Mechanical Fault Diagnosis of High Voltage Circuit Breaker based on Improved GSO-SVM Algorithm

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Abstract. The vibration signal generated by the transmission and impact of mechanical components of circuit breaker has chaotic performances, which is difficult to be analysed by conventional signal processing methods. The phase space reconstruction of vibration signal is worked on, and the signal reconstruction parameters are calculated by mutual information method and Cao algorithm respectively. The vibration signal is reconstructed into a high-dimensional space, and its permutation entropy is calculated as a feature vector. Support vector machine (SVM) is used to identify the failure type of circuit breaker, and PSO improved GSA hybrid algorithm is used to optimize the parameters of SVM so as to obtain high recognition accuracy. The experiment is carried out with the measured vibration signal of the typical operation state of the circuit breaker. The results show that the characteristics of circuit breaker vibration signals can be extracted accurately with the combination of phase space reconstruction and permutation entropy. By using PSO-GSA-SVM, the fault types of circuit breakers can be identified quickly and effectively, and the problems of path distortion, energy leakage and mode overlap of existing diagnosis methods can be solved.

1. Introduction

As the key control facility of electrified wire netting, the operation reliability of circuit breaker plays an important role in maintaining the safe and steady operation of the whole power system. From the statistical data of foreign and domestic, mechanical failure is mainly caused by fault of breaker [1,2], and the diagnosis of circuit breaker is broken by means of various following signals in operation, such as current signal, sound signal, vibration signal and image signal. Diagnosing mechanical faults of circuit breakers with vibration signals has always been the focus of domestic and foreign researches [3-12]. Some researches have used dynamic time warping (DTW) and its enhanced method to access to the time offset size of vibration signals under different states and use it as signal feature to indicate the fault of circuit breaker [3,4]. However, when extracting features from dynamic time warping, the optimal path needs to be planned, and the signal is tend to distortion, which reduces the precision of fault identification. In another research, wavelet transform (WT) is used for processing circuit breaker vibration signals [5-8], obtain the singularity index [5], energy spectrum [6], node maximum coefficient [7], characteristic entropy [8] and other parameters, and diagnose the mechanical fault of circuit breaker according to the characteristic differences of different operating states of circuit breaker, and positive diagnosis results are obtained. However, before the wavelet transform decomposes the signal, the wavelet basis function and decomposition scale are uncertain, which needs to be selected according to the experience. As a result, the signal cannot be decomposed adaptively, and there are some disadvantages such as signal band energy leakage during the process of decomposition. In
literature [9-12], an adaptive decomposition method based on the characteristics of signals -- empirical mode decomposition (EMD) is adopted. EMD is suitable for non-stationary nonlinear signals and can decompose vibration signals into finite independent eigen mode functions. Based on the eigen mode function, energy entropy [9] and total sample entropy [10] are extracted as features for circuit breakers fault diagnosis, and good diagnosis results are obtained. However, EMD has some defects in the decomposition process, such as over envelope, under envelope and mode aliasing.

Phase space reconstruction is an essential technology to deal with chaotic time series, it has been widely applied in diverse engineering fields such as transformer [11], bearing [14,15], motor fault diagnosis [16], etc. The generating mechanism of these short-time and high-frequency signals possesses complexity, with intense volatility and high vagueness. In this paper, the vibration signals of circuit breaker are reconstituted in phase space, and using mutual information method and Cao method to compute the reconstruction parameters, and the optimal reconstruction parameters are determined according to the characteristics of vibration signal. After that, the vibration signal is reconstituted into high-dimensional space, the phase space matrix is defined, and the permutation entropy feature is extracted. Finally, the Particle Swarm optimization (PSO) improved Gravitational Search Algorithm (GSA) algorithm is used to enhance the SVM parameters $C$ and $g$. The optimal SVM classifier is constructed to identify the circuit breaker failure, avoiding defects in low classification recognition rate caused by manual empirical parameter selection.

2. Signal processing algorithm

2.1 Characteristics of vibration signal of circuit breaker

The vibration signal is produced by the composition of a range of shock waves caused by the starting, moving and stopping of the mechanical parts in a certain sequence during the operation of the circuit breaker. In this paper, 10kV spring operating mechanism ZN65 high voltage circuit breaker is used for test and experiment, and four states of normal closing (A), shaft stuck (B), loose base (C) and closed (D) are simulated in closing process. The L0102T piezoelectric acceleration sensor fixed on the circuit breaker support is used to collect 20 clusters of vibration signals from each of the above four conditions. Time domain vibration signal of circuit breaker is shown in Fig.1.
It can be seen from the chaotic theory that the maximum Lyapunov exponent is positive, which indicates that the signal possesses chaotic features [17]. In this paper, the maximum Lyapunov index of the vibration signal in the normal condition and the three failure states is calculated by the minimum data methodology during closing process. The calculation results are illustrated in Table 1. The maximum Lyapunov exponent in the chart is greater than zero which indicates the vibration signal in the circuit breaker closing possesses chaotic characteristics, which can be analyzed by phase space reconstruction.

| Signal | Number | 1 | 2 | 3 | 4 | 5 |
|--------|--------|---|---|---|---|---|
| A      |        | 0.032 | 0.083 | 0.047 | 0.051 | 0.062 |
| B      |        | 0.044 | 0.031 | 0.037 | 0.080 | 0.054 |
| C      |        | 0.028 | 0.069 | 0.094 | 0.051 | 0.011 |
| D      |        | 0.050 | 0.076 | 0.014 | 0.037 | 0.062 |

In phase space reconstruction theory, the varieties of any part of the signal depend on the other parts interacting with it, in the process of the component changes implied the relevant component information. Therefore, by investigating any variables and choose the appropriate embedding dimension to be embedded in high dimensional space to reconstruct the original signal of all state information [18,19]. The DTW, WT and EMD signal processing methods that are existed possess some drawbacks which include path angulation, non-adaptive decomposition, end effect and mode mixing, and the results obtained are uncertain. After the vibration signal is reconsituted into a high dimensional space by phase space reconstruction, the signal feature entropy is extracted to characterize the chaotic features of the former signal which well solves the shortcomings of the above-mentioned methodologies.

2. 2 Phase space reconstruction algorithm
Coordinate delay method is adopted to reconstruct the system state space. For the vibration signal $X=\{x_1, x_2, \ldots, x_n\}$ with data length of $n$, the phase points of phase space reconstruction can be obtained:

$$X_j = (x_j, x_{j+\tau}, \ldots, x_{j+m\tau})$$

In formula: $j = 1, 2, \ldots, K; K = n - (m - 1)\tau$, $m$ is the embedding dimension and $\tau$ is the delay time.

In Takens theorem [19], when the signal is infinitely long and there is no noise, the reconstruction parameters $\tau$ and $m$ value can be selected at will. The vibration signal collected in the actual circuit breaker opening and closing process is of limited length and contains environmental noise, so the corresponding embedding dimension $m$ and delay time $\tau$ need to be calculated to realize phase space reconstruction. When collecting samples of high-voltage breaker vibration signals in various conditions, the mode with the same time series length is adopted to ensure that the variables generated by phase space reconstruction are as low as possible due to the sequence length factor.

2. 2. 1 Calculate the Delay Time $\tau$
The magnitude of the delay time $\tau$ represents the correlation of each component in the signal. The mutual information method in chaos theory can calculate the delay time [20]. The vibration signal in circuit breaker is set as $S = \{x(i)\}_{i=1}^{n}$, the delay time is $\tau$, after a delay the signal becomes $Q = \{x(i+\tau)\}_{i=1}^{n}$. The mutual information of signals $S$ and $Q$ is:
\[ I(Q,S) = H(Q) + H(S) - H(S,Q) \]

\[ H(Q) = -\sum_{j} P_{q}(q_{j}) \log P_{q}(q_{j}) \]

\[ H(S) = -\sum_{i} P_{s}(s_{i}) \log P_{s}(s_{i}) \]

\[ H(S,Q) = -\sum_{i} \sum_{j} P_{sq}(s_{i},q_{j}) \log \frac{P_{sq}(s_{i},q_{j})}{P_{s}(s_{i}) P_{q}(q_{j})} \]  

In formula: \( s_{i} \) and \( q_{j} \) are respectively the signal sampling values at time \( i \) and after delay at time \( j \), \( P_{s}(s_{i}) \) is the probability that \( s_{i} \) occurs, \( P_{q}(q_{j}) \) is the probability that \( q_{j} \) occurs, \( P_{sq}(s_{i},q_{j}) \) is the probability that \( s_{i} \) and \( q_{j} \) occur together. \( I(Q,S) \) is a function of \( \tau \), can be expressed as \( I(\tau) \), the optimal delay time is the first minimum point of \( I(\tau) \)[20]. Fig.2 shows the delay time curves of vibration signals under four states. The optimal delay time \( \tau \) is 5, 8, 4, 3 in sequence.

![Fig.2 The delay time curve of vibration signal](image)

### 2.2.2 The Embedding Dimension

In the improved false neighborhood method (Cao) algorithm. The value of embedding dimension \( m \) is determined largely by the geometric invariants related to the attractor [21]. When the geometric invariants of the attractor reach a stable state, the value is the final embedding dimension \( m \). The specific calculation steps are as follows:

Calculate the distance between the nearest adjacent point in the phase space under different dimensions. When the phase space dimension is \( d \), the distance between the phase point \( x_{i} \) and the nearest point \( x_{i}^{'} \) is:

\[ D_{d}(i) = \| x_{i} - x_{i}^{'} \| \]  

(3)
When the dimension of phase space is \( d+1 \), the distance between two points changes, and there is:

\[
D_{d+1}^2(i) = D_d^2(i) + \left| x_{i+dr} - x_{i+mr} \right|
\]  (4)

If \( D_{d+1}(i) \gg D_d(i) \), then the two points are false neighbors, and:

\[
a(i, d) = \frac{D_{d+1}(i)}{D_d(i)}
\]  (5)

The expansion of the phase space \( E_i(m) \) is:

\[
\begin{align*}
E(m) &= \frac{1}{N - m\tau} \sum_{i=1}^{N-mr} a(i, m) \\
E_i(m) &= E(m + 1) / E(m)
\end{align*}
\]  (6)

The correlation \( E_z(m) \) of the calculated signal is:

\[
\begin{align*}
E_z(m) &= \frac{1}{N - m\tau} \sum_{i=1}^{N-mr} \left| y_{i+mr} - y_{i+mr}' \right| \\
E_z(m) &= E_z(m + 1) / E_z(m)
\end{align*}
\]  (7)

According to the definition of Cao algorithm, when \( E_i(m) \) and \( E_z(m) \) close to 1, the optimal value of embedding dimension is \( m \). Fig.3 shows the embedding dimensions of vibration signals in four states and the optimal embedding dimension \( m \) is 8, 10, 9, 9 in order.

2.2.3 Determination of Optimal Reconstruction Parameters

The reconstruction parameters of 5 groups of vibration signals under 4 states of zn65 high voltage circuit breaker are shown in Table 2. The embedding dimensions of various vibration signals are 8, 9 and 10, and the delay times of class A-D vibration signals are 5 and 6, 7 and 8, 4 and 3 respectively.
According to the Taken theorem, the larger the embedding dimension, the better the reconstructed state information [21]; Therefore, the maximum value of the embedding dimension is chosen as the optimal embedding dimension in this paper, and $m_{\text{super}} = 10$. Considering that the collected vibration signals have certain deviation, the one with the largest proportion of delay time of various signals is selected as the optimal delay time, and $\tau_A = 5$, $\tau_B = 7$, $\tau_C = 4$ and $\tau_D = 3$ are selected in combination with Table 2.

### Table 2: Reconstruction parameters

| Signal Types | Signal number | m$\tau$ | m$\tau$ |
|--------------|---------------|--------|--------|
| A            | 1             | 5      | 8      |
|              | 2             | 6      | 10     |
|              | 3             | 5      | 10     |
|              | 4             | 6      | 10     |
|              | 5             | 5      | 9      |

| Signal Types | Signal number | m$\tau$ | m$\tau$ |
|--------------|---------------|--------|--------|
| B            | 1             | 8      | 10     |
|              | 2             | 7      | 10     |
|              | 3             | 7      | 9      |
|              | 4             | 8      | 10     |
|              | 5             | 7      | 10     |

### 3. Vibration signal feature extraction

After phase space reconstruction of various signals, the reconstruction matrix is obtained:

$$X = \begin{bmatrix}
  x_1 & x_{1+\tau} & \ldots & x_{1+(m-1)\tau} \\
  x_2 & x_{2+\tau} & \ldots & x_{2+(m-1)\tau} \\
  \vdots & \vdots & \ddots & \vdots \\
  x_j & x_{j+\tau} & \ldots & x_{j+(m-1)\tau} \\
  \vdots & \vdots & \ddots & \vdots \\
  x_k & x_{k+\tau} & \ldots & x_{k+(m-1)\tau}
\end{bmatrix}$$

(8)

The row elements of the matrix represent the reconstructed components, and the index of each element's column is $\{j_1, j_2, \ldots, j_m\}$, the reconstructed components are arranged in ascending order:

$$x_{r+(j_i-1)\tau} \leq x_{r+(j_{i+1}-1)\tau} \leq \cdots \leq x_{r+(j_m-1)\tau}$$

(9)

If the components are equal in size, the values of $j_1$ and $j_2$ are compared for sorting; If $j_1 < j_2$, then $x_{r+(j_1-1)\tau} < x_{r+(j_2-1)\tau}$.

For each reconstructed component, a set of symbol sequences $s(l) = (j_1, j_2, \ldots, j_m)$ can be obtained. In this sequence, $l = 1, 2, \ldots, K$ and $K \leq m!$. Then there are $m!$ kinds of mappings in $m$-dimensional phase space, and $s(l)$ is the $l$-th permutation. Calculate the probability $P_1, P_2, \ldots, P_K$ of the existence of each symbol sequence. The permutation entropy of $k$ different symbol sequences of signal $X$ is defined in the form of Shannon entropy:

$$H_p(m) = -\sum_{j=1}^{m!} P_j \ln P_j$$

(10)

When $P_j = 1/m!$, $H_p(m)$ will reach the maximum $\ln(m!)$, $H_p(m)$ is normalized to:
\[ H_p(m) = H_p(m) / \ln(m!) \] (11)

Where, \( H_p \) represents the randomness of sequence \( X \); The larger \( H_p \) is, the more random \( X \) is, and the smaller \( H_p \) is, the more regular \( X \) is.

According to the above permutation entropy theory, the characteristic values of vibration signals under each state are extracted, as shown in Table 3.

| Number | Entropy of signal arrangement |
|--------|-------------------------------|
|        | A    | B    | C    | D    |
| 1      | 0.964| 0.479| 0.900| 0.224|
| 2      | 0.975| 0.441| 0.902| 0.279|
| 3      | 0.968| 0.500| 0.917| 0.178|
| 4      | 0.970| 0.467| 0.921| 0.184|
| 5      | 0.967| 0.398| 0.934| 0.255|
| 6      | 0.951| 0.551| 0.913| 0.248|
| 7      | 0.948| 0.531| 0.926| 0.317|
| 8      | 0.962| 0.548| 0.859| 0.320|
| 9      | 0.973| 0.342| 0.930| 0.256|
| 10     | 0.974| 0.483| 0.939| 0.417|

From the time domain waveform (Fig.1) and characteristics (Table 3) of vibration signals, it shows that: Class A and Class C have high permutation entropy; Classes B and D are relatively small. Compared with the characteristic value under normal conditions, the characteristic value of the defect vibration signal is smaller on the whole and the characteristics of different defect types are different, indicating that the circuit breaker defect types are different and their permutation entropy characteristics are different. According to the characteristic difference, the defect type identification of circuit breaker can be realized.

4. Improved SVM Circuit Breaker Fault Diagnosis Based on PSO-GSA

4.1 PSO-GSA Improves SVM Algorithm

The Support Vector Machine (SVM) algorithm can solve the problems of small samples, nonlinearity, local minima, etc., and is often used in mechanical fault diagnosis situations with a small number of experimental samples [22]. The SVM algorithm can realize the fault diagnosis of circuit breaker with fewer samples. For different diagnostic models, kernel function parameter \( g \) and penalty parameter \( C \) are set differently in SVM classification, and appropriate \( g \) and \( C \) should be selected to achieve the best classification accuracy [23]. In this paper, the gravitational search algorithm improved by particle swarm is used to optimize the parameters of SVM. The gravitational search algorithm believes that the solution to the particle optimization problem in the search space is attracted to find the optimal position through the gravitational interaction between the particles [24]. Practice shows that the GSA algorithm optimization performance is better than GA and PSO[25]. However, due to the lack of group information sharing in speed update, the local optimization ability is poor. Therefore, The PSO algorithm with group information exchange ability is introduced to improve GSA.

The steps of PSO-GSA algorithm are as follows:

1. Initialize particle position. There are a total of \( n \) particles in the D-dimensional space, the position of the \( i \)-th particle is:

\[ x_i = (x_i^1, x_i^2, \ldots, x_i^D), i = 1 \cdots n \] (12)

2. Calculate the inertial mass \( M_\theta (t) \) of particle \( i \) at time \( t \) as:
\[
\begin{align*}
m_i (t) &= \frac{\text{fit}_i (t) - \text{worst}(t)}{\text{best}(t) - \text{worst}} \\
M_i (t) &= m_i (t) \left( \sum_{j=1}^{N} m_j (t) \right)
\end{align*}
\]  
(13)

Where: \( \text{fit}_i (t) \) is the fitness value; \( \text{best}(t) \) and \( \text{worst}(t) \) are the best value and the worst value respectively:

\[
\begin{align*}
\text{best}(t) &= \min_{j \in \{1, 2, \ldots, N\}} \{ \text{fit}_j (t) \} \\
\text{worst}(t) &= \max_{j \in \{1, 2, \ldots, N\}} \{ \text{fit}_j (t) \}
\end{align*}
\]  
(14)

(3) The gravitational force of particle \( j \) on \( i \) at time \( t \) is calculated as:

\[
F^d_{ij} (t) = G(t) \times \frac{M_{aj} (t) \times M_{pi} (t)}{R^d_{ij} (t)} \times \frac{\left( x^d_i (t) - x^d_j (t) \right)}{R^d_i (t)}
\]  
(15)

Where, \( M_{aj} (t) \) and \( M_{pi} (t) \) are the inertial masses of the acted and acted objects respectively, and \( G(t) = G_0 \exp \left( a \times t/T_{\text{max}} \right) \), \( T_{\text{max}} \) is the maximum number of iterations, \( G_0 = 100 \).

(4) Calculate the sum of the forces acting on the particle \( i \) in the dimension \( d \) at time \( t \) as:

\[
F^d_i (t) = \sum_{j=1, j \neq i}^{N} \text{rand}_j \times F^d_{ij} (t)
\]  
(16)

(5) Calculated acceleration:

\[
a^d_i (t) = \frac{F^d_i (t)}{M_i (t)}
\]  
(17)

(6) Update speed and location:

\[
v^d_i (t+1) = \text{rand}_j \times v^d_i (t) + a^d_i (t)
\]  
(18)

\[
x^d_i (t+1) = x^d_i (t) + v^d_i (t+1)
\]  
(19)

Where: \( \text{rand}_j \) is a random number between 0 and 1.

The velocity update formula of GSA algorithm only takes the current position of particles into account, and PSO is introduced for improvement, then the particle velocity formula becomes:

\[
v^d_i (t+1) = \omega v^d_i (t) + c_1 r_1 a^d_i (t) + c_2 r_2 \left( g^d_{\text{best}} - x^d_i (t) \right)
\]  
(20)

Where: \( g^d_{\text{best}} \) is the current global optimal solution, \( \omega \) is the inertia weight, \( c_1 \) and \( c_2 \) is the learning factor, \( r_1 \) and \( r_2 \) is the random number between 0 and 1.

(7) Return to step (2) until reaching the set maximum number of iterations \( T_{\text{max}} \).

Optimizing the \( g \) and \( C \) parameters in SVM by using PSO-GSA algorithm, and the optimization steps were as follows:

a) Initialize SVM parameters \( C \) and \( g \) to form a population, and initialize particle speed randomly.

b) Calculate the fitness value of the particles, and the minimum mean square error in the SVM diagnosis process was used as the fitness function:
\[ MSE = \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \]  

(21)

Where: \( n \) is the sample number, \( y_i \) and \( \hat{y}_i \) are the actual output value and expected value respectively.

c) Calculate the universal gravitation and resultant force.
d) Update particle acceleration, speed and position.
e) Return to step (2) loop until reaching the maximum number of iterations, and return the current optimal SVM parameters and classification accuracy.

4.2 Fault Diagnosis of Circuit Breaker

The fault diagnosis process of circuit breaker using SVM is shown in Fig.4. SVM adopts radial basis kernel function, and the values of \( g \) and \( C \) are in the range of \( 2^{-10} \sim 2^{10} \). After many experiments, when the training set and test set samples are each 40, the fault diagnosis rate is the highest. Therefore, 40 groups of permutation entropy of vibration signals were used as training samples to train the SVM classification model, and the remaining 40 groups of input training models are tested. The classification accuracy of SVM under different optimization algorithms was compared. As shown in Table 4, the optimization time of PSO-GSA algorithm is shorter and the classification accuracy is higher. The optimal parameters \( C \) and \( g \) are obtained by using PSO-GSA, and the process is shown in Fig.5. The final fault classification results are shown in Fig.6. All 40 test samples are correctly classified, and the identification results reach 100%.

![Fig.4 Circuit breaker defect identification process](image-url)
Fig. 5: Accuracy when parameters $C$ and $g$ take different values

Table 4: Parameters and identification accuracy of different parameter optimization algorithms

| Algorithm       | Parameters | Classification Accuracy |
|-----------------|------------|-------------------------|
| GSA-SVM         | 0.187      | 0.24                    | 9.57s  | 96.3%  |
| PSO-SVM         | 0.01       | 0.1                     | 16.71s | 92.1%  |
| PAO-GSA-SVM     | 0.01       | 3.41                    | 3.41s  | 100%   |

Fig. 6: Fault diagnosis results of FWA-SVM

5. Conclusion

The high-voltage circuit breaker vibration signal obtained by non-intrusive piezoelectric sensor has chaotic characteristics as a non-stationary vibration signal. The key to effectively identify the state of circuit breaker is the signal processing algorithm.
(1) Use mutual information method and Cao algorithm to determine the delay time and embedding dimension of the signal, and reconstruct the phase space of the signal. Taking into account the chaotic characteristics of the signal, it has great advantages in analyzing and processing the vibration signal of the circuit breaker.

(2) By combining phase space reconstruction technology and permutation entropy to extract the characteristics of circuit breaker vibration signal, and using pso-gsa optimized support vector machine algorithm, it has less time overhead and high identification accuracy.

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