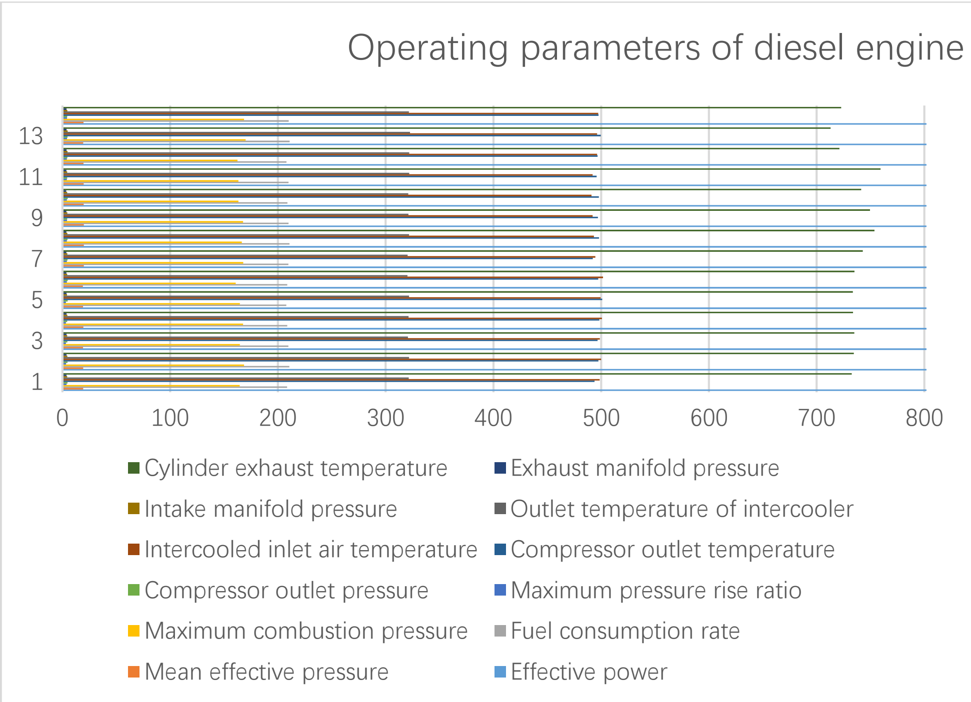

Figure 4: Diesel engine operating parameters table

The parameters of the diesel engine at the time of occurrence of various faults were learned using the radial basis neural network, and the learning results of the radial basis neural network were checked by inputting the operating parameters of the diesel engine at the time of fault occurrence.

5.2 Simulation experiment

5.2.1 Failure Simulation Experiment for Single Cylinder Oil Loss

The results of inputting the diesel engine operating parameters when a single-cylinder fuel stop occurs with and without malfunction by constructing a radial basis neural network, training the training set, and parameterizing the test set are shown in Fig.5-12.

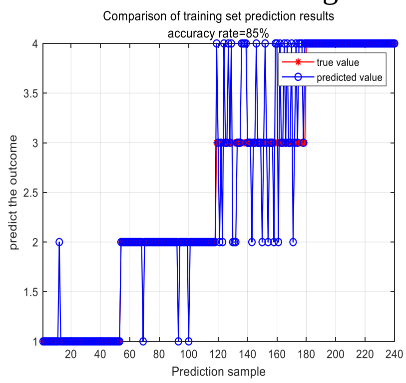

Figure 5: Sensor-based single-cylinder stopping training set prediction result plot

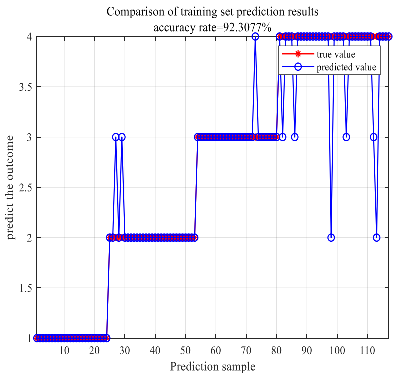

Figure 6: Plot of prediction results of single cylinder oil stop training set based on radial basis neural network

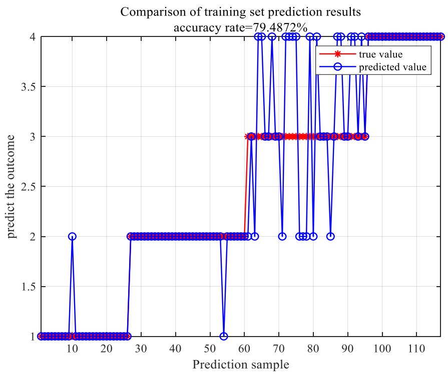

Figure 7: Sensor-based prediction results plot for single-cylinder stopping test set

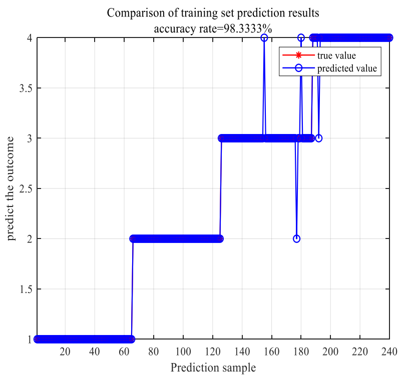

Figure 8: Radial basis neural network based single cylinder oil stop test set prediction result plot

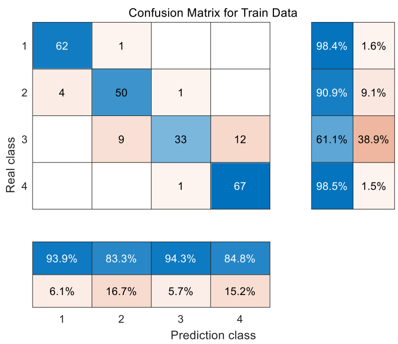

Figure 9: Sensor-based confusion matrix for single bar fuel stop training set

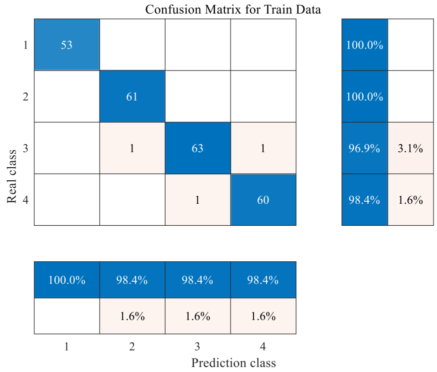

Figure 10: Radial-based neural network-based confusion matrix for single-cylinder oil stopping training set

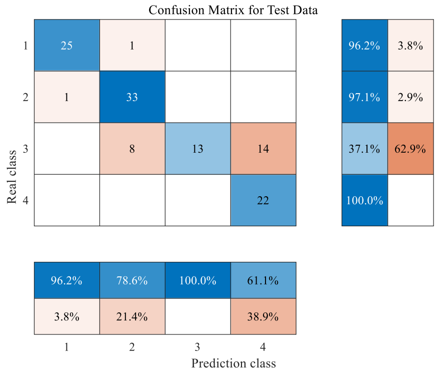

Figure 11: Sensor-based confusion matrix for single-bar fuel stop test sets

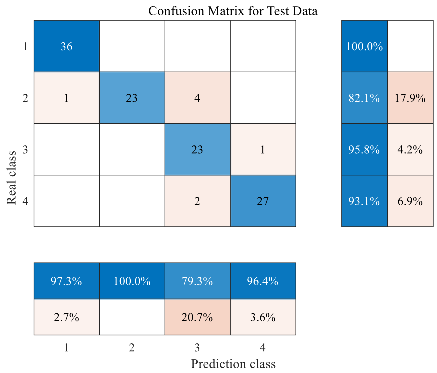

Figure 12: Single-cylinder stopping test set confusion matrix based on radial basis neural network

From the operation results, for the fault system based on sensor diagnosis, the diagnosis accuracy was approximately 85% in the training set and 79% in the test set; 28 diagnosis results in the training set confusion matrix were different from the actual results, and 24 diagnosis results in the test set were different from the actual results. For a diagnosis system based on a radial-based neural network, the diagnostic accuracy was approximately 98% in the training set and 92% in the test set, both of which met the test requirements. It can be observed that only three diagnostic results in the training set confusion matrix [5] were different from the actual results, whereas eight diagnostic results in the test set were different from the actual results. Evidently, the accuracy of the radial basis neural network-based fault diagnosis system was higher than that of the sensor-based fault diagnosis system [6], and the experiments were consistent with the expected results [7].

5.2.2 Single Cylinder Uneven Oil Supply Failure Simulation Experiment

The operating parameters of the diesel engine when an uneven single-cylinder fuel supply fault occurs and when no fault occurs are input by constructing a radial basis neural network, training the training set, and parameterizing the test set. The results are shown in Fig.13-20.

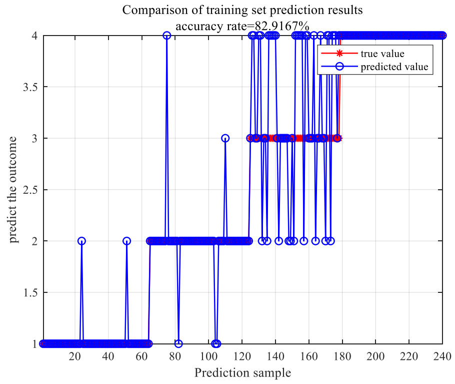

Figure 13: Sensor-based prediction result plot for single-cylinder uneven oil supply training set

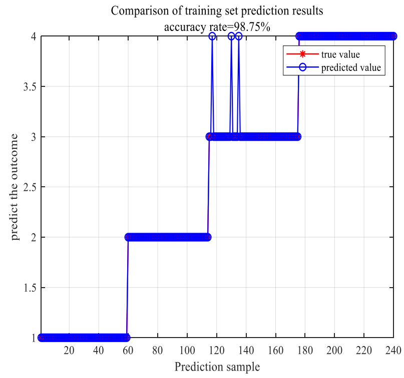

Figure 14: Plot of prediction results of single cylinder uneven oil supply training set based on radial basis neural network

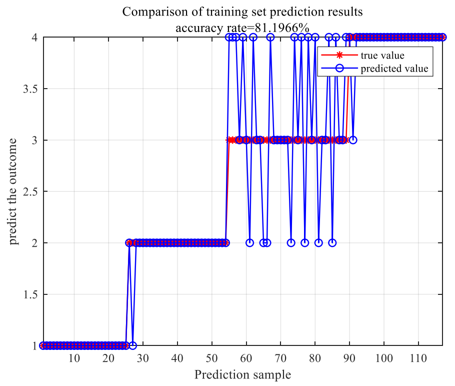

Figure 15: Sensor-based prediction results plot for single-cylinder uneven oil supply test set

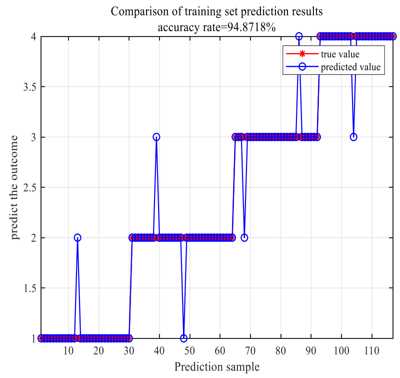

Figure 16: Prediction results of single-cylinder supply and availability uneven test set based on radial basis neural network

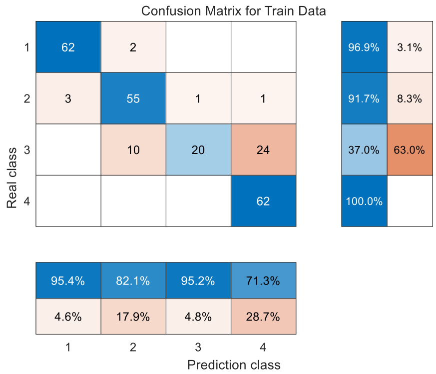

Figure 17: Sensor-Based Confusion Matrix for Uneven Fuel Supply Training Set for Single Bar

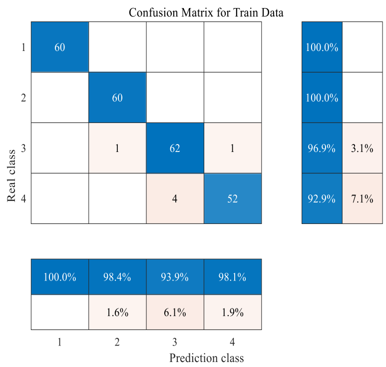

Figure 18: Radial-based neural network-based confusion matrix for single-cylinder uneven oil supply training set

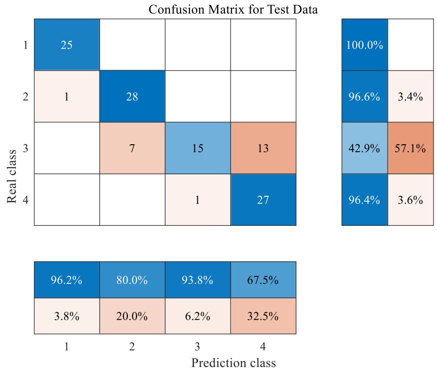

Figure 19: Sensor-Based Confusion Matrix for Uneven Fuel Supply Test Sets for Single Bar

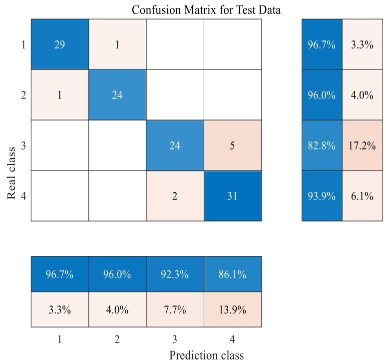

Figure 20: Radial basis neural network based confusion matrix for single cylinder uneven oil supply test set

From the operation results, for the fault system based on sensor diagnosis, the diagnosis accuracy was approximately 83% in the training set and 81% in the test set, 41 diagnosis results in the confusion matrix of the training set were different from the actual results, and 22 diagnosis results in the test set were different from the actual results. For a diagnosis system based on a radial-based neural network, the diagnostic accuracy was approximately 98% in the training set and 95% in the test set, both of which met the test requirements. It can be observed that only six diagnostic results in the confusion matrix of the training set are different from the actual results, whereas nine diagnostic results in the test set are different from the actual results. Evidently, the accuracy of the fault diagnosis system based on a radial basis neural network is higher than that of a fault diagnosis system using sensors, and the experiments are consistent with the expected results.

5.2.3 Exhaust valve valve gap too large Failure simulation experiment

The operating parameters of the diesel engine were input when an error of excessive exhaust valve gap occurred and when no error occurred by constructing a radial basis neural network, training the training set, and parameterizing the test set. The results are shown in Fig.21-28.

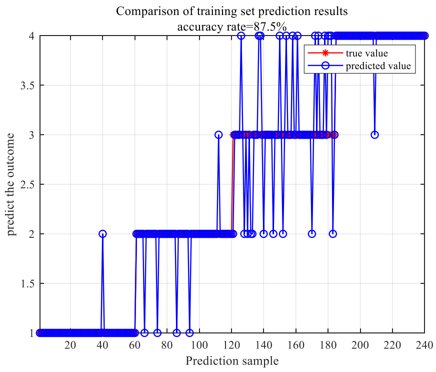

Figure 21: Plot of sensor-based prediction results for excessive exhaust valve gap training set

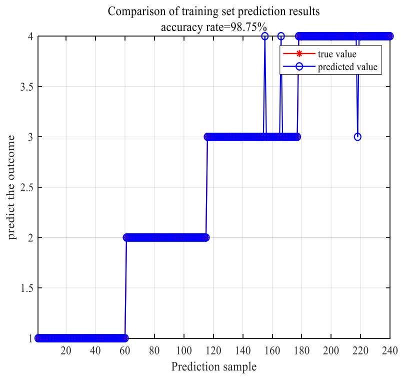

Figure 22: Prediction results of excessive exhaust valve gap training set based on radial basis neural network

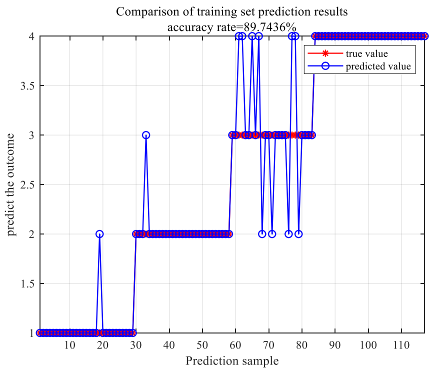

Figure 23: Sensor-Based Prediction of Excessive Exhaust Valve Clearance Test Set Results

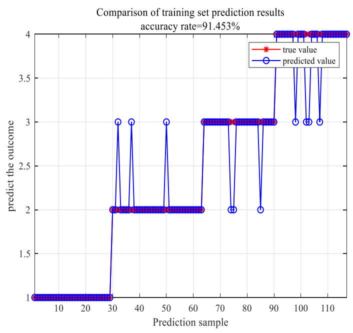

Figure 24: Prediction results of excessive exhaust valve gap test set based on radial basis neural network

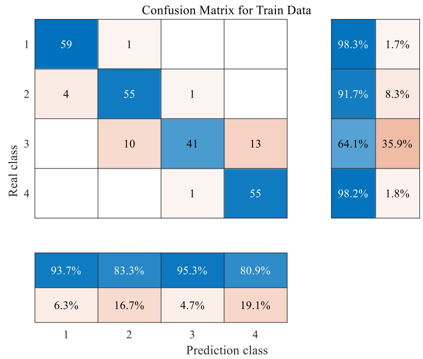

Figure 25: Sensor-Based Confusion Matrix for Excessive Exhaust Valve Clearance Training Set

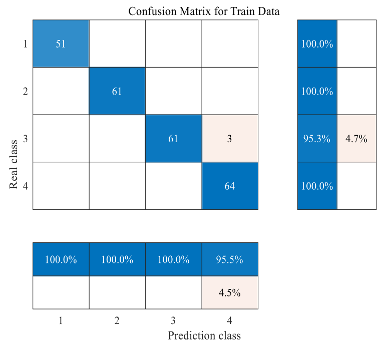

Figure 26: Confusion Matrix for Excessive Exhaust Valve Clearance Test Set Based on Radial Basis Neural Networks

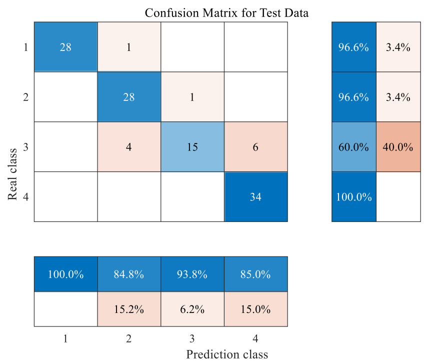

Figure 27: Sensor-based Confusion Matrix for Excessive Exhaust Valve Gap Test Sets

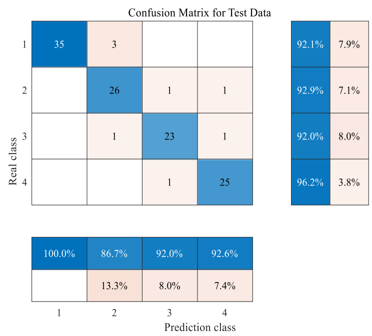

Figure 28: Confusion Matrix for Excessive Exhaust Valve Clearance Test Set Based on Radial Basis Neural Networks

From the operation results, for the fault system based on the sensor diagnosis, the diagnosis accuracy was approximately 88% in the training set and 90% in the test set. Thirty diagnosis results in the confusion matrix of the training set differed from the actual results, and 12 diagnosis results in the test set differed from the actual results. For the diagnosis system based on the radial neural network, the diagnostic accuracy was approximately 99% in the training set and 91% in the test set, both of which satisfied the test requirements. It can be observed that only three diagnostic results in the training set confusion matrix differ from the actual results, whereas the six diagnostic results in the test set differ from the actual results. Obviously, the accuracy of the fault diagnosis system based on radial basis neural network is higher than that of the fault diagnosis system using sensors, and the experiments are consistent with the expected results.

5.2.4 Failure simulation experiment with delayed injection timing

We input the diesel engine operating parameters when the injection timing delay was faulty and when it was not. By constructing a radial basis neural network, training the training set, and parameterizing the test set, the results shown in Fig. 29-36.

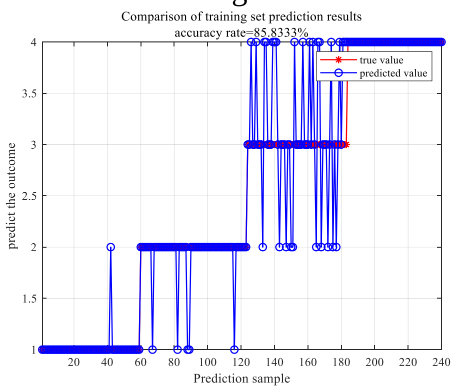

Figure 29: Sensor-based fuel injection timing lag training set prediction result plot

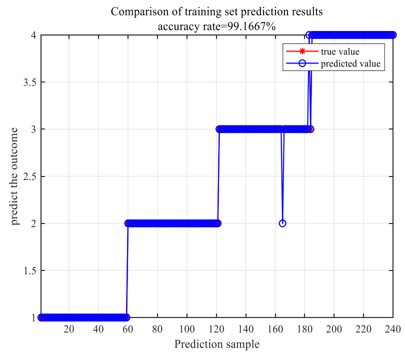

Figure 30: Prediction results of injection timing lag test set based on radial basis neural network

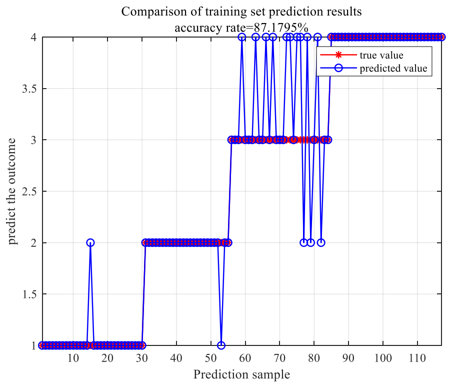

Figure 31: Sensor-based fuel injection timing lag training set confusion matrix

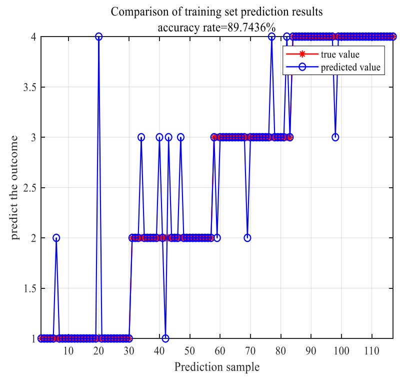

Figure 32: Radial basis neural network based confusion matrix for injection timing lag test set

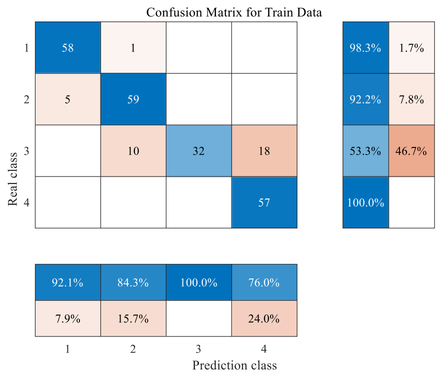

Figure 33: Sensor-based fuel injection timing lag training set confusion matrix

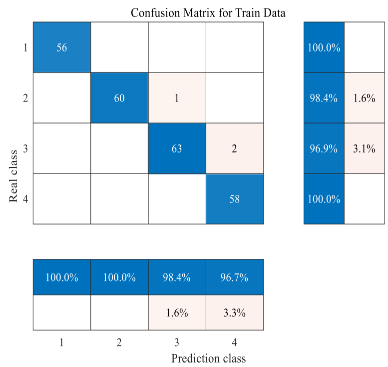

Figure 34: Radial basis neural network based confusion matrix for injection timing lag test set

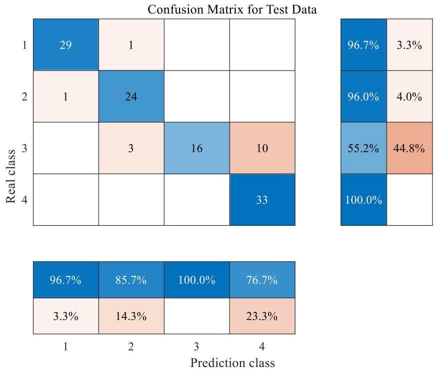

Figure 35: Sensor-based confusion matrix for injection timing lag test set

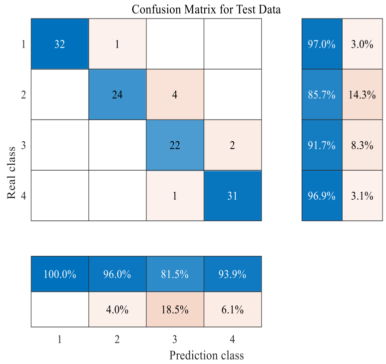

Figure 36: Radial basis neural network based confusion matrix for injection timing lag test set

From the operation results, for the fault system based on sensor diagnosis, the diagnosis accuracy was approximately 86% in the training set and 87% in the test set, 34 diagnosis results in the confusion matrix of the training set were different from the actual results, and 15 diagnosis results in the test set were different from the actual results. For a diagnosis system based on a radial-based neural network, the diagnostic accuracy was approximately 99% in the training set and 90% in the test set, both of which met the test requirements. It can be observed that only three diagnostic results in the training set confusion matrix are different from the actual results, whereas eight diagnostic results in the test set are different from the actual results. Evidently, the accuracy of the fault diagnosis system based on a radial basis neural network is higher than that of a fault diagnosis system using sensors, and the experiments are consistent with the expected results.

6. Conclusion

In this study, based on the existing marine diesel engine diagnostic technology, it is proposed to use sensors to perform a preliminary diagnosis of the diesel engine before a detailed diagnosis. A radial basis neural network was constructed in MATLAB using existing data. The data were divided into training and test sets. In the system diagnosis, the occurrence of errors was tested to determine whether the system was accurate and fast. It was found that after the initial diagnosis by the sensors, the diagnostic accuracy of the radial-based neural network was significantly improved compared with that of the sensor-only diagnosis. The diagnostic techniques proposed in this paper can also be used to diagnose other mechanical faults such as generators, transformers, and propulsion motors. A combination of pre-diagnosis and in-depth diagnosis was also proposed, laying the foundation for the future development of in-depth diagnostic techniques.

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