# Transmission Line Fault Detection Based on CEEMD-AOA-SVM

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**Abstract: To accurately extract the characteristics of transmission line short-circuit fault, a fault detection method based on comprehensive ensemble empirical mode decomposition (CEEMD), arithmetic optimization algorithm (AOA) and support vector machine (SVM) is proposed. Taking the three-phase voltage of the line after fault as the feature vector, CEEMD method is used to decompose it, and a series of modal components are obtained. Calculate the multi-scale sample entropy (MSE) of each mode and the MSE of the obtained component is composed of the fault feature set. Because the penalty parameters and kernel function of SVM have a direct impact on the classification accuracy in the classification process, the parameters are determined by arithmetic optimization algorithm (AOA), and the obtained fault feature set is used for fault detection using AOA-SVM model. The simulation results indicate that the fault detection rate of CEEMD-AOA-SVM is 98.28%, which is significantly higher than that of EMD-SVM and CEEMD-SVM.**

**Keywords: Transmission Line; Fault Detection; Complementary Ensemble Empirical Mode Decomposition; Arithmetic Optimization Algorithm; Support Vector Machine**

## 1. Introduction

The transmission line is the main component of the power system and undertakes the task of energy transmission. Due to long-term exposure to the natural environment, the failure rate of transmission lines is higher than that of indoor power facilities[1-5]. Therefore, once a line fault occurs, it is necessary to determine the fault type and remove the fault in time[6-8].

At present, the fault detection methods of transmission lines are mainly divided into two steps: the first step is fault feature extraction, and the second step is fault classification[9]. Firstly, the fault signal is properly converted and processed to extract the eigenvalue of the fault signal. Then, select the appropriate classification method to learn the eigenvalues and realize fault detection. However, due to the strong irregularity of transmission line signals, it is impossible to directly use them for fault detection.

EMD can decompose different load signals into multiple intrinsic mode function components (IMF), However, EMD is prone to IMF mode aliasing, resulting in feature extraction failure, which is not conducive to accurate fault identification[10-12]. Aiming at the problem of EMD, ensemble EMD (EEMD) is proposed, which can effectively alleviate the problem of mode aliasing, but EEMD has the problems of reconstruction error and slow calculation efficiency[13]. In view of the shortcomings of EMD and EEMD methods, scholars have applied CEEMD method to fault detection, which can effectively reduce the reconstruction error and improve the convergence speed[14-17]. On the basis of frequency domain analysis, the energy entropy is introduced into the transmission line fault analysis, which can extract the fault characteristic information of the line more effectively. SVM has strong classification ability and is widely used in the process of fault detection. However, the accuracy of SVM is greatly affected by parameters, and the selection of parameters is particularly important for SVM[18-20]. A fault detection model based on CEEMD-AOA-SVM is proposed. The parameters of SVM are determined by AOA, and the AOA-SVM model is used for fault detection.

## 2. Fault Feature Extraction

CEEMD is an improvement of EMD. Firstly, based on the EMD decomposition algorithm, CEEMD adds white noise sequences with

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opposite numbers and in pairs to the original data, which overcomes the problems of EMD mode aliasing and poor completeness of EEMD decomposition, and reduces the aggregate average from hundreds to tens or even several orders of magnitude, greatly improving the computational efficiency[21-23].

1) Add noise of a specific amplitude to $x(t)$.

$$x_j(t) = x(t) + n_j(t) \tag{1}$$

Where, $x_j(t)$ is the signal after adding noise, and $n_j(t)$ is the added positive noise.

2) $x_j(t)$ is decomposed by EMD.

$$x_j(t) \xrightarrow{EMD} + c_{1,j} + r_1 \tag{2}$$

3) Add noise of opposite amplitude in step 1 and perform EMD decomposition.

$$-x_j(t) \xrightarrow{EMD} - c_{2,j} - r_2 \tag{3}$$

4) Repeat steps 1-3, add $n$ groups of white noise with opposite symbols, and decompose them to obtain $+c_{n,j}$ and $-c_{n,j}$ modal components IMF.

5) The final result of CEEMD decomposition is the set average of multiple groups of IMF, and the decomposition result is obtained:

$$D_j = \frac{1}{2n}\sum_{j=1}^{n}(c_{n,j} + (-c_{n,j})) \tag{4}$$

Where, $D_j$ is the $j$ -th component after decomposition.

## 3. Multiscale Sample Entropy

For $x(i)\,(i = 1,2,3,\cdots,N)$, the process of MSE is:

1) The implanting dimension is used to construct the $m$ -dimensional vector of time series.

$$X(i) = [x(i), x(i+1), \cdots, x(i+m-1)] \tag{5}$$

Where, $i = 1,2,\cdots,N-m+1$.

2) The maximum distance of corresponding elements between $X(i)$ and $X(j)$ as:

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

3) Determine the similarity tolerance $r$, Calculate the value of $B^m(r)$.

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

4) When the dimension is $m+1$, repeat 1, 2 and 3 to get $B^{m+1}(r)$.

5) Define the SE as:

$$S(m,r) = \lim_{x\to\infty}[-\ln\frac{B^{m+1}(r)}{B^m(r)}] \tag{8}$$

6) When the time series is finite, the SE is:

$$S(m,r) = \ln\frac{B^{m+1}(r)}{B^m(r)} \tag{9}$$

According to the principle of sample entropy, the calculation steps of multi-scale sample entropy are as follows:

1) The signal $x(i)$ is coarsened to obtain the coarsening sequence $y_j^s$.

$$y_j^s = \frac{1}{s}\sum_{i=(j-1)s+1}^{js} x_i \tag{10}$$

Where, $j = 1,2,\cdots,\left[\frac{N}{s}\right]$.

2) The MSE is obtained by normalizing the SE value after coarse graining

## 4. Support Vector Machine

As a binary classification method, the main principle of SVM is to give a set of training data with known labels, classification or continuity, and support vector machine (SVM) analyzes these data to derive a supervised learning model. The basic idea of SVM is to map the data samples to the high-dimensional space, and find the hyperplane that can classify the data in the high-dimensional space.

Let the two types of samples be linearly separable, and their sets be expressed as:

$$A = \{(x_i, x_j) | i = 1,2,\cdots,n\} \tag{11}$$

In equation (11), $x_i \in R^n$, $y_i \in \{+1,-1\}$, the two types of samples can be effectively separated by $\omega \cdot x + d = 0$.

The hyperplane equation is:

$$f(x) = \begin{cases} \omega \cdot x + d \geq 1, y_i = 1 \\ \omega \cdot x + d \leq 1, y_i = -1 \end{cases} \tag{12}$$

In equation (12), $\omega$ is the normal vector of the hyperplane and $d$ is the constant term. When it is linearly separable, the constraints of the optimal hyperplane are as follows:

$$\begin{cases} \min \phi(\omega) = 1/2\|\omega\|^2 \\ y_i[(\omega \cdot x) + d] - 1 \geq 0 \end{cases} \tag{13}$$

For the unclassifiable problem, penalty function $C$ and relaxation variable $\xi$ are introduced. The model of SVM is:

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$$\begin{cases} \min \phi(\omega,\xi) = 1/2\|\omega\|^2 + C\sum_{i=1}^{n}\xi_i \\ s.t. \begin{cases} y_i[\omega \cdot x + d] - 1 + \xi \geq 0 \\ \xi_i \geq 0 \end{cases} \end{cases} \quad (14)$$

Where, $\xi_i \geq 0$ and $C$ are constants greater than zero. The value of $C$ is positively correlated with the penalty degree of the function. The larger the penalty parameter is, the smaller the value of the relaxation variable is required, which mainly plays a trade-off role.

Using Lagrange multiplier method, the above problem can be changed into:

$$\begin{aligned} L(\omega,d,a,\xi,\mu) &= 1/2\|\omega\|^2 + C\sum_{i=1}^{\omega}\xi_i \\ &+ \sum_{i=1}^{\omega} a_i[1 - \xi_i - y_i(\omega^T x_i + d)] - \sum_{i=1}^{\omega}\mu_i\xi_i \end{aligned} \quad (15)$$

By solving the equation (15), the decision function can be obtained as:

$$f(x) = \text{sgn}[\sum_{i=1}^{n} a_i^* y_i (x_i \cdot x) + d^*] \quad (16)$$

In order to solve the nonlinear problem, the kernel function is introduced. In this paper, the Gaussian radial basis kernel function is selected. The decision function after introducing the kernel function is as follows:

$$f(x) = \text{sgn}[\sum_{i=1}^{n} a_i^* y_i K(x_i \cdot x) + d^*] \quad (17)$$

## 5. AOA

AOA is a new method proposed in 2021 [24-26]. Arithmetic operators are usually used to study the traditional calculation methods of numbers. A simple operator is used as a mathematical optimization to determine the best elements that meet the specific criteria from a group of candidate schemes. The AOA enhances the optimization ability by using multiplication and division operations in arithmetic, and improves the search accuracy by adding and subtracting operations.

First stage, mathematical optimizer acceleration function (MOA).

The arithmetic optimization algorithm judges the next search stage through MOA. First, select the number $r_1$ . If $r_1$ is bigger than mathematical optimizer acceleration, the global search phase will be executed, or else, the local development phase will be entered. The mathematical model of MOA is shown in equation (18).

$$MOA(i) = Min + i \times [(Max - \min)/i_{\max}] \quad (18)$$

Second stage, exploration stage.

In the global exploration phase, random exploration will be carried out in multiple areas.

$$x_{i,j}(i+1) = \begin{cases} best(x_j) \div (MOP + \varepsilon) \times \\ [(UB_j - LB_j) \times \mu + LB_j], r_2 < 0.5 \\ best(x_j) \times MOP \times [(UB_j - LB_j) \\ \times \mu + LB_j], otherwise \end{cases} \quad (19)$$

Where, $x_{i,j}(i+1)$ is the solution of the $i+1$ iteration, $best(x_j)$ is the best position currently obtained, and $\varepsilon$ is the minimum value to avoid zero denominator. $UB_j$ and $LB_j$ are the upper and lower bounds of the search space, $r_2 \in [0,1]$ , When $r_2 < 0.5$ , execute the division strategy, otherwise execute the multiplication strategy. The math optimizer probability calculation formula is:

$$MOP(i) = 1 - i^{1/a} / i_{\max}^{1/a} \quad (20)$$

Third stage, development stage.

In AOA, if MOA is less than $r_1$ , the arithmetic optimization algorithm will randomly select addition or subtraction to execute the development phase. The location update model is:

$$x_{i,j}(i+1) = \begin{cases} best(x_j) - MOP \times \\ [(UB_j - LB_j) \times \mu + LB_j], r_3 < 0.5 \\ best(x_j) + MOP \times \\ [(UB_j - LB_j) \times \mu + LB_j], otherwise \end{cases} \quad (21)$$

In equation (21), $r_3 \in [0,1]$ , When $r_3 < 0.5$ , execute subtraction strategy, otherwise execute addition strategy.

## 6. Simulation Test

### 6.1 Analysis of Experimental Data

The 110kV power supply system model is built through Simulink to simulate four types of faults: single-phase grounding, two-phase short circuit, two-phase grounding and three-phase short circuit. The total simulation time of the model is 0.3s, and the fault starts at 0.1s. When a fault occurs, the voltage will change accordingly. By collecting the three-phase voltage as the fault feature, and a total of 580 fault data are collected, including 145 fault samples for 4 different short-circuit faults.

### 6.2 Experimental Analysis and Verification

The collected signal is disassembled by CEEMD. Limited to space, single-phase grounding is selected for analysis. In the fault data, a group of single-phase grounding fault data is randomly selected. The IMF component diagram after signal decomposition is shown in Figure 1-3. After 580 groups of fault signals are decomposed by CEEMD, the multi-scale sample entropy of each group of data is calculated respectively, and finally the fault feature set is formed.

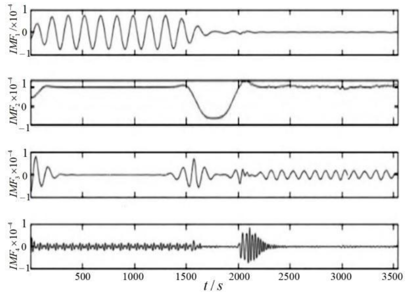


**Figure 1. Decomposition Diagram of A-Phase VMD During B-Phase Short Circuit**

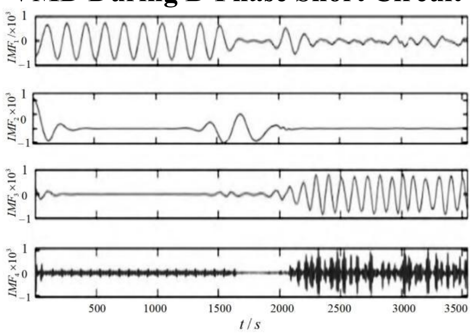


**Figure 2. Decomposition Diagram of B-Phase VMD During B-Phase Short Circuit**

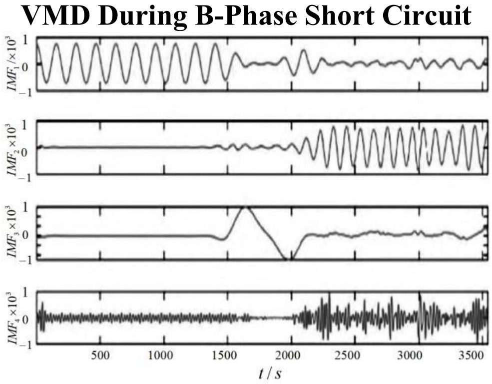


**Figure 3. Decomposition Diagram of C-Phase VMD During B-Phase Short Circuit**

Randomly allocate training and testing sets in a 4:1 ratio among 580 sets of fault data. The CEEMD-AOA-SVM, EMD-SVM and CEEMD-SVM models are used for fault detection. During the experiment, the labels corresponding to different fault types are: 1 for single-phase grounding, 2 for two-phase grounding, 3 for two-phase short circuit, and 4 for three-phase short circuit. The final fault diagnosis results are shown in the following Figures.

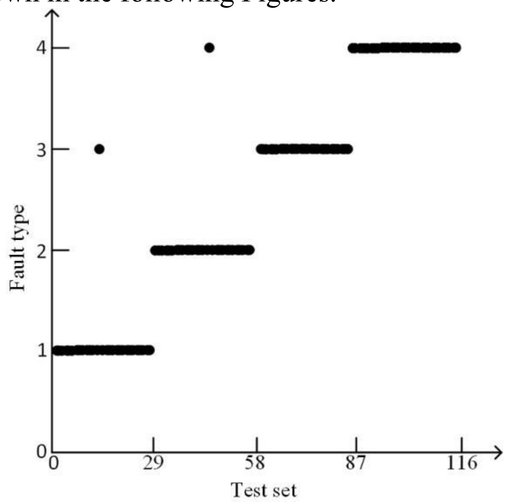


**Figure 4. CEEMD-AOA-SVM Model**

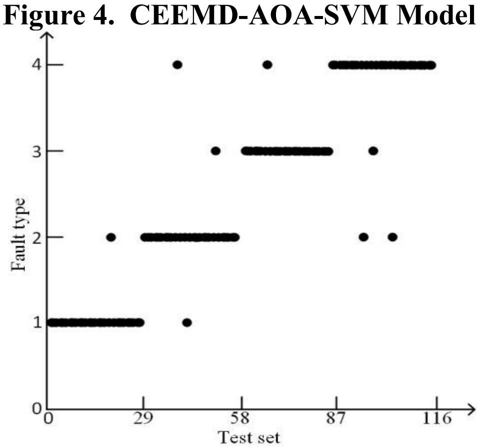


**Figure 5. EMD-SVM Model**

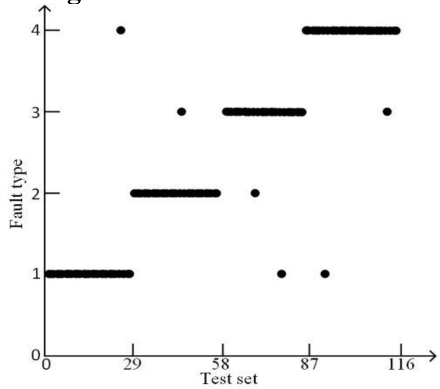


**Figure 6. CEEMD-SVM Model**

The simulation test results show that in the detection results of CEEMD-AOA-SVM method, one sample with single-phase grounding fault is wrongly divided into two-phase grounding, and one sample with two-phase grounding fault is wrongly divided into three-phase short circuit, in which the detection accuracy of single-phase grounding fault is 96.55%, the detection

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accuracy of two-phase grounding fault is 96.55%, the detection accuracy of the other two types of fault is 100%, and the detection accuracy of comprehensive fault is 98.28%. Similarly, in the detection results using EMD-SVM method, the detection accuracy of single-phase grounding is 96.55%, two-phase grounding is 81.25%, and two-phase short circuit is 96.55%, three-phase short circuit is 81.25%, and the comprehensive fault detection accuracy is 93.10. Similarly, in the detection results using CEEMD-SVM method, the accuracy of single-phase grounding is 100%, and two-phase grounding is 87.50%, and two-phase short-circuit fault detection is 87.50%, and three-phase short circuit is 87.50%, and comprehensive fault detection accuracy is 94.83%.

The above results verify the powerful effect and high accuracy of CEEMD-AOA-SVM method in power line fault prediction. It can be widely used in the real environment, so as to shorten the time required for power line fault treatment.

## 7. Conclusion

A transmission line fault detection method based on CEEMD-AOA-SVM is proposed, and the main conclusions drawn are as follows:

1. CEEMD combined with MSE can effectively extract fault features, and obtain a better fault feature set.
2. After using AOA to determine SVM parameters, the classification ability of SVM can be effectively improved.
3. The fault detection method based on CEEMD-AOA-SVM has higher accuracy than EMD-SVM and CEEMD-SVM.

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