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State identification of large diameter wet steam pipeline in nuclear power conventional island

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Abstract. The safety of nuclear power plant is an inevitable condition for maintaining the long-term and stable development of nuclear power. Pipeline vibration is one of the common causes of power plant operation faults. Therefore, the state identification of pipeline vibration is very important. Taking a nuclear power heating pipeline as an example, the original vibration signal is decomposed and reconstructed by Wavelet Packet Transform, and the energy eigenvectors in X, Y and Z directions are established. In order to analyze the state of pipeline more accurately, two recognition algorithms of support vector machine (SVM) and SOM neural network are proposed. By comparing the classification effect and classification accuracy of the SVM before and after optimization, the optimized SVM and SOM neural network, it is concluded that the optimized SVM has better effect on pipeline state recognition, and the effectiveness of this method on pipeline state recognition is verified.

1 Introduction

As the medium of conveying fluid, pipeline is widely used in oil, energy, electric power and other fields [1]. Pipeline vibration is a common cause of safety accidents. At least, it will lead to pipeline damage, reduce service life and increase additional maintenance costs. At worst, it will paralyze the whole system and cause casualties.

In 2021, China's first nuclear heating "warm nuclear No. 1" was successfully put into operation. When heating the nuclear power plant, compared with other heating and steam extraction pipelines, the heating network heater of the nuclear power conventional island is arranged outside the plant of the conventional island, and the distance of the heating and steam extraction pipeline is longer. Compared with thermal power, the working fluid entering the steam turbine for nuclear power is saturated steam, so the moisture content of steam extraction for heating supply is larger. When the wet steam moves in the pipeline, the pressure and pressure in the pipeline change constantly. Once the pressure exceeds the standard allowable threshold, the pipeline will burst and other problems. In addition, the frequency of pipeline vibration will be different, and the generated noise will also make the pipeline in an unstable state. Therefore, it is very necessary to identify the state of heating pipeline in nuclear power conventional island.

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Based on the above, this paper uses the wavelet packet energy method to extract the energy features of the measured data in six states: no extraction steam, heating pipe of heat addition tube, A-column heater input, B-column heater input, operation A&B-column heater input, and normal stage. The extracted feature vectors are input into SVM and SOM neural network for state recognition, and the proposed model method is verified.

2 Extracting energy features from wavelet packet change

2.1 Wavelet packet decomposition

In wavelet packet decomposition [2], a group of recursive relation functions generated by the standard orthogonalization of scale function is shown in formula (1):

$$\begin{cases} S_{2n}(t) = \sqrt{2}\sum_{k\in Z} h(k) S_n(2t-k) \\ S_{2n+1}(t) = \sqrt{2}\sum_{k\in Z} g(k) S_n(2t-k) \end{cases} \tag{1}$$

where: n is the number of oscillations; k is the position index; $h(k)$ and $g(k)$ are the high pass and low pass orthogonal filter coefficients derived from the scaling function; Orthogonal wavelet packet with $S(t)$ as $\varphi(t)$.

In theory, the projection coefficient of the collected signal on the basis of orthogonal wavelet packet is called orthogonal wavelet packet coefficient, which is discrete. For the actually collected signal, the wavelet packet transform coefficient can be expressed as the following recursive relationship:

$$\begin{cases} C_{i,j,2m} = \sum_{k\in Z} h_{(k-2i)} C_{k,j+1,m} \\ C_{i,j,2m+1} = \sum_{k\in Z} g_{(k-2i)} C_{k,j+1,m} \end{cases} \tag{2}$$

where: $C_{i,j,m}$ is the wavelet transform coefficient of the collected signal in the orthogonal wavelet packet space; $h_{(k-2i)}$ and $g_{(k-2i)}$ are the high pass and low pass orthogonal filter coefficients derived from the scaling function.

Wavelet transform only decomposes the low-frequency signal, and does not further decompose the high-frequency signal. Wavelet packet change decomposes both low-frequency signals and high-frequency signals. Wavelet packet analysis is more careful in signal decomposition and has good time-frequency resolution.

2.2 Wavelet packet energy method

By collecting the original vibration signals of heating pipeline under different operating states, the wavelet packet three-layer decomposition is carried out by using MATLAB software to decompose the coefficient components under different frequency bands and extract the characteristic signals.

The feature extraction process is as follows:

The pipeline signal is analyzed and processed to determine the number of wavelet packet decomposition layers.

Decompose the wavelet packet and reconstruct the wavelet packet coefficients;

Extract the energy signal of each subband, calculate the energy proportion of each subband, and construct the characteristic matrix;

The calculation formula is as follows:

Band energy [3, 4], Total energy and Energy proportion:

$$E_i = \left\| H\left(i, j\right) \right\|^2, E = \sum_{j=0}^{2^i-1} E_i, \eta = \frac{E_i}{E} \tag{3}$$

where: $H\left(i, j\right)$ is the wavelet packet decomposition coefficient of band j of layer i.

It can be seen from Figure 1 that there are different degrees of differences in the vibration characteristics of heating pipelines under different states. Therefore, using wavelet packet energy method to construct feature vector can be used to analyze pipeline vibration.

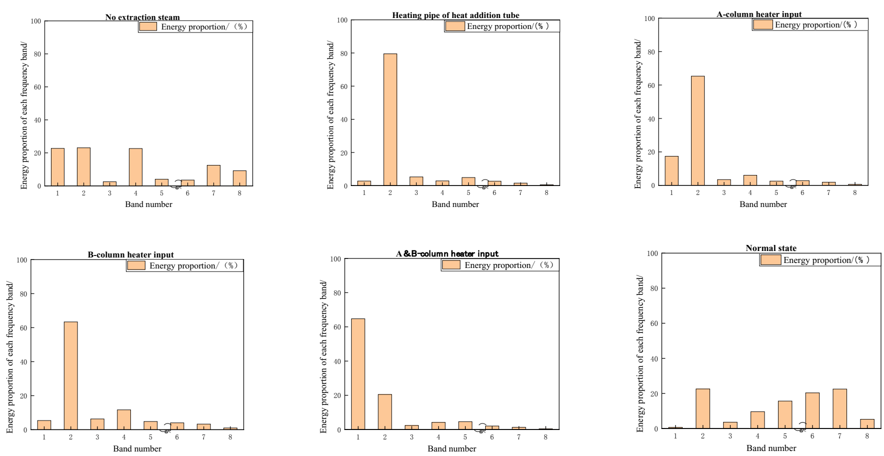

Fig. 1. Proportion of wavelet packet energy in six states.

3 Support vector machine (SVM) and SOM neural network analysis

3.1 Support vector machine (SVM)

Support vector machine was first proposed by foreign researchers *Vapnik* et al [5, 6]. Support vector machine can solve the problems of pattern classification and nonlinear regression. The theoretical basis of SVM is statistical theory. More accurately, it is the approximate realization of structural risk minimization.

Two classification SVM:

1) Training set:

$$T=\left\{\left(\mathrm{x}_1, y_1\right), \cdots, \left(\mathrm{x}_l, y_l\right)\right\} \in \left(X \times Y\right)^l \tag{4}$$

where: $x_i \in X = R^n, y_i \in Y = \{1,-1\} (i = 1,2,\cdots,l)$; x_i is Eigenvector.

2) Select the appropriate kernel function $K(x_i, x_j)$ and appropriate parameters C to construct and solve the optimization problem:

$$\min_{\alpha} \frac{1}{2} \sum_{i=1}^{j} \sum_{j=1}^{l} y_i y_j \alpha_i \alpha_j K(x_i, x_j) - \sum_{j=1}^{l} \alpha_j$$
$$s.t. \sum_{i=1}^{l} y_i \alpha_i = 0, 0 \le \alpha_i \le C, i = 1,2,\cdots,l \tag{5}$$

Optimal solution is $\alpha^* = (\alpha_1^*, \cdots, \alpha_l^*)^T$

3) Select a positive component $0 < \alpha_j^* < C$ of α^* and calculate the threshold accordingly and construct decision function:

$$b^* = y_j - \sum_{i=1}^{l} y_i \alpha_i^* K(x_i - x_j), f(x) = \mathrm{sgn}\left(\sum_{i=1}^{l} \alpha_i^* y_i K(x, x_i) + b^*\right) \tag{6}$$

However, in most problem processing, it is a multi classification problem, so we should construct a multi class classifier. There are two methods to construct multi class classifier, one is direct method, the other is indirect method. The direct method needs to combine the solutions of multiple classifications into one optimization problem. This method seems easy, but the calculation process is very complex and difficult to implement. The indirect rule is to combine multiple binary classifiers to construct a multi class classifier. This method is easier to implement than the direct method. In this paper, the one-to-one method of indirect method is used to construct multi class classifier. The principle of constructing multi class classifier by one-to-one method is to establish an SVM between any two samples, and n (n-1) / 2 support vector machines are required for n-class samples. This method analyzes and processes each sample and other samples, and the accuracy can be guaranteed. Pipeline states are diverse, so pipeline state identification is a multi classification problem.

3.2 SOM neural network

SOM neural network, also known as Kohonen network, is a teacher free, self-organizing and self-learning network proposed by foreign scholar T. Kohonen [7]. The scholar believes that the space is divided into corresponding spatial areas, corresponding to neurons. When there is signal input from the outside, different neurons make different stress responses. SOM neural network learns and classifies according to the grouping of input signals. The typical SOM structure is shown in Figure 4, and the input layer is fully connected with the mapping layer.

SOM neural network algorithm steps are as follows:

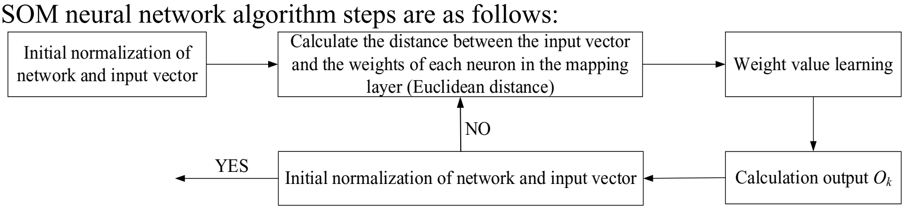

Fig. 2. SOM neural network steps.

4 Case analysis

4.1 Feature extraction

Based on the wavelet packet energy method, the measured vibration data of X, Y and Z axes in six states in the process of nuclear power heat addition are decomposed in three layers by wavelet packet, and the reconstructed coefficients of the third layer are used for energy feature extraction. A total of 972 groups of feature vectors are obtained, X. Y and Z axes 54 each.

4.2 Fault diagnosis based on support vector machine

As described in 2.1, a multi class classifier is constructed by MATLAB. Based on the wavelet packet energy method, 30 groups of feature vectors of X, y and Z axes in six states are taken as training samples, and the remaining 24 groups are taken as test samples, which are input into the SVM model for state recognition. As shown in Figure 3, the test results show that if the default parameters of SVM are used for direct recognition, the classification effect is not ideal. Therefore, this paper uses the svmcgforclass function in LISBVM toolbox to optimize the parameters in SVM. After optimization, the test feature vector is input into support vector machine for prediction. The prediction results are shown in Figure 4 and table 1 shows the test accuracy.

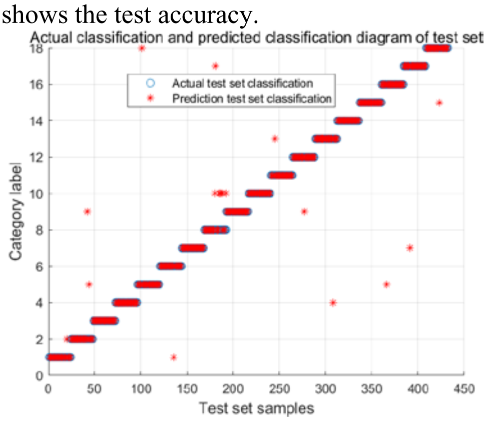

Fig. 3. SVM prediction results.

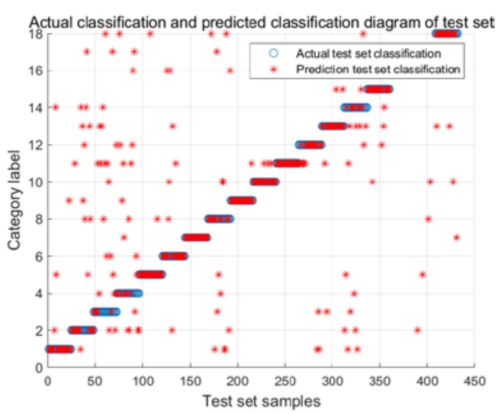

Fig. 4. Optimized SVM prediction results.

Table 1. SVM test accuracy (%).

Status category	X	Y	Z
No extraction steam	95.8	95.8	95.8
Heating pipe of heat addition tube	91.7	100	91.7
A-column heater input	100	100	100
B-column heater input	100	85.0	100
A & B-column heater input	95.8	95.8	95.8
Normal state	95.8	95.8	100

It can be seen from Figure 4 that only 18 misjudgments were made when 432 test samples were input. According to table 1, the average accuracy of SVM prediction can reach 95.83%. Moreover, the data used in this experiment is limited. The state recognition of pipeline based on wavelet packet energy method and optimized support vector machine can achieve high accuracy, so this method has a good effect on pipeline vibration state recognition.

4.3 Fault diagnosis based on SOM neural network

In this case, the wavelet packet energy method is used to extract the data set of 18 kinds of samples, and each sample has 8 feature dimensions. The SOM network is established by MATLAB. Input the test data into the trained network for fault pattern recognition and classification, and observe the classification of SOM neural network.

The accuracy of SOM neural network prediction results is shown in Table 2. It can be seen from table 5 that the classification error is very large, the lowest accuracy is only 26.4%, and the average accuracy is 68.32%. SOM neural network can carry out adaptive classification, but there are still some problems. Many categories can not be directly divided into the trained neurons, but may be divided into the nearest neurons. For example, in the prediction process, the x-axis training result of column B heater input is the third neuron. However, the third neuron is closest to the second neuron, and about 50% of the test results are second neurons.

Table 2. Accuracy of SOM test results (%).

Status category	X	Y	Z
No extraction steam	100	100	88.7
Heating pipe of heat addition tube	100	73.6	36.7
A-column heater input	44.6	75.5	95.2
B-column heater input	37.7	26.4	84.9
A & B-column heater input	30.2	47.2	50.9
Normal state	88.7	49.1	100

5 Conclusion

Aiming at the state identification of nuclear power heating pipeline, this paper first processes and analyzes the original vibration signal by wavelet packet energy method, extracts the energy feature vector, and then identifies the pipeline state by using the optimized support vector machine and SOM neural network. The results show that the classification effect of support vector machine without parameter optimization is significantly worse than that of support vector machine after parameter optimization. As shown in Figure 5, it can be seen that for the identification of pipeline vibration state, the SVM after optimizing the parameters is better than the SOM neural network.

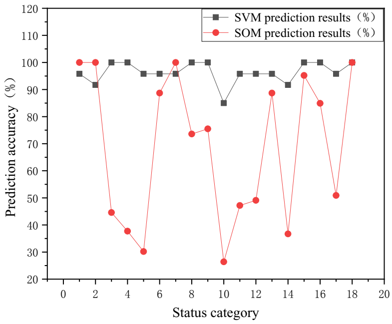

Fig. 5. Comparison of prediction results between optimized SVM and SOM.

This paper verifies that the state recognition of pipeline vibration can be carried out based on wavelet packet energy method and optimized support vector machine, and the classification can achieve high accuracy. Therefore, this method has a good effect on pipeline state recognition.

Due to the particularity of nuclear power, nuclear power plants have particularly high requirements for safety. Therefore, it is very difficult to collect pipeline vibration fault data in nuclear power plants. In this paper, the measured data in six different states are analyzed and identified, but the method verified in this paper also provides a theoretical basis for pipeline fault diagnosis and analysis. Pipeline faults mainly include deformation, displacement, pipe wall wear, leakage, pipe explosion, fracture, etc. the original vibration signals under different states are different. Wavelet packet change can well analyze the time-frequency of the original vibration signal. The energy features extracted based on wavelet packet energy method can reflect the characteristic information of the pipeline in different states, as shown in Figure 2. Therefore, the state identification method based on wavelet packet energy method and optimized SVM verified in this paper is also suitable for pipeline fault diagnosis.

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