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Research Article

Neural Network Optimization and Data Fusion Recognition Method for Intelligent Mechanical Fault Diagnosis

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With the improvement of mechanical equipment complexity and automation level, the importance of mechanical equipment fault diagnosis is more and more prominent, and the choice of appropriate diagnosis method is crucial to the accuracy of the diagnosis results. Wavelet analysis and neural network technology, as the hot spot and frontier of research, are also important research contents in the development of intelligent diagnosis of mechanical fault. Data fusion can process multisource information to obtain more accurate and reliable methods. At the same time, because of its good nonlinearity, adaptability, and fault tolerance, neural network has become the preferred method of mechanical fault diagnosis. This paper first describes the research content and significance of fault diagnosis technology and introduces the main methods and steps of fault diagnosis, and through the introduction of mechanical fault vibration signals, vibration signals were analyzed in time domain and frequency domain. Secondly, the definition and classification of data I fusion and RBF neural network are introduced in detail and compared with BP neural network. Because the prediction accuracy of the RBF network is higher than that of the BP neural network and the training time of the RBF network is obviously shorter than that of the BP network, the RBF network has significant advantages over diagnostic errors. In this paper, six valve signals were collected under normal conditions and errors, and by analyzing and comparing different theoretical foundations, the 4-second network crisis time was effectively reduced, which provided the basis for teaching monitoring.

1. Introduction

With the acceleration of modernization, people have higher requirements on mechanical equipment. Mechanical equipment has gradually developed into the field of automation, scale, and specialization, and its safety and accuracy have therefore been valued. It is important to diagnose equipment faults timely and effectively. As an important measure to ensure the safe and reliable operation of equipment, mechanical fault diagnosis technology can not only predict the occurrence and development of mechanical equipment faults in advance but also predict the causes of faults and put forward countermeasures and suggestions for fault management. Therefore, it is necessary to improve the utilization rate of mechanical equipment, understand the precursors of equipment failure, prevent the occurrence of accidents, and ensure the safe operation of mechanical equipment [1].

Data fusion theory is a method and theory that studies the processing of multisource information and then draws more accurate and credible conclusions. In other words, it is a kind of simulation of the human and animal brains: people can analyze something through color vision, taste, hearing, and other aspects and then come up with a conclusion; animals can also capture prey by means of multifaceted information. Data fusion theory is a method similar to this, which can be used to draw more reliable and effective conclusions from various sources. Data fusion involves a wide range of applications in many fields, it is difficult to use the general concept to describe a unified definition. It was first used in the military field by the army to determine the precise position of the target through multisensor detection, correlation, combination, and estimation.

Fault diagnosis of complex mechanical equipment in agricultural production, industrial processing, weapons, and equipment is of great significance in preventing accidents and ensuring the safety of equipment operators and the surrounding environment and improving economic efficiency and timely prediction of faults to avoid the occurrence of major accidents [2, 3]. In order to improve the accuracy of fan fault diagnosis, Jiawei proposed a new method of fan fault diagnosis combining evidence theory and support vector machine. Firstly, Wegener-Weil spectrum entropy is extracted from vibration signal as the characteristic of fault diagnosis of fan. Secondly, different kernel function support vector machines (SVM) are used to build subclassifiers for fan fault diagnosis. Finally, DS evidence theory is used to fuse the output results of the subclassifier, and its performance is simulated and tested. The experimental results of Jiawei show that this method can make full use of all fault information, the diagnostic results are closer to the expected value, and the diagnostic effect is better than other methods for fan fault diagnosis [4]. The performance of traditional vibration-based fault diagnosis methods depends largely on the manual features extracted by signal processing algorithm, which need a lot of domain knowledge and manpower, and cannot be well extended to the new diagnosis field. In recent years, Jiang et al. express that learning is based on good learning ability of unmarked data, which provides a new solution for feature extraction in traditional fault diagnosis. Considering that vibration signals usually contain multiple time structures, Jiang et al. proposed a MSRL framework of multiscale representation learning to directly learn useful features from original vibration signals to obtain rich and complementary fault mode information at different scales. In the method proposed by Jiang et al., coarse-grained process is first used to obtain multiple scale signals from the original vibration signals. Then, a newly developed unsupervised learning algorithm, sparse filtering, is used to automatically learn useful features from each scale signal [5]. In order to process a large number of fault data quickly and provide accurate diagnosis results automatically, Feng et al. have done a lot of research on intelligent fault diagnosis of rotating machinery. In these studies, the commonly used method is based on artificial neural network, which uses signal processing technology to extract features and then inputs the features into the neural network for fault classification. Although these methods have played a certain role in intelligent fault diagnosis of rotating machinery, there are still some shortcomings: these features are manually extracted by relying on a large number of prior knowledge of signal processing technology and diagnosis expertise. In addition, these manual features are extracted according to specific diagnostic problems and may not be applicable to other problems [6].

This paper takes marine air compressor as an example to study. The online monitoring system of air compressor has been developed abroad, which can observe and monitor the cylinder, piston ring, valve, and other parts of reciprocating compressor and judge the working state of reciprocating compressor according to the measurement signal. At present, fault diagnosis of reciprocating compressor is mostly based on experience, which is far from the actual application. The fault diagnosis system of reciprocating compressor has complex structure, many vibration sources, and imperfection. This document confirms that the error pattern detection method based on systematic analysis of wave power and radial base operation network can improve error pattern recognition and reduce network training time.

2. Proposed Method

2.1. Classification and Characteristics of Mechanical Faults

2.1.1. Classification of Mechanical Faults. From the perspective of fault diagnosis, a commonly accepted definition is that the abnormal operation of mechanical equipment fails to meet the predetermined performance requirements or the performance described by parameters exceeds the specified limit, which may lead to partial or total loss of function of the equipment [7].

(1) Classify according to the Fault Cause. Deterioration failure: after the mechanical equipment is put into use, with the passage of time, under the influence of various factors, parts and components will undergo irreversible change process, such as wear, fatigue, corrosion, and structural change of metal materials, which will make the mechanical equipment function gradually weakened with the passage of time. The fault produced is called deterioration fault or time-related fault [8].

Human fault: the fault caused by the general principle system is not sound enough, violating the operation and maintenance procedures, also known as fault use.

(2) Classification according to the Duration of Failure. Temporary failure: loss of local function within a short time.

Continuous fault: a fault that causes the loss of function of the equipment for a long time, and the working ability of the equipment cannot be restored until the defective parts are replaced or repaired [9, 10].

(3) Classification according to the Fault Formation Velocity. Sudden failure: it is the result of adverse factors and unexpected external factors.

Progressive failure: failure of equipment as it ages.

(4) Classification according to Fault Nature. Functional failure device: unable to continue performing its intended function.

Parameter fault device: a fault caused by a specified parameter exceeds the allowable range.

(5) Classification according to Fault Hazards. Catastrophic failure: failure of mechanical equipment safety protection device, transmission system braking device, and other key components, resulting in damage to mechanical equipment or casualties [11].

General fault: no damage to mechanical equipment or casualties and other nondangerous fault.

(6) Classify according to Whether the Fault Occurs. Actual failure: equipment failure that occurs.

Potential failure: possible failure of the equipment itself.

2.1.2. Characteristics of Mechanical Failure

(1) Imbalance. In all kinds of abnormal phenomena of rotating machinery, the vibration caused by imbalance is very large. The so-called unbalance is the vibration phenomenon caused by centrifugal force in the process of rotation, which is generated by the uneven mass distribution around the axis of the rotating object. Its main characteristic vibration time-domain waveform is sinusoidal wave, with harmonic energy concentrated on the fundamental frequency, stable phase, and amplitude, and the axial track of the rotor is elliptical [12, 13].

(2) Rotor Friction Fault. According to mechanism analysis, there are two main types of rotor friction faults, namely, dry friction faults between rotor and stator. The reasons for such fault friction mainly include too small gap between rotor and stator, too large or too small bearing gap, too large shaft deflection, too large shaft or shaft displacement, inconsistent thermal expansion of rotor and stator components, lubrication system failure, and other causes of vibration of large rotor [14]. The internal friction of the rotor will lead to instability, which is mainly caused by the elastic lag of the rotor material, sliding friction of the shaft components, and friction of the toothed coupling.

(3) Wrong. Misalignment is the phenomenon that the centerlines of two shafts connected by a coupling do not overlap. The main characteristics of vibration are dual frequency, and the vibration characteristics are stable. The vibration direction is radial and axial, and the phase characteristics are relatively stable. The track of the axis is a double-ring ellipse, and the amplitude varies with the speed and load [15].

(4) Oil Film Vortex. Rotating oil film is a type of regenerative vibration caused by the strong features of the oil-bearing oil film. The mechanism can be simply described as the result of the combined current action and the reduction of the active action in the oil membrane. The main characteristics of oil film rotation are as follows: there are many low-frequency components, mainly concentrated in half or less of the frequency; amplitude in the vicinity of the power frequency accounted for the largest proportion, vibration, and phase characteristics are relatively stable, and the axis tracking is double elliptic, mainly radial vibration direction.

(5) Bearing Damage. Main features: bearing defect frequency and harmonic components are abundant, there are wide random high-frequency vibration bands, side band components are obvious or prominent, and bearing temperature is high.

(6) Surge. When the vibration occurs in the ultralow frequency component (0.5~20 Hz), the vibration is unstable, the phase is unstable, and the axis trajectory is disordered.

(7) Loose Bearing. The loose vibration is mainly radial vertical vibration. In the spectrum diagram, in addition to the fundamental frequency, there are high-frequency components such as 2f and 3f and even frequency division, axis confusion, and center of gravity drift. However, the energy is mainly concentrated in the low-frequency region less than 1/2 frequency, and the axial trajectory is disordered.

2.2. Fault Diagnosis of Artificial Neural Network

2.2.1. Concept and Diagnostic Method of Neural Network. Artificial neural network is an abstract mathematical model reflecting the structure and function of human brain. In essence, neural network is composed of many simple parallel computing units, and its learning mode is inductive learning mode. It has functions such as data integration, pattern separation, performance measurement, performance calculation, and performance measurement. Error diagnosis is one of the most important areas of neural implant network application. Basic technology is pattern recognition and neural network error diagnosis. It can not only be deployed in a variety of complex space decision models but also has the ability to be flexible. Because of the advantages of artificial neural network, the traditional diagnosis method cannot be used, so the artificial neural network in the mechanical fault diagnosis role is increasingly prominent. Therefore, neural network is widely used in information processing fields such as robots, fault diagnosis, automatic control, and artificial intelligence [16, 17].

The fault diagnosis method of neural network is to store the knowledge and diagnosis rules of experts in this field in the interconnection of a large number of neurons and express the weight distribution of each connection through network learning and training. In fault diagnosis, the network uses its good associative memory ability to recall expert's diagnosis knowledge, compares it with the network output of the sample to be diagnosed, and finally, gives the diagnosis result. In the process of acquiring knowledge, only the domain experts need to provide fault diagnosis examples and corresponding solutions, then through specific learning algorithm, and then through the internal adaptive adjustment algorithm of connecting weights. The knowledge and experience of sample domain experts learning fault diagnosis rules in problem solving are stored in the interconnection and connection weights of the network. According to the concluding information, with a specific input method, the neural network calculates the logical concepts represented by each output node using a predefined calculation and then finds a specific solution by comparing the details and stored information with the output node. Create output mode, the network itself, diagnosis. In this process, the remaining solutions are removed so that the neural network can complete the same error detection process [18].

2.2.2. Basic Composition and Type of Neural Network. As a typical feedforward neural network, BP is widely used both in theory and in practice. Due to the topological structure and activation function characteristics of RBF network, the prediction accuracy of this network is higher than that of the BP neural network, and the training time of RBF network is significantly lower than that of the BP neural network. The comparison between RBF neural network and BP network is as follows.

From the perspective of network structure, RBF network is a three-layer forward network with implicit layer, which connects directly from the input layer to the hidden layer and from the hidden layer to the output layer. The topology of BP network can realize all potential layers, which are connected to each other by more than three or three layers. BP neural network is the number of hidden layers and nodes of static feedforward neural network. It is not easy to determine and is not universally applicable. Once the network structure is in the training stage, the network structure will not change. RBF neural network is a three-layer static feedforward neural network, which can adaptively adjust the hidden layer of the network according to the specific problems studied in the training stage. That is, the structure of the network makes the network more suitable. BP network adopts general nonlinear function as transformation function, while RBF network adopts radial basis function, which can quickly respond to local information and meet real-time requirements in practical applications.

From the perspective of training algorithm, BP network approaches the minimum error by continuously adjusting the weight of neurons. The method is usually gradient descent. However, the BP algorithm also has many drawbacks, in particular, limited localization. The learning process changes slightly. It is difficult to determine the number of hidden levels and hidden level nodes. Most importantly, whether the new BP neural network can change after training depends on the ability of the training samples, the selected algorithm, and the structure of the network (input node, hidden node, output node, and output node transfer function), errors are expected and a number of training measures. RBF network is an effective feedforward neural network, and its excitation function is different from the s-type function of BP network, which is usually Gaussian function. The Gaussian calculates the weight by the distance from the input to the center of the function. Therefore, the structural parameters of RBF network can be learned quickly to avoid falling into the local minimum. At present, many RBF neural network training algorithms support online and offline training, which can dynamically determine the data center and extension constant of network structure and hidden layer unit and show better performance than BP algorithm.

From the perspective of network resource utilization, RBF network has a good explanatory ability, and its basic theory can be explained by many existing theories. For example, RBF neural networks implement a mapping from input to output, similar to pattern recognition theory. The purpose, design, and specificity of the RBF neural network learning algorithm determine the distribution of the hidden layer units per volume, phase, and distribution of training samples. If the nearest neighbor integration method is used for network training, the distribution parameters will affect the final RBF network prediction accuracy: the smaller the extension, the more accurate the approximation, but the less smooth the approximation. Therefore, the design of RBF network is to find a set of optimal parameters to optimize the network performance. In the design of a network, several propagation values need to be adjusted until better accuracy is achieved. Make full use of your network resources. This is completely different from BP neural network. The weight and threshold of BP neural network are directly determined by the sum of mean square error of each task (output node). Thus, a trained network can only be a compromise between different tasks. RBF neural network can reduce the influence between tasks to a lower level, so that each task can achieve better results. This parallel multitask system will make the application of RBF neural network more and more extensive [19, 20].

2.3. Data Fusion. Data fusion technology is the result of military applications, in the complex battlefield environment, in order to achieve accurate investigation to identify the target, typically using a large number of different types of sensor multiazimuth to obtain the characteristic information of the target as a feature to identify a person cannot alone; need to the nose, eyes, ears, and other characteristics of integrated identification can be accurate to identify the target. Data fusion technology mimics the human brain to combine various data to obtain a consistent result, using a variety of sensors collected from a large number of similar or different quality data combinations and accurate targeted recognition. Today, fusion technology is widely used in many fields. The feature information of the target can be collected comprehensively by the way of spreading the sensor, and the data deviation caused by the fault of a single sensor and the cognitive deviation caused by unilateral information can be eliminated [21–25].

There are many kinds of data fusion classification methods, which can be divided into centralized and distributed according to the mode of data fusion processing. In the centralized detection method, the local sensors directly transmit all the observed values to the fusion node, and all the sensors globally determine the whole observation space to obtain the detection results [26]. This method processes a large amount of raw data at the fusion node, which makes the processor heavy. In order to obtain the detection value of each sensor, the bandwidth must be increased, so it is not practical. Unlike the Chinese method, the acquired distribution method does not require a large load of communication, but the efficiency is reduced because node fusion does not get all the sensory perception. However, this approach can reduce the pressure of system performance and improve system performance. Therefore, it has become the primary means of discovering the purpose of multiple sensors.

According to the levels of data fusion operation, it can be divided into data level fusion, characteristic level fusion, and decision level fusion. Data level fusion directly processes and separates the original data collected by the sensor, which belongs to the most front-end fusion. This method can reduce the loss of data; the accuracy of the obtained data is

Table 1: Percentage of reciprocating compressor faults.

Failure parts	Air valve	Packing	Process problems	Piston ring	Liner	Unloader	Instrument
The proportion (%)	36	17.8	8.8	7.1	6.8	5.1	1.3

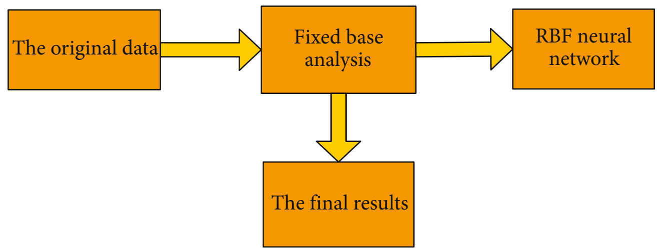

Figure 1: Air compressor fault diagnosis model.

relatively high and also the assurance of information accuracy and reliability. Feature-level data fusion belongs to the data fusion of the middle levels, which extracts and fuses the features of the data from different sensors. This fusion can compress the data, reduce the amount of data, and provide a basis for later decisions.

3. Experiments

3.1. Fault Mechanism and Experimental Design of Air Compressor. The test object in this paper is marine air compressor zky-1, which is a four-stage compressed high-pressure air compressor driven by an electric motor. The piston is differential, arranged in two v-shaped columns, and cooled by water. There are two parallel job, the first and the second cylinders are divided into four cylinders, I-II-III and I-II-IV two columns of cylinder, and piston component. During the process of air compressor, the valve often fails, failure of the valve in time; otherwise, it will cause serious damage to the cylinder. Zky-1 air compressor speed 1450 r/min, 380/298 A current, voltage 220/320 V, power 75/85 kW, and temperature increase 80.

3.1.1. Fault Mechanism. Marine air compressor is mostly use for reciprocating air compressor, it can be divided into:

(1) Low pressure air compressor: discharge pressure 0.2 MPa–1 MPa

(2) Medium pressure air compressor: discharge pressure 1 MPa–10 MPa

(3) High-pressure air compressor: discharge pressure 10 MPa–100 MPa

(4) Ultrahigh-pressure air compressor: discharge pressure is more than 100 MPa

According to the series of compressor, air compressor can be divided into single-stage compressor and multistage compressor.

According to the type of prime, mover can be divided into electric compressor, internal combustion compressor, and steam compressor.

Table 2: Time-domain parameter indexes of zero-channel first scheme.

	Waveform indicators	Peak metric	Pulse index	Root-mean-square value	The maximum
1st layer	1.23	4.98	6.13	1.98	9.84
2nd layer	1.80	16.28	29.41	0.22	3.58
3rd layer	2.23	13.6	30.41	0.58	7.83
4th layer	1.38	8.07	11.14	0.14	1.10
5th layer	1.32	5.24	6.93	0.83	4.37
6th layer	1.52	7.63	11.62	0.36	2.78

According to the form of cylinder, centerline can be divided into vertical, horizontal, V, and W compressor.

3.1.2. Working Principle of the Experiment. The prime mover rotates by driving the crankshaft, and this connecting rod drives the piston to move back and forth. As the piston moves from TDC to TDC, the volume around the piston and cylinder increases, and the pressure decreases. When the pressure is less than the external pressure of the suction valve, the pressure difference on both sides of the suction valve can exceed the spring strength and open the suction valve. The air from the suction hose flows into the cylinder and begins to smell. When the piston passes to the lower stop position, the closing value is no longer increased, the suction valve closes automatically, and the suction force is eliminated by elastic power and the whole suction process. As the piston moves from BDC to BDC, the closing volume of the piston and cylinder decreases, and the intake and exhaust valves close. The air in the enclosed space is compressed, the pressure increases, and the air temperature increases. When the pressure in the volume is higher than the pressure outside the exhaust valve, the pressure difference overcomes the spring elasticity, the exhaust valve opens, the compression ends, and the exhaust process begins. When the piston moves to TDC, the closed volume no longer decreases, the exhaust valve closes, and the exhaust process ends.

When the piston reaches TDC, there is a gap between the cylinder head and the top of the piston. At the end of

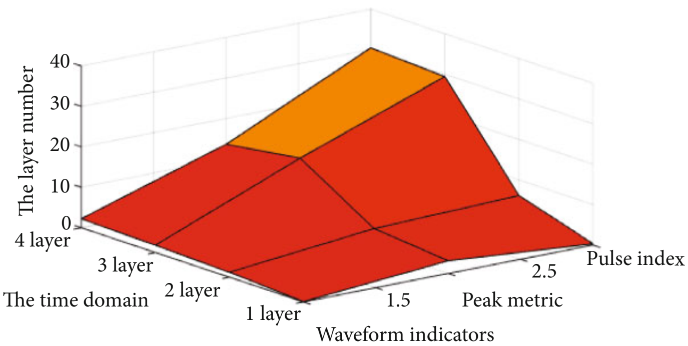

Figure 2: Time-domain parameter changes of zero-channel fourth scheme.

the exhaust, air in the gap cannot be removed. The volume of the gap is called the volume of the gap. When the piston is moved from the TDC to the TDC, the air in the room is compressed, and the pressure is high, so that the air will not smell faster. The air in the gap expands and compresses, beginning the expansion process. When the pressure is lower than the external pressure of the suction valve, the suction valve opens, the expansion process ends, and the suction begins. Piston reciprocating motion, compressor cylinder in turn to perform suction, compression, elimination, and expansion of four processes of motion can complete a cycle.

4. Discussion

On marine air compressor, ZKY-type 1 valve fault signal is studied; the experimental collection of valve under normal and fault condition of six signal multiresolution analysis is shown in Table 1, using waveform index, peak index, pulse index, and root-mean-square value of the maximum five indicators, each index comparison of the six state. It is impossible to extract fault features by observing only the indicators of the original signal. Wavelet multiresolution analysis can extract fault feature models of each layer, as shown in Figure 1, and obtain fault features of each indicator. When the method of fixed-time base point is applied in the wavelet transform and multiresolution analysis, the waveform index, peak index, pulse index, root-mean-square value, and maximum value of the valve under the fault state are all larger than the waveform index, peak index, pulse index, root-mean-square value, and maximum value of the valve under the normal state. In the analysis of multiple wavelet transform solutions, waveform index, peak index, pulse index, root-mean-square value, and the maximum number of other errors are all below the waveform index, peak index, pulse index, and mean root equivalent value in the normal condition of the air valve. Because wavelet transform does not have time-shift invariance, the method using fixed-time base point is more effective than ordinary wavelet analysis. Wavelet fixed-time base analysis can effectively eliminate the redundancy in the fault signal of compressor valve, reduce the input dimension of neural network, and improve the convergence performance of the network.

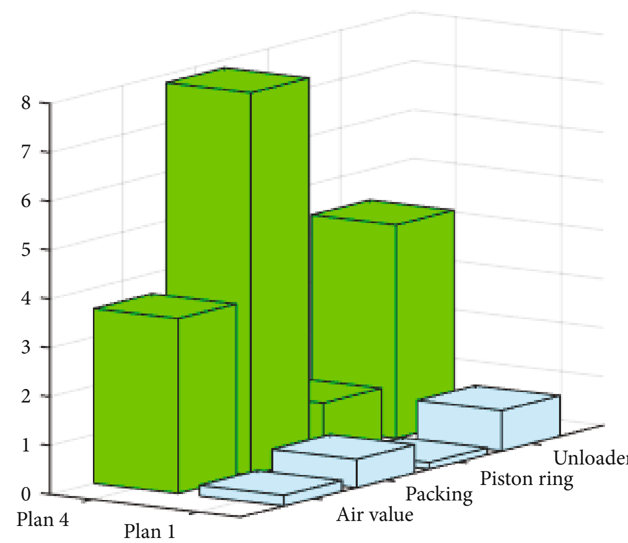

Figure 3: Time-domain parameter changes of the first and fourth schemes of the first layer of zero channel.

4.1. Application of Multiresolution Analysis in Compressor Fault Diagnosis. The waveform difference between normal state and fault state can be clearly seen on the sixth layer. The time-domain parameters commonly used in mechanical fault diagnosis include waveform index, peak index, pulse index, and effective value. For the first scheme, when ch0 measures the new exhaust valve and ch1 measures the new intake valve, the waveform index, peak index, pulse index, effective value, and maximum value of each channel are obtained (as shown in Table 2).

For the fourth scheme, when ch0 measures the fault exhaust valve and ch1 measures the fault suction valve, the waveform index, peak index, pulse index, effective value, and maximum value of each channel are obtained (as shown in Figure 2).

Comparing Table 2 and Figure 2, in the first, second, fourth, and sixth layers, each index of the valve in the fault state is larger than that of the valve in the normal state. In the third layer, the root means that the square value of the valve in case of error is greater than the root-mean-square value and the highest value of the valve under normal conditions. The waveform index, altitude index, and pulse voltage

Figure 4: Time-domain parameter changes of the first layer of zero-channel of the second scheme and the fifth scheme.

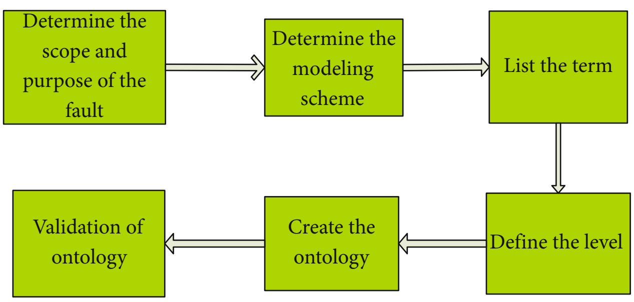

Figure 5: Output flow of output volume in the field of fault diagnosis.

index in the third layer are lower than under normal conditions.

4.2. Wavelet Fixed-Time Basis Analysis of Zero Channel. It can be seen from Figure 3 that the waveform index, peak index, pulse index, root-mean-square value, and maximum value of the valve under the fault state are all larger than the waveform index, peak index, pulse index, root-mean-square value, and maximum value of the valve under the normal state.

As shown in Figure 4, the waveform index, peak index, pulse index, root-mean-square value, and maximum value of the valve under the fault state are all larger than the waveform index, peak index, pulse index, root-mean-square value, and maximum value of the valve under the normal state.

4.3. Design Principle of RBF Neural Network in Experiment

4.3.1. Selection of Input Quantity. It is better to choose flexible ones that have a big impact on the output and are easy to find or remove. In addition, the relationship between each input must be kept very small and it is often not possible to send inputs directly to the neural network. A variety of signal processing techniques and feature detection technology

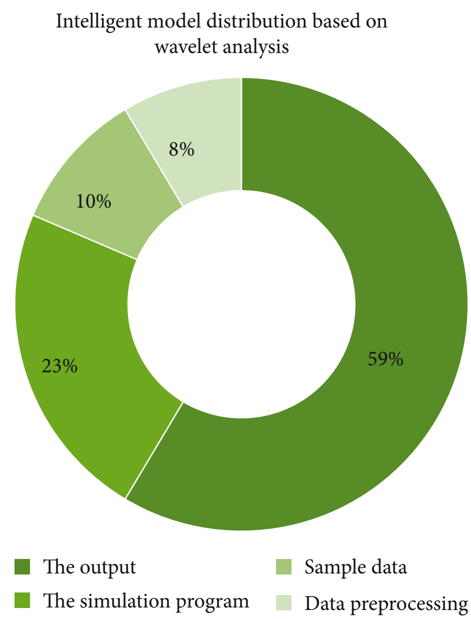

Figure 6: Content distribution of neural network intelligent diagnosis model for wavelet analysis.

are required, and parameters that best reflect the input characteristics are extracted from the original input as the input of the network (as shown in Figure 5).

4.3.2. Selection of Output. The output actually refers to the expected output of neural network, such as classification of problems. The output can be expressed either verbally or numerically. Common language representations are “n choose 1” notation and “n-1” notation. However, numerical representation is only applicable to the classification of two types of contradictions, and it is difficult to apply it to progressive classification. The neural network BP typically accepts a function as a neuron transfer function, and the output range is 0~1 or -1~1. Without data processing, the

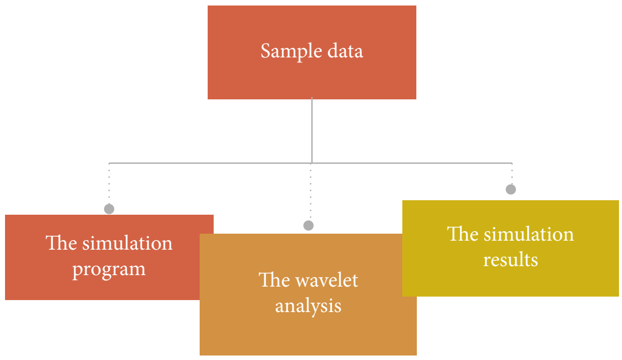

FIGURE 7: Input and output steps.

total network error to the total error will increase, which will significantly affect learning speed and training and network error. Therefore, the frequency is required to normalize the input and output and to convert the sample distribution to an irrational distribution. The neural network intelligent diagnosis model based on wavelet analysis is shown in Figure 6.

(1) Collect and normalize the sample data of air compressor valve in normal and fault state

(2) Write the simulation program

(3) Conduct simulation experiments. The normalized samples were used for network training, and the expected output during network training was set as a logical value corresponding to the state of the input samples and then sent to the trained neural network for identification

(4) Output corresponding simulation results (as shown in Figure 7)

5. Conclusion

In recent years, the study of mechanical fault intelligent diagnosis system has become a hot spot in the field of mechanical fault diagnosis. The degree of intelligence and diagnostic accuracy of the system depends on the quantity and quality of knowledge in the system knowledge base, as well as the organization, classification, and further knowledge sharing and reasoning. Through the development of the theory of mechanical fault diagnosis system, this paper analyzes the mechanism of typical rotating machinery faults, studies the related theories of mechanical equipment diagnosis technology, and chooses the vibration diagnosis technology based on neural network and data fusion recognition as the theoretical basis of mechanical equipment fault diagnosis.

In the experiment of this paper, 6 signals of the valve under normal and fault conditions were collected, and the 6 signals of the valve were analyzed with multiresolution, and the analysis results with time-domain fault characteristics were extracted. Waveform index, peak index, pulse index, root-mean-square value, and maximum value are selected to compare each index under 6 conditions. Since it is impossible to extract fault features only by observing each indicator of the original signal, multiresolution analysis can extract fault features of each layer and obtain fault features of each indicator. In the process of fault signal wavelet analysis, it is found that the wavelet transform does not have time-shift invariance, and the spectra obtained at different time starting points are also different. By this method, the waveform index and peak value of each layer and the waveform index, peak value, pulse index, root-mean-square value, and maximum value under the fault state of the valve are greater than the waveform index, peak value, pulse index, root-mean-square value, and maximum value under the normal state of the valve. RBF neural network is used for pattern recognition of the obtained data, and the fault can be accurately judged by MATLAB simulation. Wavelet pretreatment can effectively eliminate the redundancy of compressor valve fault signal, reduce the input dimension of neural network, improve the convergence performance of the network, reduce the training time of the network, and avoid the network falling into local minima.

The novelty of this paper is that it proposes a fixed-time method to overcome the variable wavelength of the nonvariable wave, and the RBF neural network is effectively used in air compressor fault detection. The implementation of this project provides another effective case for the application of air compressor condition monitoring and diagnostic errors, which have a certain value of reliability.

Data Availability

No data were used to support this study.

Conflicts of Interest

The author states that this article has no conflict of interest.

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