Circuit Breaker Fault Detection Based on OOA-VMD-SVM

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Abstract: To extract the fault characteristic signal of circuit breaker, a fault detection method based on Osprey optimization algorithm (OOA) optimization variable modal decomposition (VMD) and support vector machine (SVM) parameters is proposed. First, use OOA to determine the parameters of VMD. Secondly, Utilize the OOA-VMD to decompose the circuit breaker signals, take the energy entropy as the fault analysis feature vector. The obtained components are used as the samples of SVM for fault analysis. Experiments show that OOA-VMD-SVM model can better extract the fault characteristics of each sample, and has good fault diagnosis effect. Compared with other models, this model has higher diagnostic accuracy and better generalization ability.

Keywords: Osprey Optimization Algorithm; Variational Modal Decomposition; Support Vector Machine; Circuit Breaker; Fault Detection

1. Introduction

As the breaking element in the power grid, it is the key element to ensure the stable operation of the system[1]. The proportion of circuit breaker operating mechanism in the overall fault is high, and the fault is difficult to accurately identify. Therefore, it is necessary to study its fault detection strategy[2-6].

When the circuit breaker is opened and closed, the movement and impact of the operating mechanism will cause vibration response, and the impact vibration signal generated by the interaction of various mechanical parts contains a large amount of information related to the equipment status[7-10]. Therefore, the in-depth analysis of the opening and closing vibration signals can reflect the running state of the equipment and realize fault diagnosis. In terms of vibration signal feature extraction, because of the non-stationary of the vibration signal, there are high requirements for the analysis of the vibration signal[11-15]. The traditional time-domain or frequency-domain analysis can not process the above non-stationary signals. Therefore, time-frequency analysis method is needed[16-18].

When EMD is used for signal decomposition, some defects such as modal confusion and boundary effect have not been well solved. Aiming at the problems of EMD algorithm, Konstantin dragomiretskiy proposed the VMD algorithm in 2014, which decomposes the signals with different center frequencies through a new method of non recursive signal decomposition[19-23]. However, VMD needs to preset algorithm parameters, if it is not properly selected, it will affect the later fault detection effect. Therefore, this paper proposes to use OOA to determine the relevant parameters of VMD to realize the adaptive decomposition of the signal, and introduces the modal component energy entropy as the eigenvalue, to improve the accuracy. Firstly, the minimum envelope entropy is used as the fitness function to optimize the parameter combination $[K, a]$ of VMD algorithm in different states through OOA, and the signal is decomposed by VMD using the parameter combination, and the energy entropy is calculated as the feature input into the SVM model for fault detection.

2. Research Method

2.1 VMD

The decomposition step of VMD algorithm is:

2.1.1 Variational problem construction. The special process is:

$$\begin{cases} \min\limits_{\{u_k\},\{\omega_k\}} \left\{ \sum\limits_k \left\| \partial(t) \left[(\delta(t) + \frac{j}{\pi t}) * u_k(t) \right] e^{-j\omega_k t} \right\|_2^2 \right\} \\ s.t \sum\limits_{k=1}^{k} u_k = f(t) \end{cases} \quad (1)$$

Where, $u_k=\{u_1,u_2,\cdots,u_k\}$ is the modal function set, and $u_k=\{u_1,u_2,\cdots,u_k\}$ is the central frequency set.

2.1.2 Solution of Constrained Variational Problems

On the basis of equation (1), Lagrange operator λ and quadratic penalty factor a are added to transform inequality constraints into equality constraints.

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

Where, a can reduce the influence of Gaussian noise, and λ is to ensure the strictness of the constraint problem.

2.1.3 Fourier transform solution of modal components and center frequency

The problem can be solved by alternating direction multiplier and Fourier transform.

$$\hat{u}_k^{n+1}(\omega)=\frac{f(\omega)-\sum_{i\neq k}\hat{u}_i(\omega)+\frac{\hat{\lambda}(\omega)}{2}}{1+2a(\omega-\omega_k)^2} \quad (3)$$

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

$$\hat{\lambda}^{n+1}(\omega)=\hat{\lambda}^{n}(\omega)+\gamma(f(\omega)-\sum_k \hat{u}_k^{n+1}(\omega)) \quad (5)$$

Where, γ is the noise tolerance.

To sum up, VMD updates the center frequency of each mode in the cycle iteration, and finally synthesizes the decomposed frequency domain modes into the time domain through the inverse Fourier transform.

2.2 OOA

OOA is a relatively new swarm intelligence optimization algorithm proposed by Dehghani Mohammad and others in 2023. Its inspiration comes from the natural behavior of Osprey fishing on the water[24-26]. When flying on the water, the Osprey will constantly search for prey. When it determines the prey, it will quickly hunt and take it to the right place to eat. The whole behavior is divided into two stages: hunting target and processing target. These two stages include the updating of the position of the Osprey and prey. The updating of the position of the Osprey in the two stages is also quite different, which corresponds to the local optimization based on the global search. The position updated by the Osprey after completing the second stage is regarded as the optimal candidate solution for each iteration, and the candidate solution is updated through the objective function to complete the iterative optimization.

2.2.1 Osprey population initialization.

The model of Osprey population is shown in equations (6) to (8).

$$X=\begin{bmatrix} X_{1,1} & \cdots & X_{1,j} & \cdots & X_{1,m} \\ \vdots & \ddots & \vdots & \iddots & \vdots \\ X_{i,1} & \cdots & X_{i,j} & \cdots & X_{i,m} \\ \vdots & \iddots & \vdots & \ddots & \vdots \\ X_{N,1} & \cdots & X_{N,j} & \cdots & X_{N,m} \end{bmatrix} \quad (6)$$

Randomly initialize the Osprey search location:

$$X_{i,j}=l_j+r_{i,j}\cdot(h_j-l_j) \quad (7)$$

Where, N is the number of osprey, and m is the number of problem variables. $r_{i,j}$ is the random number from the interval [0,1], l_j is the lower bound of the problem variable, and h_j is the upper bound of the problem variable.

An evaluation function is established for each Osprey in the population.

$$F=\begin{bmatrix} F(X_1) \\ \vdots \\ F(X_i) \\ \vdots \\ F(X_N) \end{bmatrix}_{N\times 1} \quad (8)$$

2.2.2 Positioning and fishing phase

OOA is a swarm intelligence algorithm. The fish group corresponding to each Osprey is represented by equation (9):

$$EP_i=\{X_k|K\in\{1,2,\cdots,N\}\wedge F_K\le F_i\}\cup\{X_{best}\} \quad (9)$$

When the Osprey finds the food moving towards it, its position is updated as shown in equation (10). If the update of the position causes the value of the objective function to increase, the previous position is replaced according to equation (11).

$$x_{i,j}^{P1}=x_{i,j}+r_{i,j}\cdot(S_{i,j}-I_{i,j}\cdot x_{i,j}) \quad (10)$$

$$\begin{cases} x_{i,j}^{P1}, F_i^{P1}<F_I \\ x_i, otherwise \end{cases} \quad (11)$$

2.2.3 Prey handling phase

In order to simulate the behavior that the Osprey moves its prey to a safe place to eat, equation (12) is used to generate a new position as the target safe position. If its target value becomes better, the original position is replaced according to equation (13).

$$x_{i,j}^{P2} = x_{i,j} + \frac{l_j + r \cdot (h_j - l_j)}{t} \quad (12)$$

$$x_i = \begin{cases} x_{i,j}^{P_2}, F_i^{P_2} < F_i \\ x_i, otherwise \end{cases} \quad (13)$$

2.3 Objective Function

Envelope entropy is an index that can evaluate signal sparsity. The specific calculation method is:

$$e_i = \frac{h(i)}{\sum_{i=1}^{K} h(i)} \quad (14)$$

$$E_e = -\sum_{i=1}^{K} e_i \lg e_i \quad (15)$$

In equation (14), $h(i)$ is the envelope signal of $u(i)$ after Hilbert transform.

2.4 SVM

SVM is a classification method based on the interval of feature space to solve multi classification problems, with good generalization ability[27-30]. The core idea of SVM algorithm is to find an optimal segmentation plane, so that all points of the training data set mapped to the high-dimensional space have the farthest geometric distance from the segmentation plane in the high-dimensional space. At this time, for the classification problem, the optimization objective of SVM can be described as follows:

$$\begin{cases} \min_{\omega} \left(\frac{1}{2} \|\omega\|^2 + c \sum_{i=1}^{m} g_i \right) \\ s.t. y_i (\omega^T \varphi(x) + b) \ge 1 - g_i, g_i \ge 0 \end{cases} \quad (16)$$

SVM algorithm is based on different working conditions to select different kernel parameters, map the data set from low dimensional space to high dimensional space to make the data set linearly separable, and then simplify the optimization process of the optimal plane. At present, the common kernel functions include linear kernel function, Gaussian radial basis function kernel function, neural network kernel function, etc. in order to improve the accuracy of algorithm classification, this paper uses polynomial kernel function.

$$K(x_i, x_j) = (\gamma x_i^T x_j + b)^d \quad (17)$$

Where, γ , b and d are kernel functions. At this time, the SVM classification interval expression can be simplified as follows.

$$f(x) = \sum_{i=1}^{m} a_i y_i K(x_i, x_j) + b \quad (18)$$

3. Optimize VMD Algorithm Parameters and Fault Detection Process Based on OOA

The specific steps of fault detection process of OOA-VMD-SVM are as follows:

Collect vibration signals for four operating states of circuit breakers.

The data of the impact part in the original vibration signal is intercepted and preprocessed by high pass filtering and denoising.

Determine VMD parameters using OOA with the minimum envelope entropy as the objective function.

Using OOA-VMD to process signals, and the energy entropy eigenvector matrix is constructed from the modal components obtained by parameter optimization.

The samples of four states in the eigenvector matrix are labeled and classified. Using SVM for fault detection.

4. Experimental Verification

4.1 Experimental Data Collection

In this paper, the laser vibration meter is used to measure the opening and closing vibration of high voltage circuit breaker. The experimental object is the magnetic control column circuit breaker. When it opens and closes, the laser vibrometer simultaneously collects the displacement changes on the measuring points. The closing vibration signals under four working conditions of normal state, iron core jamming, spring fatigue and base looseness are collected.

4.2 Experimental Analysis

The time-domain diagrams obtained by preprocessing the signals of four operating conditions are shown in Figure 1. The movement of parts in the operating mechanism will produce vibration, and the vibration propagates outward from the vibration source in the form of waves, including multi-stage shock attenuation process. In the time domain, the peaks of the four states are relatively scattered and their amplitudes are different, but it is unable to determine the type of fault. So the VMD and energy entropy are used to extract the fault characteristics in the signal.

Using OOA to determine VMD parameters. In order to optimize VMD parameters, the range of setting and value optimization is [1, 20] and [1, 6000] respectively. The final parameter optimization results are: normal state [6, 983], iron core jamming [5, 1037], spring fatigue [8, 1132], base looseness [7, 1135].

Taking the normal closing vibration signal as an example, after VMD decomposition of the signal, seven modal components are obtained. The correlation coefficient method was used for feature selection.

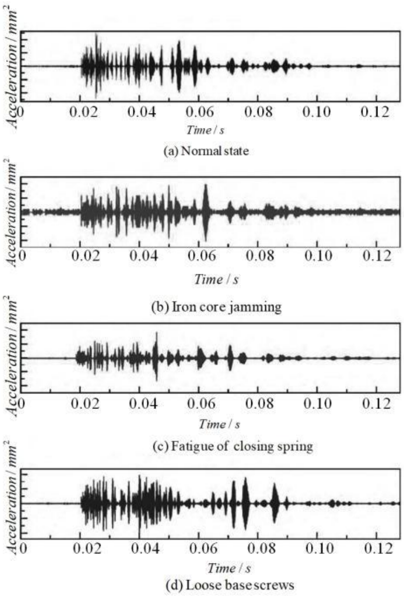

Figure 1. Four Working States Time Domain Spectrum

In this paper, energy entropy is selected as the eigenvalue, and the specific calculation formula of each mode energy entropy is as follows.

$$E_k = \int_{-\infty}^{+\infty} |u_k(t)|^2 dt \tag{19}$$

$$p_k = \frac{E_k}{\sum_{k=1}^{K} E_k} \tag{20}$$

Where, E_k and p_k are the energy and energy proportion of the k th modal component respectively. Therefore, the calculation method of energy entropy is:

$$H_k = -\sum_{k=1}^{K} p_k \lg p_k \tag{21}$$

Screen the first three modal components with high correlation according to the correlation coefficient, and reorder them according to the correlation from high to low, and using SVM for fault detection. Each of the four states in the experimental data contains 20 samples, and the four states have a total of 80 samples. Among them, randomly select 10 samples for training, and the remaining 10 samples for fault testing. The final classification results of the four states are shown in Figure 2.

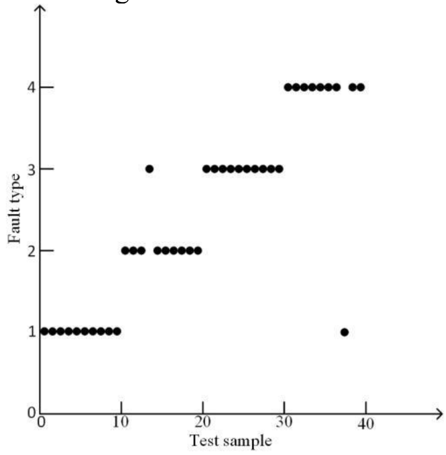

Figure 2. Fault Detection Results

In Figure 2, tag 1 is in normal state, tag 2 is iron core jamming, tag 3 is spring fatigue, and tag 4 is base looseness. The accuracy of fault detection in normal state is 100%, that of iron core jamming is 90%, that of spring fatigue is 100%, that of base looseness is 90%, and that of comprehensive fault detection is 95%.

5. Conclusion

In this paper, a circuit breaker fault detection method based on OOA-VMD-SVM is proposed. Firstly, OOA is proposed to determine VMD parameters, and the signal is decomposed based on the parameter optimization VMD algorithm, and the energy entropy is extracted as the eigenvalue. Selecting a single energy entropy as the eigenvalue can avoid the problem of large amount of calculation. SVM is used for fault detection, and the final comprehensive fault detection rate is 95%, which verifies the advancement of the OOA-VMD-SVM method for circuit breaker fault detection.

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