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Mechanical Fault Diagnosis Method of High Voltage Vacuum Circuit Breaker Based on Vibration Signal

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Abstract

Aiming at the problem that the mechanical faults of high-voltage vacuum circuit breakers are difficult to identify, a high-voltage vacuum circuit breaker fault diagnosis method based on Ensemble empirical mode decomposition (EEMD) and support vector machine (SVM) is proposed. Use the laboratory 10kV indoor vacuum high voltage circuit breaker to collect the vibration data of 9 states such as normal opening and closing actions, loose screws, falling screws, jammed transmission mechanism, insufficient closing spring energy storage, etc., and solve the collected data. The energy entropy value of the EEMD component constitutes a feature vector set. The feature vector set is divided into a training set and a test set. The training set is used to train the SVM to obtain an intelligent fault recognition model. The test set is input to the model for testing to realize the high-voltage vacuum circuit breaker mechanism. Troubleshooting. Experiments show that the mechanical fault diagnosis method of high-voltage vacuum circuit breakers based on EEMD and SVM can effectively identify mechanical faults in different states.

Keywords

High-voltage vacuum circuit breaker; Mechanical failure; Vibration signal; Fault diagnosis.

1. PREAMBLE

The rapid development of society and economy has led to increasing power demand, which puts forward higher requirements for the stable operation of the power system. As a protection device in power production, high-voltage vacuum circuit breakers are one of the important power equipment, and their reliable operation is very important to the stability of power production activities.

Existing studies have shown that mechanical faults in circuit breaker faults account for the vast majority. The existing mechanical fault diagnosis methods for circuit breakers are based on current signals, vibration signals, and sound signals. The current research is mainly based on vibration signals [1-2]. The use of vibration signals for fault diagnosis belongs to non-electrical signal diagnosis, and the collected signal fault information is rich and the signal-to-noise ratio is high. The vibration signal during the opening and closing action of the circuit breaker is a superimposed signal of multiple nonlinear signals. Nowadays, circuit breaker fault analysis methods include S transform [3], wavelet packet decomposition [4-5], neural network [6-8] Etc., the window width of S transform has a fixed trend, and it is not very adaptable to abrupt signals. Wavelet packet decomposition has excellent decomposition characteristics, but the amount of calculation is large, which is not conducive to the rapid diagnosis requirements, and there is

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frequency band energy leakage. problem. Neural network has a good classification effect, but it is easy to fall into problems such as local optimal solution and over-learning.

The empirical mode decomposition (EMD) method decomposes the signal into a number of intrinsic mode functions (IMF). The frequency contained in each IMF is only related to itself and is not affected by the sampling frequency. It is suitable Analyze and process nonlinear and non-stationary vibration signals [9-11]. However, the distribution of the extreme points of the original signal will affect the rationality of the IMF. For example, if the extreme points are insufficient, the decomposition will stop. If the extreme points are not uniformly distributed, the envelope generated by the extreme point fitting will also produce errors. , Causing modal aliasing phenomenon [12].

In 2009, Huang proposed a new signal processing method-ensemble empirical mode decomposition. This method adds white noise with a mean value of zero to the signal, so that the signals with different time scale features will be automatically distributed to the appropriate reference scale, and after After averaging multiple times, the noise will cancel each other out, keeping the average value of each eigenmode component within a normal dynamic range, which not only preserves the original signal, but also reduces the modal aliasing phenomenon. This method has been applied For the processing of non-stationary signals. EEMD is to add white noise to the signal to make the signal have continuity on different scales, thereby solving the problem of modal aliasing [13-15].

At this stage, the theory of information entropy is widely used in the field of circuit breaker fault diagnosis, using sample entropy, multi-scale entropy and other theories to extract original signal features, and the diagnosis effect is better. However, some entropy theories also have shortcomings. For example, multi-scale entropy is slow to calculate for longer signals and is susceptible to the application of abrupt signals. Sample entropy will produce inaccurate estimates on short time series. Energy entropy is used as a description sequence An information measure of the degree of unknown, which can have an intuitive distinction for different types of sequences, which is conducive to fault diagnosis.

In the current fault identification, the commonly used identification and classification algorithms ELM, neural network, etc. have some problems. Neural network needs experience in parameter setting, the training speed is slow, and it is easy to fall into the problem of over-learning. Although the learning speed of the extreme learning machine is fast, because the parameters between the models are randomly set during training, the model is not stable, SVM can effectively solve the problem of few circuit breaker samples and data nonlinearity and difficult to classify [16].

Use EEMD algorithm to extract energy entropy, compose feature vector, establish SVM diagnosis model, and input feature vector into model for diagnosis. Experiments show that this method can effectively identify different types of faults. And through algorithm comparison experiments, the performance of this algorithm in fault diagnosis is verified.

2. FEATURE EXTRACTION

2.1. Wavelet Packet Denoising

In order to reduce the interference of noise to the signal and obtain a better feature expression effect, wavelet packets are used to denoise the signal. Compared with the wavelet change, the wavelet packet change divides the time-frequency plane more finely, decomposes the high-frequency part of the signal, has a higher resolution, and retains the advantages of the wavelet change. The common steps are as follows:

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(1) Select the basis function and the number of wavelet packet decomposition layers to decompose the signal. This article uses db10 wavelet, and the number of decomposition layers is 3.

(2) Calculate the best wavelet packet decomposition tree according to the standard entropy;

(3) Determine the decomposition threshold and filter out interference. The common threshold is derived from the following formula,

$$th1 = \sigma\sqrt{2\ln(n)} \tag{1}$$

(4) Use the filtered wavelet packet components to reconstruct the signal.

2.2. Ensemble Empirical Mode Decomposition Method

EEMD decomposition method is an improved method based on empirical mode decomposition (EMD). In order to make up for the deficiencies of empirical mode decomposition in modal separation, Huang proposed collective empirical mode decomposition. This method will add Gaussian white noise to make the signal have continuity on different frequency scales, thereby solving the modalities that exist in EMD. The problem of state aliasing.

The EEMD algorithm decomposes the non-stationary vibration signal, and several stationary intrinsic mode functions (IMF) can be obtained. These IMFs of different scales contain various main information of the vibration signal, which completes the separation of the vibration events of the vibration signal, and lays the foundation for the subsequent feature quantity calculation.

The main decomposition steps of EEMD:

Step 1: First, add white noise $n_i(t)$ with a mean value of 0 and a constant standard deviation to the original signal $x(t)$ multiple times, namely:

$$x_i(t) = x(t) + n_i(t) \tag{2}$$

Where $x_i(t)$ is the signal after adding white noise for the i-th time.

Step 2: Perform EMD decomposition on the signal $x_i(t)$ to obtain a series of IMF components $c_{ij}(t)$ and a residual term $r_i(t)$. Where $c_{ij}(t)$ is the j-th IMF component obtained by adding Gaussian white noise decomposition for the i-th time.

Step 3: Repeat steps 1 and 2 for N times, and then perform the overall average operation on each order of IMF components according to the characteristic that the statistical mean value of the uncorrelated random sequence is 0 to eliminate the influence of adding white noise to the real IMF. The final IMF after EEMD decomposition is:

$$c_j(t) = \frac{1}{N}\sum_{i=1}^{N} c_{ij} \tag{3}$$

Where: $c_j(t)$ is the j-th IMF component obtained after EEMD decomposition of the original signal. The EEMD decomposition result of the signal at this time is:

$$c_j(t) = \frac{1}{N}\sum_{i=1}^{N} c_{ij} \tag{4}$$

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Where: $r(t)$ is the final residual component. In this way, the signal $x(t)$ is decomposed into the sum of several IMFs and a residual component through EEMD.

The two important parameters used in the EEMD algorithm are the amplitude of the white noise and the total number of repeated EMD decomposition M. The amplitude of the white noise is the ratio K of the standard deviation of the original signal amplitude when the white noise is added. The author set the overall average number N in the EEMD decomposition to be 100, and the standard deviation of Gaussian white noise is 0.2 times the standard deviation of the original signal.

2.3. Energy Entropy

Energy entropy is used as an information measure to describe the unknown degree of a sequence, and there is an intuitive distinction for different types of sequences.

The energy entropy formula of each segment calculated by the energy entropy definition formula is as follows:

$$H=-\sum_{i=1}^{N} q(i)\lg q(i) \tag{5}$$

Through experimental analysis, the energy distribution of the first, second, third, fourth, and sixth component is more prominent, so these five IMF components are selected to extract the energy entropy feature. Then the fault feature vector set extracted after EEMD decomposition is H, $\boldsymbol{H}=[H_1,H_2,H_3,H_4,H_6]$, where H_1 is the energy entropy of the first IMF component.

3. SUPPORT VECTOR MACHINE

SVM can effectively solve the problems of fewer circuit breaker samples and data nonlinearity that is difficult to classify. The basic principle is: the existing sample space composed of N multi-dimensional feature samples, the sample space is used as the input of the model, and the model input is mapped through a certain non-linear transformation, so that the feature space is obtained in a higher-dimensional space. The hypersurface model formed by the multi-dimensional irregular sample space is transformed into a regular hyperplane model after mapping to realize linear classification.

The SVM structure is shown in Figure 1.

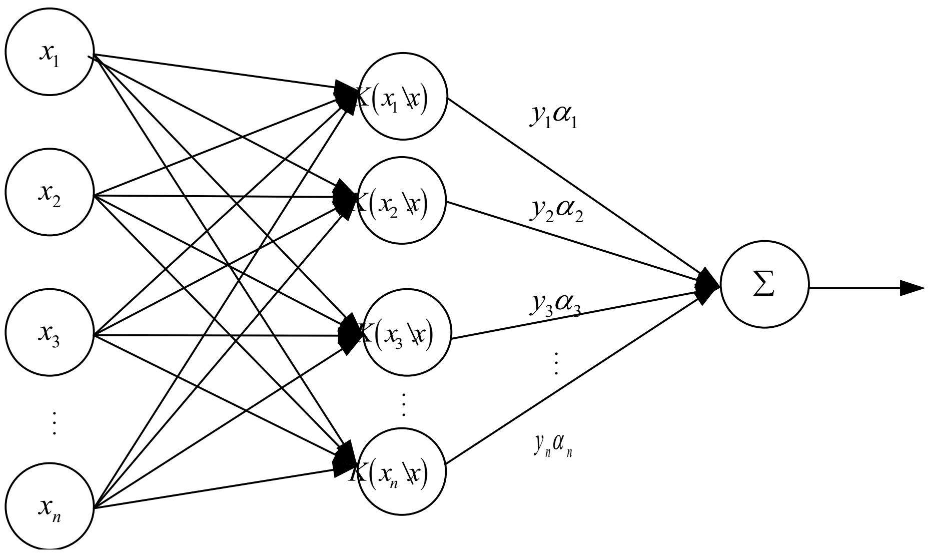

Figure 1. Basic structure diagram of SVM

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(1) The input layer sample $\boldsymbol{X} = \{(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)\}$, y_n is the feature vector and x_n is the corresponding category label. The kernel function uses the radial basis function, and its expression is:

$$K\left(x_i, x\right) = \exp\left(-\left\|x_i - x\right\|^2 / 2\sigma^2\right) \tag{6}$$

Where σ is the radial basis function parameter, x is the test sample, and x_i is the training sample.

(2) The discriminant function is:

$$f(x) = \operatorname{sgn}(\sum_{i=1}^{n} a_i y_i K(x_i \bullet x) + b) \tag{7}$$

Where α_i is the optimal Lagrangian multiplier, b is the classification threshold, and $K(x_n \bullet x)$ is the kernel function. The performance of SVM mainly depends on the penalty factor c and the radial basis function parameters σ.

The grid search method is to divide the grid within the range $[c, \sigma]$, and then find the optimal parameters by traversing each point in the grid. For the division of small sample types, it can quickly find the global optimal solution, avoiding Model error caused by artificial setting of parameters.

Diagnosis method of mechanical fault of high voltage vacuum circuit breaker based on EEMD and SVM

The method proposed in this paper is to denoise the vibration signal by wavelet packet and then use EEMD to decompose the original signal, and calculate the energy entropy of each IMF decomposed by EEMD, select the five components with larger energy entropy to form the feature vector, and input it into SVM The model is trained, and fault diagnosis is performed on this basis. The steps are as follows.

(1) Use piezoelectric sensors to collect vibration signals, and transmit the collected signals to the host computer.

(2) Use wavelet packet algorithm to denoise the collected signal.

(3) Use EEMD to decompose the signal and calculate the energy entropy of each IMF component.

(4) The five components with larger energy entropy are selected as feature vectors.

(5) Input the feature set to the SVM model for training and testing.

(6) Output diagnosis results

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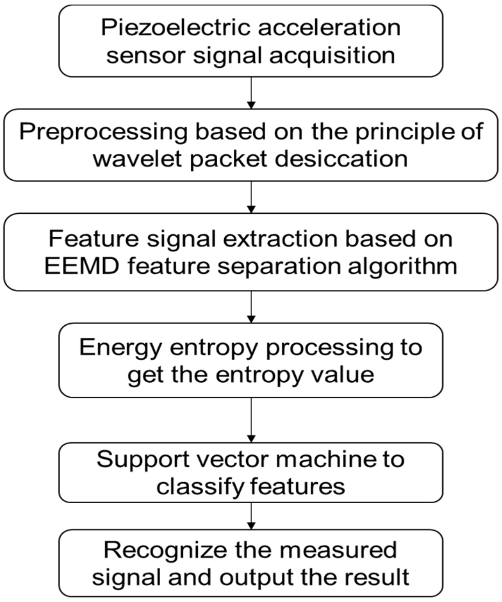

Figure 2. Overall flow chart of fault diagnosis

4. EXPERIMENTAL ANALYSIS

The experimental data comes from the 10kV indoor vacuum high-voltage circuit breaker (ZN-63A) under laboratory conditions, which simulates 9 states of screw loosening, transmission mechanism jamming and insufficient closing spring energy storage during closing action, and collects the corresponding vibrations in each state Signal data. Preprocess the collected 189 sets of vibration data, extract EEMD energy entropy, use 126 sets as training samples, and the remaining 63 sets as test samples.

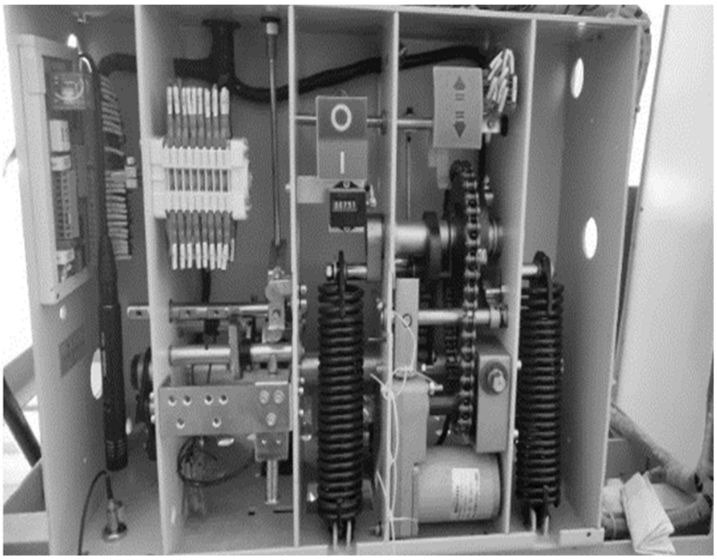

Figure 3. Indoor high-voltage vacuum circuit breaker in the laboratory (ZN-63A)

4.1. SVM Model Training and Testing

The SVM model selects the radial basis number (RBF) as the kernel function, uses the grid search method to find the best penalty factor c and kernel function parameter g, and establishes a fault diagnosis model. Where c=0.4506 and =0.1301.

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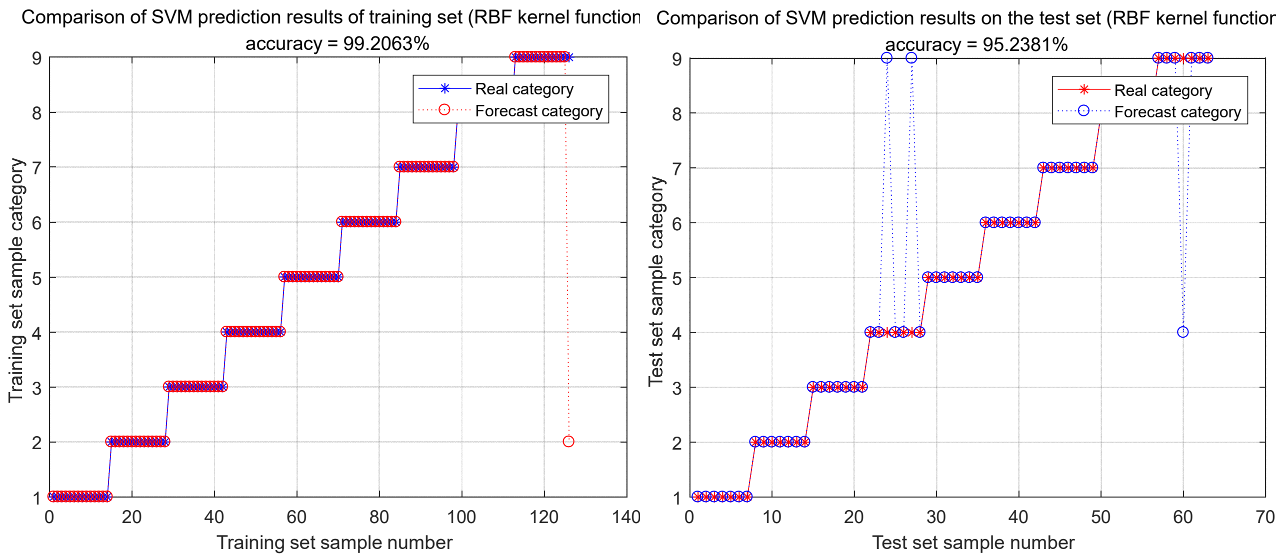

Figure 4. Diagnosis results of SVM training set and test set

1 is the transmission mechanism jam, 2 is the circuit breaker refused to close, 3 and 4 are the opening and closing of the base screw respectively, 5 is the insufficient spring energy storage, 6 and 7 are the opening and closing of the base screw respectively Gates, 8 and 9 are opening and closing in normal state respectively.

It can be seen from the above figure that the SVM model judges the fault type with a training set accuracy of more than 99%, and the test set accuracy can reach a correct rate of more than 95%, which has a good diagnostic effect.

4.2. Algorithm Comparison Analysis

In order to verify the advantages of SVM compared to other classification methods, a probabilistic neural network (PNN) and an extreme learning machine (ELM) are selected for model training and testing on the same data feature sample set.

Use trial and error method to select model parameters. In a large number of experiments, the hidden layer parameter of ELM is selected as 30, and the spread parameter of PNN is selected as 0.6152.

Table 1. Diagnosis results under different training models

Training model	test set accuracy
SVM	95.2831%
PNN	85.7143%
ELM	77.7778%

The experimental results show that the accuracy of diagnosis under the SVM model reaches 95%, which can accurately identify the common faults of circuit breakers, while the PNN and ELM models have poor diagnostic effects on the unified feature set, which verifies the effectiveness of the SVM model.

5. SUMMARY

This paper proposes a mechanical fault diagnosis method for high-voltage vacuum circuit breakers based on mechanical vibration signals. By collecting the vibration signals of 9 fault

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states such as the base, spring, and transmission mechanism when the high-voltage vacuum circuit breaker is operating, the wavelet packet algorithm is used to denoise, and the denoised signal is extracted through EEMD-energy entropy to extract the feature vector. Input the feature set to the support vector machine for fault diagnosis. The experimental results show:

(1) The EEMD-energy entropy proposed in this paper can effectively reflect the characteristics of different fault states.

(2) The support vector machine model used in this paper can effectively classify faults, and has a better effect than other models.

The research of this subject describes the non-linear and stable circuit breaker fault vibration data analysis and the establishment of the fault diagnosis model, which has a good fault diagnosis effect.

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