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Fault diagnosis model of rolling bearing based on parameter adaptive VMD algorithm and Sparrow Search Algorithm-Based PNN

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Highlights

- Optimization of the parameters of the VMD algorithm through the genetic algorithm (GA) to achieve adaptive extraction of rolling bearing fault features.
- Optimization of the model parameters of the probabilistic neural network (PNN) using the sparrow search algorithm (SSA) to improve the recognition accuracy of the network model.
- A fault pattern recognition model for rolling bearings was constructed by combining the fault feature adaptive extraction method and the sparrow probabilistic neural network.

Abstract

Fault diagnosis of rolling bearings is essential to ensure the proper functioning of the entire machinery and equipment. Variational mode decomposition (VMD) and neural networks have gained widespread attention in the field of bearing fault diagnosis due to their powerful feature extraction and feature learning capacity. However, past methods usually utilize experiential knowledge to determine the key parameters in the VMD and neural networks, such as the penalty factor, the smooth factor, and so on, so that generates a poor diagnostic result. To address this problem, an Adaptive Variational Mode Decomposition (AVMD) is proposed to obtain better features to construct the fault feature matrix and Sparrow probabilistic neural network (SPNN) is constructed for rolling bearing fault diagnosis. Firstly, the unknown parameters of VMD are estimated by using the genetic algorithm (GA), then the suitable features such as kurtosis and singular value entropy are extracted by automatically adjusting the parameters of VMD. Furthermore, a probabilistic neural network (PNN) is used for bearing fault diagnosis. Meanwhile, embedding the sparrow search algorithm (SSA) into PNN to obtain the optimal smoothing factor. Finally, the proposed method is tested and evaluated on a public bearing dataset and bearing tests. The results demonstrate that the proposed method can extract suitable features and achieve high diagnostic accuracy.

Keywords
rolling bearing, failure diagnosis, adaptive variational mode decomposition, sparrow probabilistic neural network

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1. Introduction

Rolling bearings as the core components of the mechanical transmission system, widely used in various types of precision machinery and equipment; bearing failure often causes catastrophic consequences. Under the condition of good lubrication, correct installation and moderate working condition, the rolling bearing failure is mostly fatigue[5]. At present, when domestic and foreign scholars research rolling bearing fault diagnosis, they usually assume that the bearing failure is fatigue failure. By drilling holes and EDM engraving on bearing rings and rolling bodies to simulate fatigue pitting and fatigue spalling of bearings, the bearing signals with more obvious fault characteristics are obtained through experiments[19]. However, the actual operation of the bearing will be affected by many external conditions, which may produce other forms of failure, such as wear, scoring, plastic deformation, etc. And the fault feature signal may be hidden among other noise signals and

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challenging to observe. Therefore, the timely detection of bearing failure and determination of its failure taking, and then taking the necessary measures to maintain.

The diagnosis method based on vibration signal is a relatively popular and effective detection method at home and abroad. Bearing vibration signals exhibit non-smooth and complex frequency components features, and the fault features are easily drowned by environmental noise, which makes it challenging to extract the features of faults[30].EMD[6], EEMD[26], CEEMD[22], LMD[21], LCD[2] and other time-frequency analysis methods are commonly used to process signals. However, these methods suffer from deficiencies such as modal confounding. Variational modal decomposition (VMD) is widely used in the study of bearing fault diagnosis because of its good noise robustness and ability to suppress modal aliasing and endpoint effects effectively [7]. However, the model parameters significantly influence the effect of decomposition. Wang Fengtao et al. used the energy difference of the decomposed signal as a criterion to determine the parameter k[3]. Lian et al. proposed to set the range of k in advance, decompose the signal in the set range, and calculate the energy loss for different numbers of decomposed modes to obtain the optimal k[12]. Li Hua et al. optimize the number of decompositions k according to the theory of maximum IMF cliffness[13]. However, they only optimize for the number of decomposition layers K, so the obtained parameters are not necessarily globally optimal solutions.

Therefore, Wenjie Shi et al. used the differential search (DS) algorithm to optimize the VMD to achieve adaptive signal decomposition and then reconstructed the components after weighting them[23]. Gu Ran et al. used an adaptive variational modal decomposition (AVMD) method to reconstruct the signal of the effective modal components[18]. Chen Peng et al. used the whale algorithm to determine and improve the threshold noise reduction for the optimal components to extract fault features effectively[17]. Ren Xueping used the energy difference as the evaluation indicator to select the number of decomposition layers and combined it with the envelope derivative energy operator to achieve early fault diagnosis[24]. Cheng Junsheng et al. combined the firefly algorithm and the principal modal analysis method to determine the best combination of the influence parameters [k,α] of the VMD, and used it for the fault diagnosis of tooth root crack[10]. In this paper, a genetic algorithm is used to optimize the parameters of the VMD algorithm to further enhance the adaptiveness of the parameters.

With the development of intelligent algorithms, neural networks are used extensively. Compared with general algorithms, it has the characteristics of fast training and convergence, high accuracy and fault tolerance. Du Zhendong et al. combined sensitivity analysis (SA), empirical modal decomposition (EMD) and PNN to achieve fault recognition of plunger pumps[29]. Chen hui et al. used multiscale entropy with PNN to diagnose the type and extent of bearing fault[8]. And Chen Shuai et al. further combined composite multiscale scattering entropy and probabilistic neural network for bearing fault diagnosis[20]. Zhao Ningning et al. proposed a bearing fault feature extraction method based on adaptive local iterative filtering and PNN[16]. Although PNN has many advantages, the value of the smoothing factor of its model parameters has a significant impact on its classification results and mainly selected based on experience, for which Qin Xing et al. used PSO to optimize PNN networks for the effective identification of power quality disturbances[25]. Liu Fuzheng et al. used PSO to optimize PNN and extract the energy vantage of the signal to achieve fault diagnosis of bearings[4]. Dang Jian et al. used the Firefly algorithm to determine the optimal parameters and used FA-PNN to achieve fault diagnosis of wind turbine gearboxes[11]. The Sparrow Search Algorithm (SSA) has a strong merit-seeking ability and convergence speed. Chen et al. used the SSA algorithm to solve the problem of overlapping adjacent spectral peaks of elements in the X-ray fluorescence analysis method[27]. Ma Chen et al. used the SSA to optimize SVM to diagnose bearing faults effectively [15]. Tang Yanqiang et al. proposed an adaptive variational sparrow search algorithm, which greatly improves the accuracy of the algorithm's search[28]. Hu, Hongzhi et al. used EMD and SVM method optimized by SSA to achieve tool wear status identification[9]. Combining the above research, this paper uses the SSA algorithm to optimize the parameter smoothing factor of PNN.

In summary, this paper proposes a rolling bearing fault diagnosis method based on AVMD and SPNN. Using the genetic algorithm to determine the parameters in the VMD algorithm model, realized the adaptive extraction of fault features of bearing vibration signals and then constructed the fault feature matrix. Meanwhile, the SSA determines the optimal smoothing factor for the PNN network. And constructing the sparrow probabilistic neural network (SPNN). The fault feature matrix is substituted into the SPNN network for training and prediction to achieve diagnosis of rolling bearing faults.

The main content of the article is organized as follows. Section Ⅱ describes in detail the adaptive extraction method based on the AVMD algorithm; Section Ⅲ gives the detailed procedure of the rolling bearing fault diagnosis model; The feasibility of the model is verified through experiments in Section Ⅳ; Finally, Section Ⅴ gives the conclusion of the article.

2. Adaptive feature extraction

In this section, the adaptive extraction method based on the AVMD algorithm is described in detail. First, we introduce the variational modal decomposition method, The GA algorithm is then used to perform an adaptive decomposition of the vibration signal, on the basis of which the feature matrix is constructed.

2.1.Variational modal decomposition

Variational modal decomposition (VMD) was first introduced as a signal decomposition method by Dragomiretskiy et al.[1]. The essence of this method is to use the vibration signal to construct a variational mode, and to convert the signal into intrinsic mode components with central frequency and bandwidth by iterative search and solution. This method can effectively avoid the endpoint effect and modal mixing problem in the empirical modal decomposition. It can also eliminate noise interference in the extraction of fault components and realize the decomposition of the signal [14].

Decompose the vibration signal f into K natural modal components $\mu_k(t)$ with center frequency ω_k. Then the variable modal problem can be represented as a problem of finding K intrinsic modal components. With the sum of the modal components being f, minimise the sum of the estimated bandwidths of each modal component. The model is：

$$\begin{cases} min_{\{u_k\}\{\omega_k\}}\left\{\sum_k \left\|\partial_t\left[\left(\sigma(t)+\frac{j}{\pi t}\right)\times u_k(t)\right]e^{-j\omega_k t}\right\|_2^2\right\} \\ s.t. \sum_k u_k = f \end{cases} \quad (1)$$

In order to transform the variational modal decomposition problem into an unconstrained problem, we introduce an enhanced Lagrangian function. The model is：

$$L(u_k,\omega_k,\lambda)=\alpha\sum_k\left\|\partial_t[(\delta(t)+\frac{j}{\pi t})\times u_k(t)]e^{-j\omega_k t}\right\|_2^2+ \|f-\textstyle\sum_k uk\|_2^2+\langle\lambda, f-\sum_k u_k\rangle \quad (2)$$

The iterative solution formula for the modal components μ_k, the central frequency ω_k and λ_k is:

$$u_k^{n+1}(\omega)=\frac{f(\omega)-\sum_{i\neq k}u_i(\omega)+\frac{\lambda(\omega)}{2}}{1+2\alpha(\omega-\omega_k)^2} \quad (3)$$

$$\omega_k^{n+1}=\frac{\int_0^\infty \omega|u_k(\omega)|^2 d\omega}{\int_0^\infty |u_k(\omega)|^2 d\omega} \quad (4)$$

$$\lambda^{n+1}(\omega)=\lambda^n(\omega)+\tau(f(\omega)-\textstyle\sum_k u_k^{n+1}(\omega)) \quad (5)$$

Until the iterative stopping condition $\sum_k(\|u_k^{n+1}-u_k^n\|_2^2/\|u_k^n\|_2^2)\leq\varepsilon$ is met, the variational solving process ends. At this point, get K modal components with finite bandwidth.

In the VMD method, the decomposition modal number K and the penalty factor α greatly impact the decomposition results, and their combination in the VMD method is shown in Table Ⅰ. As can be seen, the choice of K value is crucial for the accurate determination of the resonance band in which the fault characteristic frequency is located, and the correct choice of α value ensures the accuracy of the VMD algorithm when reconstructing the signal. Therefore, reasonable VMD model parameters are especially important to extract fault information from bearing vibration signals effectively.

Table 1. Effect of VMD parameters on the final results.

K-value	a-value	Consequences
oversize	oversize	Modal Mixing
	too small	Missing valid information
too small	oversize	Missing valid information
	too small	Modal Mixing

2.2.Adaptive feature extraction basic on AVMD

The choice of the modal number K and penalty factor α for the parameter decomposition of the VMD relies heavily on the experience of the technician. The traditional method of determining K values is to try one by one from small to large and analyze the results with the decomposition to determine K values: As the value of K increases each major frequency band data can be distributed into different IMF components. No spurious components are generated, then the value of K is more appropriate. And the penalty factor α determines the bandwidth of the IMF components. Too small a bandwidth can lead to some signals being lost, and too large a bandwidth can cause some components to contain signals from other components. The common range of penalty factor is 500~3000.

Selecting the right combination of parameters is the key to signal decomposition using the VMD algorithm. If one parameter is set unchanged and the other parameter is optimized, the influence of the interaction of the two parameters is ignored, which makes the optimization of the objective function easy to become a local optimization. To obtain the best model parameters and avoid human influence on the parameters, it is necessary to use algorithms to optimize the parameters of the VMD algorithm..

Genetic algorithm has the ability of fast global search and wide adaptability. It has been used in various parametric optimization problems, such as SVM and BP neural networks. In the optimization process, the first step is to determine a reasonable objective function. The entropy value can effectively reflect the randomness and complexity of the bearing vibration signal. The stronger the cyclical components of the vibration signal decomposition, the more fault information it contains, and the lower the entropy value. Conversely, the more noise signal components will become, the less obvious the periodicity will be, and the higher the entropy value.

Selecting the sample entropy as the goal function, the sample entropy of the component $\{x(n)\} = x(1), x(2), \dots, x(N)$ for the original vibration signal of the bearing after decomposition by VMD can be expressed as:

Form the data into an m-dimensional vector sequence $X_m(1), X_m(2), \dots, X_m(N-m+1)$ according to the data serial number, where $X_m(i) = \{x(i), x(i+1), \dots, x(i+m-1)\} 1 \leq i \leq N-m+1$.

Form the data into a sequence of vectors X of dimension m according to their serial numbers

This vector sequence represents m consecutive data starting from the i-th data point.

The distance between vectors $X_m(i)$ and $X_m(j)$ is:

$$d[X_m(i), X_m(j)] = max_{k=0,1,\dots,m-1} (|x(i+k) - x(j+k)|) \tag{6}$$

The number of $X_m(i)$ and $X_m(j)$ distances less than to r is recorded as B_i.

For $1 \leq i \leq N-m$, define as :

$$B_i^m(r) = \frac{1}{N-m-1} B_i \tag{7}$$

Define $B^{(m)}(r)$ as:

$$B^{(m)}(r) = \frac{1}{N-m} \sum_{i=1}^{N-m} B_i^m(r) \tag{8}$$

Similarly, when the number of dimensions is m+1, the number of individuals is defined as A_i.

Define ${A_i}^{(m)}(r)$ as

$$A_i^m(r) = \frac{1}{N-m-1} A_i \tag{9}$$

Define $A^{(m)}(r)$ as:

$$A^{(m)}(r) = \frac{1}{N-m} \sum_{i=1}^{N-m} A_i^m(r) \tag{10}$$

The sample entropy is defined as:

$$SampEn(m, r) = \lim_{N \to \infty} \left\{ -\ln \left[\frac{A^m(r)}{B^m(r)} \right] \right\} \tag{11}$$

When N is a finite value, the equation is:

$$SampEn(m, r, N) = -\ln \left[\frac{A^m(r)}{B^m(r)} \right] \tag{12}$$

Based on the fault diagnosis of the vibration signal of the bearing, it is essential to extract the fault characteristics that are indicative of the bearing's operating conditions. Based on the adaptive decomposition of the original signal using the AVMD method proposed in Chapter Ⅳ. Analysis in terms of time domain, frequency domain, and entropy, select root means square, cliffs, envelope entropy, and singular value entropy to construct the feature matrix and substitute it into the SPNN network for training prediction. It can achieve diagnosis of rolling bearing faults.

The root means square is defined as:

$$X_{rms} = \sqrt{\frac{\sum_{i=1}^{N} (x_i)^2}{N}} \tag{13}$$

Cliffness is defined as:

$$q = \frac{\sum_{i=1}^{N} x_i^4}{N} \tag{14}$$

The envelope entropy is defined as:

$$E_{i_1} = -\sum_{j=1}^{N} p_{i_1,j} \lg p_{i_1,j}, p_{i_1,j} = a_{i_1}(j) / \sum_{j=1}^{N} a_{i_1}(j) \tag{15}$$

Where i_1 ($i_1 = 1,2,3\dots$) is the ordinal number of the IMF component obtained by decomposing the original signal $x(i)$ of length N; $p_{i_1,j}$ is the normalized form of $a_{i_1}(j)$; $a_{i_1}(j)$ is the envelope signal of the IMF component of the signal after Hilbert demodulation.

According to the k components obtained from the VMD decomposition, perform singular value decomposition on it. The singular value spectrum is obtained as $\delta = \{\delta_1, \delta_1, \ldots, \delta_n\}$, and the entropy of the singular value spectrum is defined as:

$$S = -\sum_{i_1=1}^{k} P_{i_1} \log_2 P_{i_1}, P_{i_1} = \delta_{i_1} / \sum_{i_1=1}^{k} \delta_{i_1} \qquad (16)$$

Where, p_{i_1} is the weight of the i_1 singular value in the spectrum of singular values.

3. Rolling bearing failure diagnosis

In this section, the construction process of the fault diagnosis model is described in detail. We introduce the sparrow probabilistic neural network, and then we introduce the process of diagnosing rolling bearings.

3.1.Sparrow probabilistlc neural network

Probabilistic Neural Network (PNN) is an optimization algorithm consisting of four layers: input layer, mode layer, accumulation layer and output layer. Compared with the general BP neural network, it has the characteristics of fast training and convergence, high accuracy and fault tolerance.

However, in the process of practical application, it is found that the value of the smoothing factor α of the model parameters in the probabilistic neural network has a significant impact on its classification results, so how determining the optimal smoothing factor is crucial to obtaining accurate recognition results.

In this paper, the sparrow search algorithm (SSA) is used to optimize the PNN model to determine the optimal parameters α, then construct the sparrow probabilistic neural network (SPNN). The sparrow search algorithm classifies population data into finders, followers and warners by imitating the sparrow's foraging and anti-predatory behavior. The sparrow search algorithm is superior to other single-objective optimization algorithms in terms of search precision.

Assume that the population size of the optimization algorithm is N and the number of maximum iterations is T, and the number of optimization objectives is d. The sparrows' positions are X_{ij}（i=1,2,...,n; j=1,2,...，d）

Discoverers, which typically makeup 10-20% of the population, provide direction to followers by constantly iterating and updating to find better adaptations. Whose position iteration formula is shown in equation (17).

$$X_{i,j}^{t+1} = \begin{cases} X_{i,j}^{t} \, exp\left(\frac{-i}{\alpha T}\right), R_2 < S_T \\ X_{i,j}^{t} + QL, R_2 \geq S_T \end{cases} \qquad (17)$$

Followers are poorly adapted individuals in the population, and when a better-adapted individual is found among the discoverers, the followers will change their position to obtain a better adaptation. Whose position iteration formula is shown in equation (18).

$$X_{i,j}^{t+1} = \begin{cases} Q \, exp\left(\frac{X_{worst}^{t} - X_{i,j}^{t}}{i^2}\right), i > \frac{n}{2} \\ X_{best}^{t+1} + \left|X_{i,j}^{t} - X_{best}^{t+1}\right| A^{+} L, i \leq \frac{n}{2} \end{cases} \qquad (18)$$

Warners generally make up 10-20% of the whole, and their original positions are chosen at random, whose position iteration formula is shown in equation (19)

$$X_{i,j}^{t+1} = \begin{cases} X_{best}^{t} + \beta \left|X_{i,j}^{t} - X_{best}^{t}\right|, f_i > f_g \\ X_{i,j}^{t} + K\left(\frac{X_{i,j}^{t} - X_{worst}^{t}}{(f_i - f_w) + \varepsilon}\right), f_i = f_g \end{cases} \qquad (19)$$

The training error of PNN is used as the fitness function of SSA to determine the optimal parameters σ, and the obtained sparrow probabilistic neural network can be used for subsequent failure diagnosis research. The parameter description table is shown in Table 2.

Table 2. Parameter description table.

Parameter	Mathematical implications
t	Number of current iterations
α	A random number of (0,1]
Q	A random number obeying the standard normal distribution
R_2	The warning value, located at [0,1]
S_T	The safety value, located at [0.5,1]
X_{worst}^{t}	The global worst position
X_{best}^{t+1}	The global best position
A	A 1*d matrix
β	The step control parameter
f_i f_w f_g	The fitness, worst and best fitness values
K	A random number of [-1,1]

3.2. Failure diagnosis for rolling bearings

Based on the method of adaptive feature extraction of AVMD mentioned above, the feature matrix is substituted into the SPNN network for training and prediction to achieve diagnosis of rolling bearing faults. The framework flow chart for the method described in this paper is shown in Figure 1.

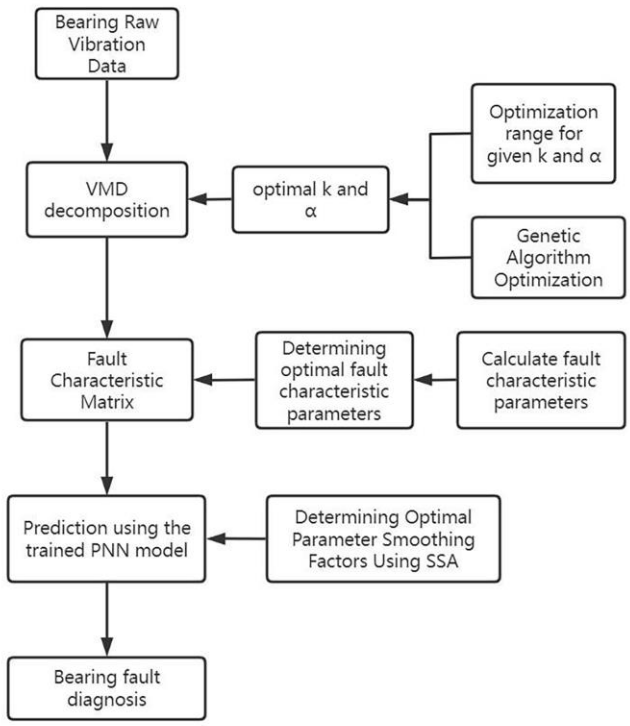


Fig. 1. Flow chart of rolling bearing fault diagnosis algorithm framework.

The algorithm process is as follows:

1) Adaptive feature extraction based on AVMD: The VMD algorithm optimized by the genetic algorithm decomposes the original vibration signal of the bearing into several relatively independent intrinsic modal components. Calculate the root mean square, cliffs, singular value entropy and envelope spectral entropy of each order component to construct the fault feature matrix.
2) Rolling bearing fault diagnosis using SPNN network: Using the rolling bearing accelerated life test bench to obtain failure data for a wide range of bearing conditions. Create a fault feature matrix and divide the data into training and test samples. Building SPNN fault diagnosis models using training samples, fault diagnosis of rolling bearings using test specimen testing.

4. Engineering example

4.1.Validation of public datasets

This paper uses real damage data generated from accelerated life tests on the Paderborn bearing dataset at the University of Paderborn, Germany, for validation. The test uses a rolling bearing accelerated life test bench to accelerate the examination of 6203 deep groove ball bearings. It accelerated bearing damage through increased radial load and selection of low viscosity lubricant. The purpose of using low viscosity lubricants is to allow improper lubrication conditions for the bearings, thus accelerating the appearance of bearing damage and saving test time and resources. The final bearing failure takes the form of fatigue pitting and plastic deformation.

The test bearing has four working conditions, and the data under the last working condition is selected for analysis. The bearing speed is 1500rpm and the radial load is 400 N, the sampling frequency is 64KHz, take 0.1s data as a sample, three kinds of (outer ring pitting, inner ring pitting, plastic deformation) state a total of 240 randomly selected training samples and 120 test samples. Take an inner ring pitting sample as an example, its original vibration signal and frequency spectrum are shown in Figure 2 and Figure 3. The adaptive feature extraction method of AVMD is used to decompose the signal, the optimized decomposition layer $k = 8$, the penalty factor $\alpha = 1953$, the iteration curve of the fitness function is shown in Figure 4, and the multilayer intrinsic modal components obtained from the decomposition are shown in Figure 5.

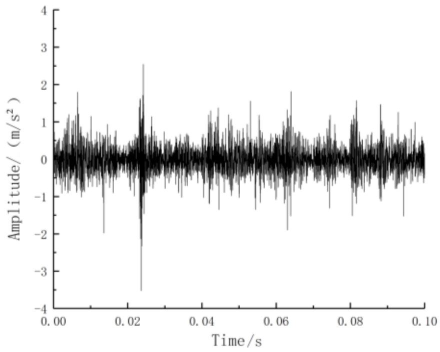


Fig. 2. Original vibration signal of inner ring pitting failure.

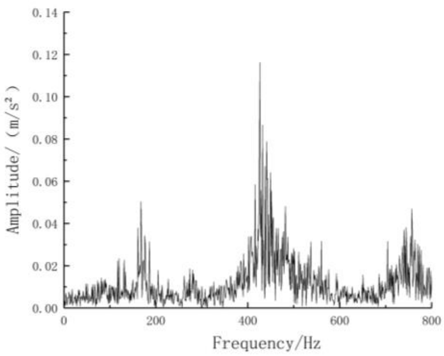


Fig. 3. Signal spectrum of inner ring pitting failure.

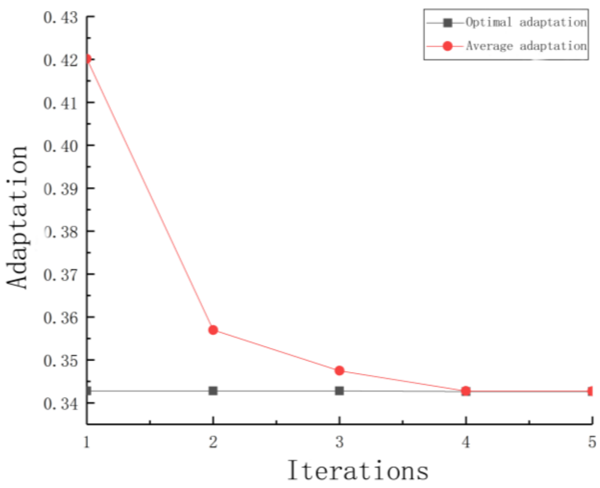


Fig. 4. Adaptation function iteration curve.

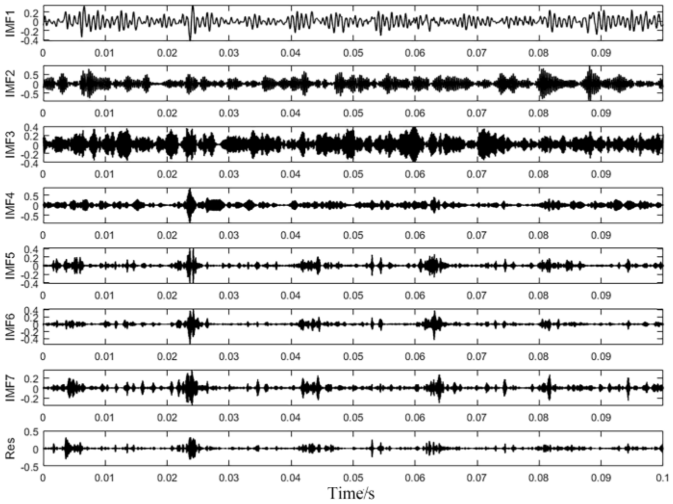


Fig. 5. Inner ring pitting fault signal VMD decomposition results.

For the samples with different failure modes, set the value range of decomposition layers K to [3,10] and the value range of the penalty factor to [500,2000]. Extraction of fault features according to the components of adaptive decomposition, where the cliffs, the cliff and envelope entropy are both 1*10 vectors. Calculate the cliffness and envelope entropy of each component. If the number of decomposition layers after optimization is less than 10, zero is added after this vector. Together with the root mean square and the singular spectrum, they form the fault characteristic matrix. Table 3 shows the values of the failure characteristics of the bearings in different failure modes. As can be seen from the table, there are obvious differences in the fault characteristic values between different failure modes, laying the foundation for the accurate identification of subsequent failure modes

Table 3.Failure characteristics of bearings under different failure modes.

Bearing fault type	root mean square (m/s^2)	Singular value spectral entropy	Cliffness	Envelope entropy
Outer ring pitting	0.418	1.719	(0.0124, 0.0046, 0.0087, 0.0011, 0.0006, 0.0001, 0.0001, 0,0,0)	(9.26,8.66, 8.53,8.67， 8.52,8.21, 8.17,0,0,0)
Inner ring pitting	0.326	1.605	(0.0061, 0.0029, 0.0011, 0.0018, 0.0001, 0.0001, 0,0,0,0)	(9.57,8.66, 8.63,8.55, 8.15,8.21, 0,0,0,0)
Plastic deformation	0.340	2.018	(0.0002, 0.0070, 0.0008, 0.0004, 0.0004, 0.0004, 0.0001, 0.0001, 0.0001, 0)	(9.10,8.69, 8.64,8.57, 8.18,8.14, 8.21,8.26, 8.50,0)

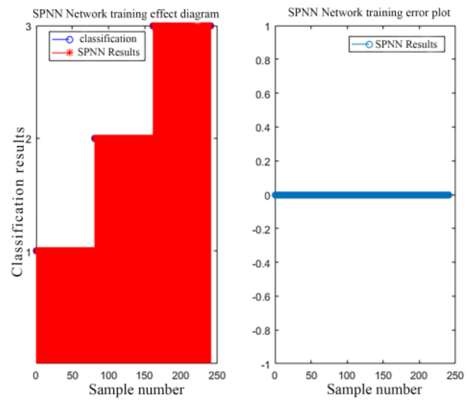


Fig. 6. SPNN network training error graph.

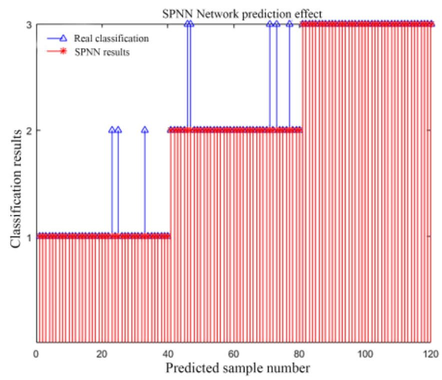
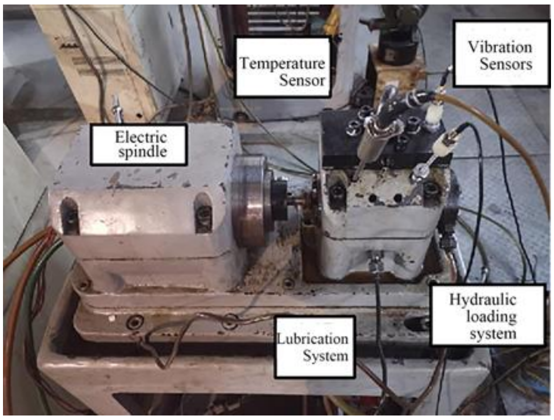


Fig. 7. SPNN Network prediction results.

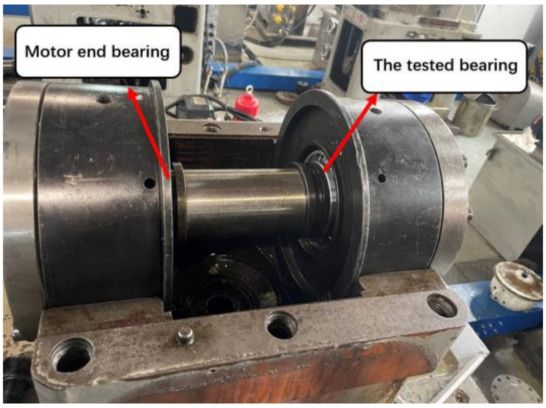
Based on obtaining the characteristics of the bearing fault, outer ring pitting, inner ring pitting and plastic deformation are marked as 1~3. Set the value range of the smoothing factor to [0.0001,2]. Training of data using sparrow probabilistic neural network and its optimized smoothing factor $\sigma = 0.0581$. Its training error is shown in Figure 6 and the prediction results in Figure 7, reaching 93.3%. Based on the empirical selection of the smoothing factor $\sigma = 0.5$, the accuracy of the PNN network recognition is 86.7%. Comparison of the results of the recognition, it can be seen that the PNN network optimized by the sparrow search algorithm has higher accuracy than the PNN network using empirically selected smoothing factors. It shows that the proposed AVMD and SPNN rolling bearing fault diagnosis method has excellent diagnostic effects and superiority.

4.2.Experimental verification

To further validate the efficacy of the described method, we used actual rolling bearing failure signals for verification.



a)



b)

Fig. 8. Machine tool spindle bearing test bench:(a) Machine tool spindle bearing test bench structure diagram,
(b) Machine tool spindle bearing test bench partial diagram.

The test uses the rolling bearing performance test bench of Luoyang Bearing Research Institute. The machine tool spindle bearing test bench structure diagram and partial diagram are shown in Figure 8. The diagram shows the bearing mounting positions on the motor end and the non-motor end of the test bench. During the test, it took approximately 30 minutes to remove the old bearing and replace it with a new one. The sensor used is the IEPE voltage output acceleration sensor, and the MI-7008 signal acquisition and analyzer of Yiheng Company is used to collect the bearing vibration signal. The signal acquisition instrument is shown in Figure 9.

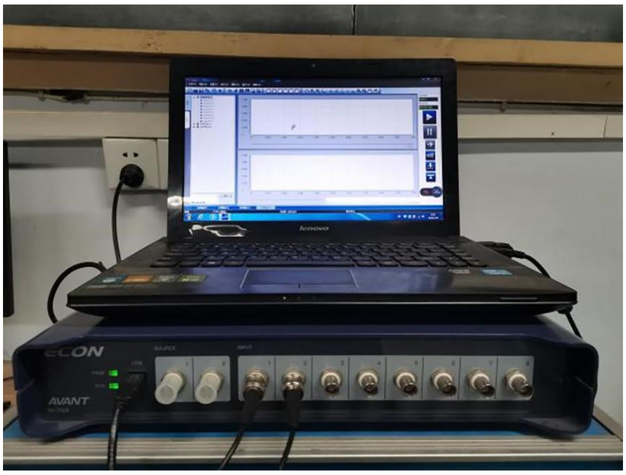


Fig. 9. MI-7008 Signal Acquisition and Analyzer.

The test bearing uses angular contact ball bearing B7005C, bearing parameters as shown in Table 4.

Table 4. Test basic bearing parameters.

name	Inner diameter (mm)	Outer diameter (mm)	Diameter of rolling element (mm)	Number of rolling element	Bearing width (mm)	Contact angle (°)
value	25	47	6.35	14	12	15

The electrical discharge machining technique was applied to construct craters in the rings of the bearings respectively to simulate the fatigue spalling of the bearings during the actual operation, the shape of which is shown in Figure 10 and Figure 11.

Fig. 10. Simulation topography of bearing fatigue spalling fault.

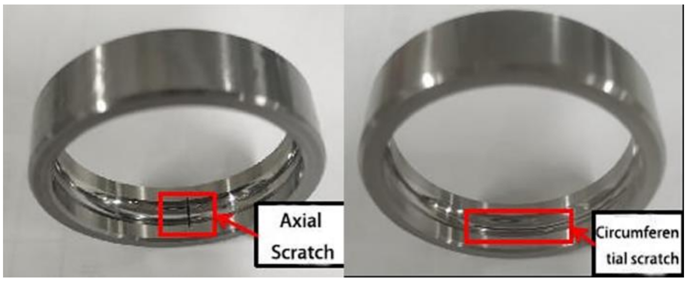


Fig. 11. Simulation topography of bearing outer ring scratch fault.

After the test bearings had been installed and were running steadily, vibration signal data were collected from the same bearing for approximately 20 minutes at different time periods.

For samples with different failure modes, set the value range of the decomposition layer K to [3,10] and the value range of the penalty factor $\sigma$to [500,2000]. Based on the components of adaptive decomposition, root means square, singular value spectral entropy, cliffness and envelope entropy are extracted to construct the fault feature matrix. Mark outer ring spalling, outer ring axial scratches, and outer ring circumferential scratches as 1-3 respectively. Set the value range of the smoothing factor to [0.0001,2]. The SPNN is used to train the data for recognition, and its optimized smoothing factor is 0.0614. Its training error is shown in Figure 12 and its prediction results in Figure 13, with 139 correct samples and an accuracy rate of 92.7%.

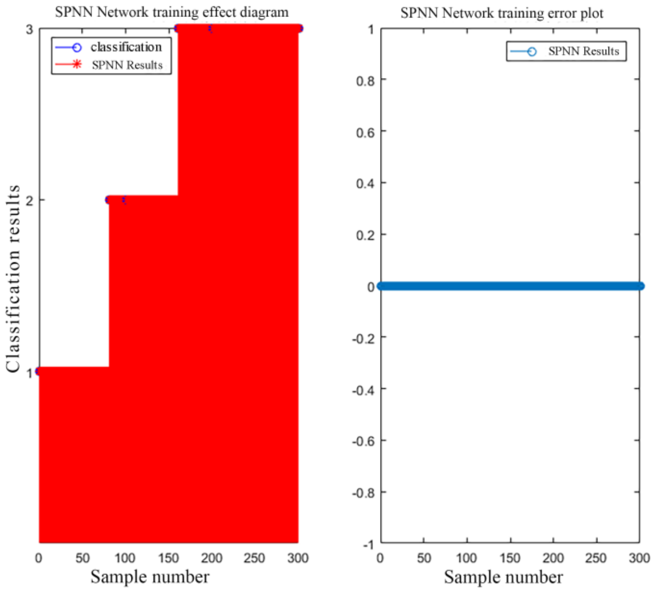


Fig. 12. SPNN network training error graph.

And the accuracy of the PNN network recognition is 80.6%. Comparison of the results of the recognition, it can be seen that the SPNN network has higher accuracy than the PNN network. The results are shown that the method described in this paper has good recognition of rolling bearing failure modes.

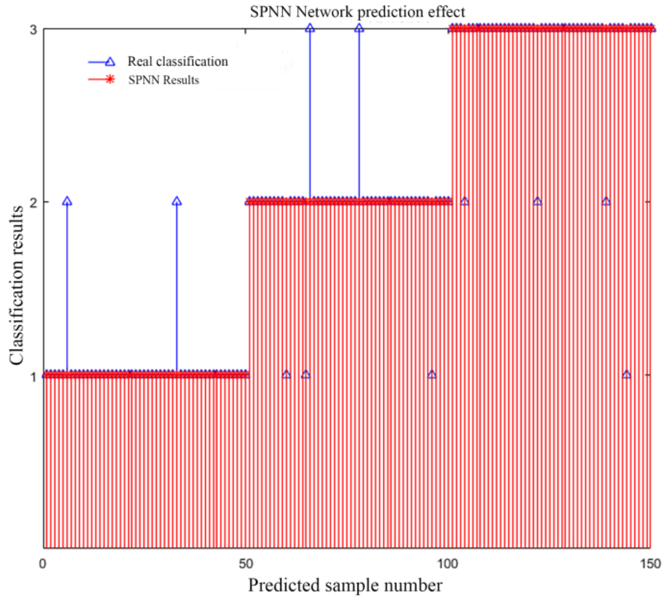


Fig. 13. SPNN Network prediction results.

5. Conclusion

This paper proposes a rolling bearing fault diagnosis method based on AVMD and SPNN. Using genetic algorithm to select the optimal values of the number of decomposition layers K and the penalty factor α in the VMD algorithm. Adaptively extract fault features such as cliffness, singular value entropy, envelope spectrum entropy of the bearing and construct fault feature matrix. Then, using SSA algorithm to determine the optimal value of the smoothing factor α in the PNN network model. Finally, a sparrow probabilistic neural network bearing fault diagnosis model is constructed to diagnose the bearing fault signals of different failure mode states.

We validated the proposed approach with publicly bearing datasets and bearing tests, and compare it with traditional PNN networks. The results show that the SPNN network has a more effective diagnostic performance. Optimization of the parameters with greater influence can significantly increase the accuracy of bearing fault diagnosis.

But when bearing failure tests are performed, we set a single failure point and scratch size for bearings and fewer forms of failure. We will follow up with further experimental analysis by increasing the size of the bearing failures and increasing the form of the bearing failures to explore the generalisability of the article's methodology.

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