Fault diagnosis of vacuum circuit breaker based on coil current of release

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Abstract. The release is the key component of operation mechanism of circuit breaker. Its current waveform contains many information. The fault diagnosis of circuit breaker can be realized by analyzing the current waveform of coil. Firstly, the combination method of wavelet analysis and seeking extreme points in region extremum is proposed to obtain the feature values of coil current of circuit breakers. Then, a novel intelligent particle swarm optimization (PSO) algorithm was adopted to search the optimal parameters of support vector machine (SVM). Finally, a high-performance SVM with optimal parameters is constructed for fault diagnosis. The experimental results show that the method can achieve a high fault diagnosis accuracy.

1. Introduction

High voltage circuit breaker is an important electrical equipment in the power system, which plays a dual role of protection and control. The reliability of its operation plays a vital role in the normal operation of power system[1]. According to statistics, the failure of mechanical operation mechanism of circuit breaker is one of the main factors leading to the failure of circuit breaker [2-3]. Therefore, the study of fault diagnosis of operation mechanism of circuit breaker is an effective way to improve the reliable operation of operation mechanism of circuit breaker. Mechanical fault diagnosis of circuit breakers can be accomplished by monitoring various electrical or mechanical parameters of circuit breakers, among which the current of closing and opening coils is one of the most important parameters [4-5]. Coil current can not only reflect the state of coil itself and control loop, but also reflect the state information of operation process of circuit breaker[6]. Many documents use the key points of coil current signal to analyze the mechanical fault of circuit breaker [7-8].

The intelligent multi-classification method of support vector machine is good at solving the small sample problem and has the characteristics of good robustness and high learning ability [9-11]. However, the selection of kernel function parameters of support vector machine directly affects the classification results, so the selection of kernel function parameters is very important. Firstly, a new algorithm is proposed to extract features from coil current. Then, POS algorithm is used to determine the parameters of kernel function in SVM to improve the performance of classifier. Coil features are used as training and recognition samples of SVM. The experimental results show that this method can effectively classify circuit breaker faults. The fault diagnosis model has great application value.
2. Coil current feature extraction

2.1 Determination of coil features
This paper simulates four common states: coil normal, coil jam, coil overvoltage and coil undervoltage. The current waveform is shown in Fig. 1. $I_1$ can represents the starting current of the coil; The actual starting current of iron core is difficult to monitor, but it has a mathematical relationship with $I_2$, so $I_2$ can approximately represent the starting current of iron core; $I_3$ can represent the current when the tripper is released; $I_4$ can represent the current at auxiliary disconnection; $t_1$ can represent time of release; $t_2$ can represent auxiliary disconnection time.

Fig. 1. Current waveform of coil
It can be seen from the figure that $I_2$, $I_3$, $I_4$, $t_1$ and $t_2$ have changed obviously, so the characteristic parameters of coil current waveform are composed of three vectors of current and two vectors of time.

2.2 Determining the best parameters for noise reduction
Let $\varphi(t)$ be the basic wavelet function. $x(t)$ is quadratic integrable function. That is $x(t) \in L^2(R)$, the $x(t)$ wavelet transform is equation (1). In the formula, $a$ is a wavelet scale expansion and $b$ is a wavelet displacement [12].

$$WT_v = \frac{1}{\sqrt{a}} \int x(t) \varphi\left(\frac{t-b}{a}\right) dt$$ (1)

In fact, wavelet transform decomposes the signal into a series of wavelet combinations with different scales. In the high frequency region, small-scale wavelet is used to characterize the high-frequency detail signal; in the low frequency region, large-scale wavelet is used to reproduce the overall situation of the signal. The denoising function of wavelet analysis can distinguish the high frequency part of noise from the clean signal [13].

Compared with the traditional method, the advantage of wavelet threshold denoising is that it can not only remove the noise, but also preserve the abrupt part of the signal and the edge of the image. The basic steps of optimal wavelet threshold denoising are as follows:

- Step1: Selection of appropriate wavelet basis functions
  Wavelet basis function must be able to carry out discrete wavelet transform, because the collected signal is discrete signal. At the same time, the wavelet basis function should have orthogonality, compact support, symmetry and vanishing matrix order. The selection of wavelet bases should be similar to the signal to be analyzed. Three wavelet bases DB, SYM and COIF are selected according to the properties of the wavelet bases in the Fig.2.
Step 2: Layer of wavelet decomposition
The choice of layers of wavelet decomposition layers is mainly based on experience. Engineering is generally tested in three layers first, and the number of layers is increasing gradually. However, with the increase of decomposition layers, the amount of calculation will become more complex and the time of calculation will become longer, but the effect will not change much. So this paper chooses three layers, four layers and five layers.

Step 3: Selection of threshold policy function
Hard threshold function can well preserve the local features such as the signal edge; soft threshold function is relatively smooth but can cause edge blurring and distortion. According to the location where the feature points of current waveform are concentrated, this paper chooses soft threshold function.

Step 4: Selection of threshold estimation rules
The appropriate threshold is selected as the quantization standard, and the high frequency coefficients of each layer are quantized by threshold. In this paper, we try to find the best threshold estimation rules by using different threshold selection.

Step 5: Signal reconstruction
The low-frequency coefficients of N-layer and the high-frequency coefficients of wavelet decomposition of each layer are inversely transformed to reconstruct the denoising signal. According to the signal-to-noise ratio (SNR), minimum mean square error (MES) and smoothness (R), the best wavelet parameters are selected to reduce noise, of which SNR and MES are the most important basis. As shown in Fig. 3, when SNR is larger, MES is smaller and R is closer to 1, the effect of noise reduction is better. So this paper chooses sym6 wavelet basis and three layers decomposition. The threshold strategy is soft threshold and the threshold estimation rule is rigrsure.

2.3 Feature extraction algorithm
The coil current is denoised by wavelet transform, and the first singular point of the signal (I1 mentioned above) is extracted at the same time, which is the S point as shown in Fig. 4.
Taking the first singular point as the reference point, the current value and time value of the maximum point are recorded at the same time. Five milliseconds around the datum point is used as the region to search the whole signal from the datum point. If the value of the first discovery point is equal to the maximum value in the region, jump out of the cycle and record the first maximum point. If the value of the first discovery point is equal to the minimum value in the region, jump out of the cycle and record the first minimum point. The flow chart of the algorithm is shown in Fig. 5.

The collected data are brought into the algorithm, and the feature quantities are obtained as Table 1. Because of the limited space, only a part of it is listed.
Table 1. Coil current characteristic parameters and corresponding fault types.

| Serial number | I₁(A) | I₂(A) | I₃(A) | t₁(ms) | t₂(ms) | State         |
|--------------|-------|-------|-------|--------|--------|---------------|
| 1            | 0.94  | 0.45  | 1.25  | 15.50  | 27.20  | coil normal   |
| 2            | 0.94  | 0.45  | 1.26  | 15.40  | 27.20  | coil normal   |
| 3            | 1.20  | 0.63  | 1.32  | 26.00  | 36.40  | coil jam      |
| 4            | 1.20  | 0.63  | 1.32  | 25.80  | 36.00  | coil jam      |
| 5            | 1.01  | 0.52  | 1.31  | 14.30  | 23.40  | coil overvoltage |
| 6            | 1.00  | 0.52  | 1.32  | 14.20  | 23.40  | coil overvoltage |
| 7            | 0.72  | 0.27  | 0.72  | 24.20  | 12.10  | coil undervoltage |
| 8            | 0.72  | 0.27  | 0.72  | 24.20  | 12.70  | coil undervoltage |

3. Support Vector Machine

SVM method is based on VC dimension theory and structural risk minimization principle of statistical learning theory. According to the limited sample information, the best compromise between the complexity of the model (i.e. the learning accuracy of a specific training sample) and the learning ability (i.e. the ability to identify arbitrary samples without error) is sought in order to obtain the best generalization ability.

SVM was originally used to classify samples. As shown in Fig.6, the dividing line in the graph is a set of functions formed by SVM. The points on the function are support to vectors, which means that these vectors support the boundaries. It can be seen that, unlike the neural network, it does not need a large number of samples, but only the support vector on the boundary. As long as other vectors do not cross the bounds, SVM does not care. This ensures the sparsity and generalization ability of the learning machine.

Circuit breaker fault diagnosis is a multi-classification problem, which is realized by one-to-one multi-classification method. The basic idea is to construct all possible two classifiers in class K. Each classifier only trains two training samples in class K, so only K (K-1) two classifiers are needed. In recognition, multiple classifiers are synthetically judged. Using the voting method, the most voted categories are the sample categories to be tested.

Fig. 6. Simple classification of support vector machines

3.1 Kernel function selection and parameter optimization

The introduction of kernels function enables operations to be performed directly in the input space rather than in the potential high-dimensional feature space, which can avoid dimensionality disasters. In this paper, different kernels functions are selected to test, and the RBF kernel function in fault diagnosis of circuit breaker shows better classification performance. The penalty factor parameter c and the parameter g in RBF are two parameters that can be adjusted artificially. The values of the parameters are different, and the corresponding classifier properties and the recognition rate are also
very different. In this paper, particle swarm optimization algorithm is used to optimize the parameters of the kernel function, which greatly improves the performance of the classifier.

4. Results and analysis of simulation experiment
The diagnostic flow chart is shown in Fig.7. 73 samples were selected for SVM training, and the training model was obtained. Another 73 samples were used as test samples for fault diagnosis.

Fig. 7. Diagnostic flow chart

The penalty parameter $c$ and the kernel function parameter $g$ need to be adjusted in order to obtain satisfactory classification accuracy. In this paper, PSO algorithm is used to find the best parameters. The fitness function is defined as the accuracy of support vector machine training. The initial parameter $C_1$ for determining PSO's local search ability is 1.5, the initial parameter $C_2$ for determining PSO's global search ability is 1.7, the maximum evolutionary number is 200, the population number is 20, the variation range of SVM parameter $c$ is 0.1 to 50, and the variation range of SVM parameter $g$ is 0.1 to 1000. Through POS algorithm, the optimal parameters $c=3$ and $g=5.6$ of SVM are finally determined. The fitness curve of PSO to find the optimal parameters is shown in the Fig.8. The comparison between the fault class label diagnosed by the SVM model and the actual fault class label is shown in the Fig.9. The accuracy of fault diagnosis is 100%.

Fig. 8. The fitness (accuracy rate) curve in the process of finding the optimal parameters
Fig. 9. Fault class labels diagnosed by SVM model compared with actual fault class labels

The optimal parameters and randomly parameters are used to establish the model respectively, and then the test samples are input for comparison. The experimental results are shown in Table 2. The results show that the method proposed in this paper has good effect.

Table 2. Comparison of experimental results

| Operation times | c | g | Accuracy rate  |
|-----------------|---|---|----------------|
| 1               | 2 | 3 | 94.52%         |
| 2               | 5 | 8 | 94.348%        |
| 3               | 10| 30| 95.6296%       |
| 4               | 3 | 5.6| 100%           |

5. Conclusion
A method of extracting eigenvalues of current signals of circuit breakers based on wavelet analysis and regional extremum is proposed, and a fault diagnosis model of vacuum circuit breakers based on support vector machine (SVM) is established. Because the selection of kernel function parameters of support vector machine directly affects the classification results, particle swarm optimization (PSO) is used to determine the optimal parameters of kernel function in support vector machine (SVM) in order to improve the performance of classifier. The experimental results show that the SVM model trained by optimized parameters has better performance than the support vector machine model trained by randomly selected parameters. Some mechanical faults of high voltage circuit breakers are classified effectively.

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