FAULT DIAGNOSIS OF HIGH-VOLTAGE CIRCUIT BREAKERS USING WAVELET PACKET TECHNIQUE AND SUPPORT VECTOR MACHINE

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ABSTRACT

The subject addressed in the paper is mechanical fault diagnosis of high-voltage circuit breakers (HVCBs) based on vibration signal analysis. In this paper, the vibration signature measured from the SF_6 HVCB is processed using the fast Fourier transform (FFT) and the wavelet packet technique (WPT). With the FFT and the WPT, the vibration signature is decomposed into different frequency bands, and the energy of the signal is extracted from individual frequency bands and calculated as the individual condition eigenvector. Followed by that, parameters captured from the WPT are optimized with the particle swarm optimization (PSO) and the result is used to train a multi-fault classification model based on the kernel method of the support vector machine (SVM). At the end, fitness values are evaluated with the trained SVM to classify conditions and diagnose faults of the SF_6 HVCB.

INTRODUCTION

High voltage circuit breakers (HVCBs) are considered as 'active link', which is used to make and break an electrical circuit under conditions of varying severity [1]. Mechanical failure of HVCBs is one of the most important failure modes that affect the reliability of power systems operation. Traditionally, HVCBs have been maintained using a scheduled maintenance scheme [2][3]. These overhauls, where the entire circuit-breaker is disassembled are however, time-consuming and expensive. Condition-based maintenance of HVCBs has been increasingly requested by power utilities in recent years because it can detect premature failures and thus prevent serious failure of the equipment and also prevent financial losses [4].

Vibration analysis is used extensively because the method is non-invasive and the majority of faults are of mechanical origin therefore affecting the vibration spectrum. The spring fatigue failure and the screw losing in the base are typical problems that can be detected by vibration analysis [5]. A basic hypothesis applied in signature analysis is that any minor change in the mechanical properties of HVCBs will cause slight differences in statistical characteristics of vibration signature. These slight differences can be detected by comparing the previous statistical characteristics in healthy state with the new recorded results from the same HVCB in both time-domain and frequency-domain [6].

As we all known, the vibration signature of HVCBs is transient which is difficult to process with traditional methods such as event time extracting in time domain and Fourier analysis in frequency domain. The WPT is a useful method to process non-stationary signals effectively [6]. In this paper, the FFT and the WPT are used to capture signal characteristics of vibration signature. A SVM classifier whose parameters are optimized with the PSO method [7] is employed.

With PSO algorithm, WPT and SVM, a novel hybrid intelligent fault detection and classification method for HVCBs is presented. This paper starts with an introduction in section I. In section II, a description of the methodologies used for processing the vibration signature is presented. Section III presents an introduction of the experimental program about vibration signature acquisition and fault simulation, while Section IV proposes the details of signal analysis procedure which contains the decomposition of vibration signature with the WPT, parameters optimization with the PSO and the fault classification and detection with the SVM. Finally, conclusions are given in Section V, where the methodology performance is evaluated.

METHODOLOGIES

Wavelet Packet Technique

The WPT is a mathematical tool that transforms a signal from time domain to time-frequency domain. The WPT has been used to analyze the vibration data of HVCBs for the detection of incipient faults by converting measured vibration signals captured from healthy and defective HVCBs into wavelet features [2]. After transforming, the original signal is decomposed to a set of wave like signals, called 'wavelet'. These wavelet signals are the scaled (dilated) and shifted forms of the mother wavelet.

With the WPT, we can decompose the signals in different frequency bands, and then calculate the energy of each frequency bands. Once a HVCB is failed, the feature of vibration signals will be different from the normal ones in both time and frequency domain. Thus, we can detect the failure through comparing the difference of vibration signals under various states.

Optimization and classification method of PSO-SVM

The fault detection and identification procedure based on the SVM consists of data collecting and processing, selection of a kernel, training and optimal SVM classifier. The kernel function adopted in this research is the Gaussian radial basis function (RBF). This method provides an efficient approach which can search for optimal parameters for the SVM classifier.

Above all, parameter selection is a very important problem, which has great influence on the performance of the SVM. The PSO is an efficient algorithm and it is

broadly used in many research areas like pattern recognition and so on. In order to improve the learning and generalization ability of the SVM classifier through parameter optimizing, a PSO algorithm is used. The flow chart of optimizing the SVM parameters with a PSO algorithm is shown in Fig. 1 [5].

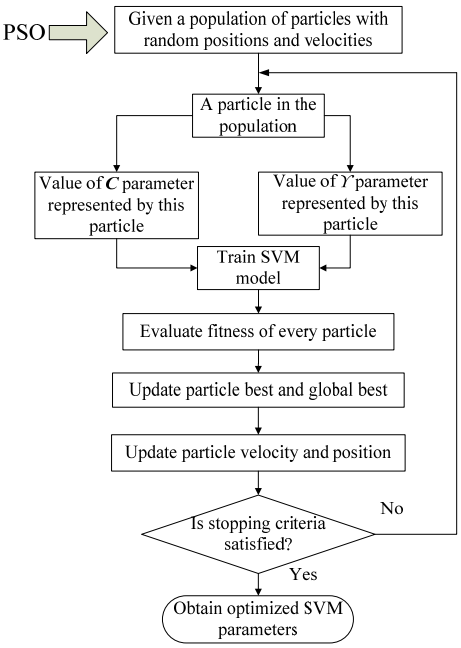

Fig. 1. The process of optimizing the SVM parameters with PSO.

PSO algorithm

The PSO algorithm proposed by Kennedy and Eberhart in 1995 is an optimization algorithm. which comes of the bird swarm behaviour of preying on food [8]. The algorithm searches for optimal solutions by cooperation of individuals. Owing to its simple concept and easiness to implement, PSO is widely applied in pattern recognition and other areas.

PSO performs searching via a swarm of particles that updates from iteration to iteration. Suppose the solution space of optimization problem is of D dimensions and the swarm consists of N particles. While the location of ith particle is $X_i = (x_i^{(1)}, x_i^{(2)},\cdots, x_i^{(D)})$, the fly speed and personal extreme of this particle are $V_i = (v_i^{(1)}, v_i^{(2)},\cdots, v_i^{(D)})$ and $P_i = (P_i^{(1)}, P_i^{(2)},\ldots, P_i^{(D)})$ separately. The global extreme of particle swarm is $P_g = (P_g^{(1)}, P_g^{(2)},\cdots, Pg^{(D)})$. Particles update their own location and speed according to the following two formulas [5][6].

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1) \quad i = 1,2,\ldots,N; d = 1,2,\ldots,D \tag{1}$$

$$\begin{aligned} v_{id}(t+1) &= k \times v_{id}(t) \\ &+ c_1 \times rand_1() \times [p_{id}(t) - x_{id}(t)] \\ &+ c_2 \times rand_2() \times [p_{gd}(t) - x_{gd}(t)] \end{aligned} \tag{2}$$

Where v_{id} and x_{id} are the dth velocity and location of ith particle. c_1 and c_2 are acceleration coefficients and they present the weights of statistical acceleration items in approaching to P_i and P_g of a particle. $Rand()$ is a uniformly distributed random variable with the range [0, 1] and ω is inertia coefficient which makes particles keeping fly inertia. The dth dimension component of location changes in the range of $[-x_{maxd}, x_{maxd}]$ and the maximal speed is v_{max}.

The SVM classifier

SVM was proposed by Vapnik in 1990, it is a new machine learning method based on structural risk minimization and statistical learning theory, which solves the problems of 'over-fitting', local optimal solution and low convergence rate [9]. It searches for the best compromise between complexity of model and learning ability on the basis of limited sample information, aiming to obtain the best generalization ability. Since the learning ability and generalization performance of SVM rely heavily on the parameters of RBF, parameters selection becomes a very important problem.

It's summarized that the basic idea of SVM learning algorithm is divided into two steps. Firstly, transform the input space to a higher dimensional linear feature space by a nonlinear transform function φ. Then in this higher dimensional feature space, the optimal linear separating plane can be constructed and the nonlinear transformation can be realized by defining proper kernel function [6]. The objective function and constraints of SVM are

$$\begin{aligned} \min_{w,b,\xi} \quad & \frac{1}{2} w^T w + C \sum_{i=1}^{l} \xi_i \\ \text{subject to} \quad & y_i (w^T \phi(x_i) + b) \geq 1 - \xi_i, \\ & \xi_i \geq 0, i = 1,2,\ldots,l \end{aligned} \tag{3}$$

where x_i is the train set, C is the upper bound, ξ_i is the slack variable and $\phi(x_i)$ is a function mapping the train set into a high dimensional space. Besides, a RBF $k(x_i, x_j)= \phi(x_i)^T\phi(x_i)$ is chosen to be the kernel function of classifier

$$\begin{aligned} & k(x_i, x_j) = \exp(-\gamma \| x_i - x_j \|^2) \\ & i = 1,2,\ldots,l; j = 1,2,\ldots,l; i \neq j; \gamma > 0 \end{aligned} \tag{4}$$

where Υ is the kernel parameter.

VIBRATION SIGNAL ACQUISITION AND FAULT SIMULATION

Diagnostic testing by vibration analysis is to compare a vibration pattern recorded during an opening/closing operation with a reference and quantify the difference. Deviations in the vibration signature indicate deviations in the HVCB's conditions [4].

When a HVCB is new, a vibration signature can be taken as a reference for subsequent comparison. Any changes that are found to the signature may indicate a change in the mechanical condition of the HVCB. Further analysis may be used to identify the condition or the presence, nature and extent of any incipient faults.

Data collection System

Through a lot of research, we compared different types of data acquisition modules. Considering the parameters of the measurement accuracy, test range, error range and

price parameters, the data acquisition system is chosen as described in Fig. 2 and Fig. 3.

Fig. 2. Data acquisition system in the laboratory.

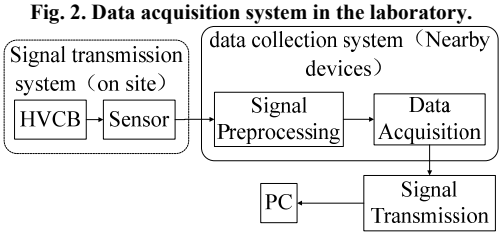

Fig. 3. Data acquisition system of vibration signal.

The key factors in the vibration signals acquisition are the sensor accuracy and its installation location. The monitor system carries out data acquisition and processing, including the extraction of significant features. All of the results reported here are from tests on a typical spring-operated SF_6 HVCB whose voltage is 40.5 kV.

FAULT SIMULATION PROCEDURES

An accelerometer (TST145A50) is used in this work, it's designed for a nominal shock of 5000 g and gives out 1 mV/g (g=9.81 m/s^2) to measure vibration signals. In all the performed tests, the accelerometer is mounted on solid metal in the operating mechanism of HVCB in a short distance from the main shaft. The accelerometer used here is only a few grams in weight, and is properly fixed to the screw in the shell of charging motor simply by using superglue. The flow chart of signal acquisition and processing is described as Fig. 5.

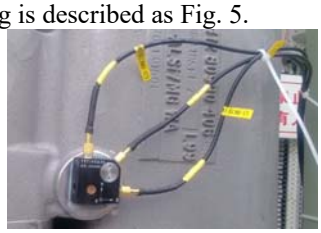

Fig. 4. The mounting position of the accelerometer.

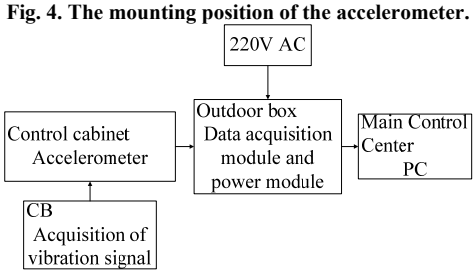

Fig. 5. Flow chart of signal acquisition and processing.

A spring fatigue fault is simulated by adjusting the spring compression. Through adjusting the bolt position below the closing spring, the spring compression can be changed. The initial value of thread length (*D*) is 40 mm, as shown in Fig. 6. The adjustment ranges are 35 mm, 30 mm, 25 mm, 20 mm, 15 mm and 10 mm. A screw losing failure is simulated by releasing the screw on the base gradually.

Fig. 6. Schematic of adjust the bolt of closing spring.

SIGNAL ANALYSIS

Signal Analysis in Time Domain

After acquiring the vibration signals in various states, these signals are analyzed in time domain. The waveforms of vibration signals in time domain under different states are depicted in Fig. 7.

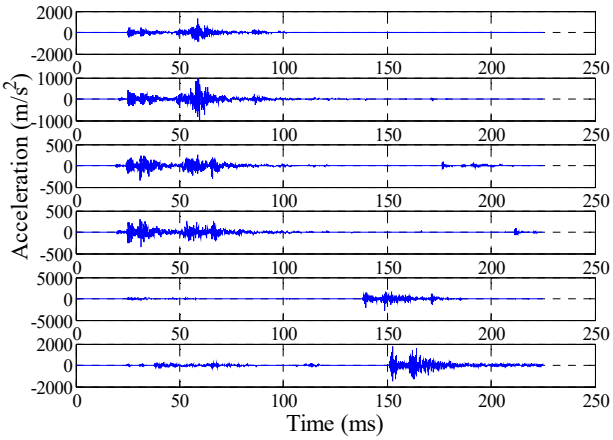

Fig. 7. The waveforms of vibration signals in time domain under different states.

In Fig. 7, it is demonstrated that, in a spring fatigue fault mode, the waveform amplitude of vibration signal reduced obviously. While in a screw losing fault mode, vibration signals delayed obviously in the time domain [10].

Signal Analysis in Frequency Domain with FFT and Energy Envelope

In this part, FFT and energy envelope are used to analyze vibration signals in the frequency domain. The waveforms of vibration signals in various states are depicted in Fig. 8.

It's summarized that, comparing with the normal state, when the HVCB is in a spring fatigue state, the amplitude of signal frequency decrease obviously and when the HVCB is in a screw losing state, the signal frequency gathered in the high frequency band.

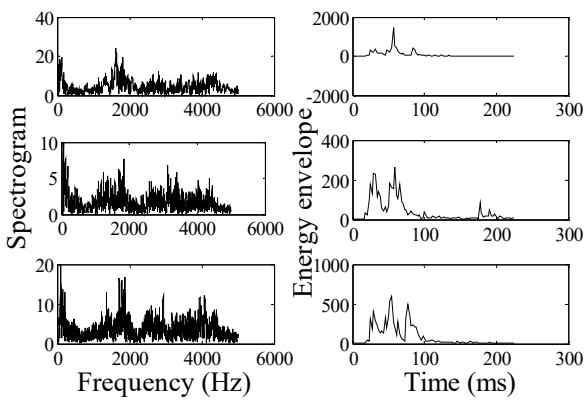

Fig. 8. Spectrogram and energy envelope of vibration signals in different states.

Signal Analysis with WPT

In order to detect a spring fatigue fault and a screw losing fault, the WPT is used to get energy envelopes of vibration signals [12][13][14]. The method can be divided into three steps.

1) Daubechies4 wavelet packet is chosen to decompose the vibration signal $S(0,0)$ in four layers, decomposition tree is shown in Fig. 9. Each layer covers all signal frequencies and frequency resolution increases with the increased number of layer. Since the sampling frequency of the vibration sensor used here is 10 kHz, according to the Nyquist sampling theorem, the detectable signal band is 0-5 kHz. The frequency distribution is shown in Table 1.

Table 1 Frequency distribution of each node after 3 layer decomposition using daubechies4 wavelet

Nodes	Frequency bands (kHz)	Nodes	Frequency bands (kHz)
[3,0]	0.000-0.625	[3,4]	3.750-4.375
[3,1]	0.625-1.250	[3,5]	4.375-5.000
[3,2]	1.875-2.500	[3,6]	3.125-3.750
[3,3]	1.250-1.875	[3,7]	2.500-3.125

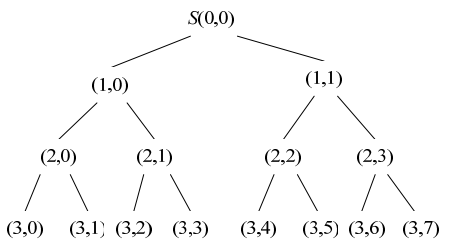

Fig. 9. Three-layer wavelet packet decomposition tree.

2) Reconstruct the decomposition coefficients step by step to extracting the signal of each band. If the data length of the original signal $x(k)$ is N, the wavelet packet decomposition and reconstruction is expressed as

$$E_n = \sum_{k=1}^{N} | x_n^j(k) |^2 \tag{5}$$

In order to analyse data easily, we normalize the energy e_n as

$$e_n = \frac{E_n}{E} (n = 1,2,...,2^j) \tag{6}$$

where the value of E is

$$E = \sum_{n=1}^{2^j} E_n \tag{7}$$

Vibration signals in normal state, in a spring fatigue fault state and in a screw losing state are chosen to conduct the WPT, the transform results are depicted in Fig. 10.

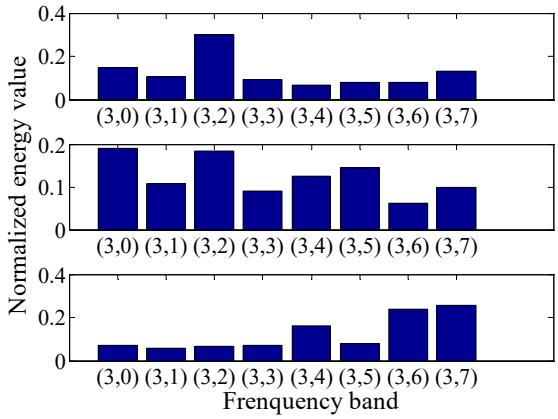

Fig. 10. Vibration signals after wavelet packets transform in different states.

In the whole, when the HVCB is in normal state, the vibration energy is gathered in 0-0.625 kHz, 1.875-2.5 kHz and 4.375-5 kHz. When the HVCB is in a spring fatigue state, the vibration energy decreases obviously. And when the HVCB is in a screw losing state, the vibration energy increases obviously and is gathered in 2.5-3.75 kHz. The energy distribution result is similar to those of FFT and energy envelope.

Fault classification test of PSO-SVM method

In this section, a PSO-SVM method which is previously trained by the normal training samples is used to separate the normal and fault conditions of HVCBs. A PSO algorithm is used to optimize the parameters and improve the classification ability of traditional SVM classifier [15]. While the simulations and optimisations are implemented in the MATLAB. Finally, if the conditions of HVCBs are judged as a fault condition by the PSO-SVM method, the type of mechanical fault is recognized by a SVM classifier. Results and discussions are addressed at the end of this section. The PSO-SVM method consists of three steps.

1) Collect vibration signals in various states and acquire features of the vibration signals with WPT.

2) Each group of features is labelled with fault types and normalized. After which, the PSO is used to search for the best upper bound C and the best kernel parameter Υ based on those labelled and normalized features.

3) With the best C and the best Υ (C=1.0045, Υ=0.01), an improved classification model is built and employed in the condition diagnosis stage. To approve the reliability of the model, 30 groups of features with known labels are predicted by the model and the results of the classification are shown in Fig. 11 The predication accuracy is high to 93.33%, and then the validity and accuracy of the model is proved.

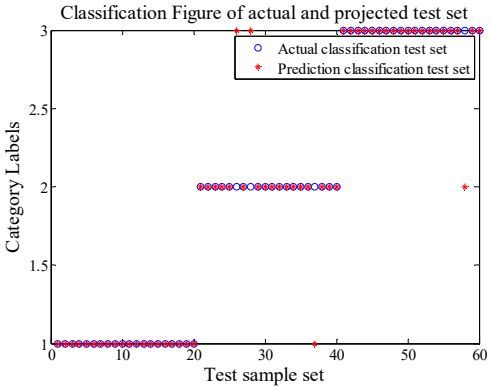

Fig. 11 Results of classification of test set using acquired model.

CONCLUSIONS

Continuous monitor and analysis of vibration signals seem to be a promising method for the mechanical diagnosis of important HVCBs. In this paper, a novel hybrid intelligent classification method based on the FFT, WPT, PSO algorithm and SVM for fault diagnosis of HVCBs is presented. In the presented method, FFT and WPT are performed to pre-process vibration signature, after which the frequency-domain and energy envelope features are captured. The PSO algorithm is used to seek optimized parameters of the SVM. Classification results from the SVM classifier shown that the accuracy of the predication is high to 93.33%, which certificates a good accuracy and proves the method proposed is effective in condition classification and fault diagnosis of HVCBs. It should be noted that, although the proposed method is only tested by using a spring fatigue and a screw losing example, it can be easily applied to other classification problems of fault diagnosis applications.

REFERENCES

[1] S. Strachan, M. Stephen, and J. McDonalds, 2005, "Trip coil signature analysis and interpretation for distribution circuit breaker condition assessment and diagnosis", *The 18th International Conference and Exhibition on Electricity Distribution*, TURIN, ITALY, vol. 1, 559-563.

[2] D. S. S. Lee, B. J. Lithgow, and R. E. Morrison, 2003, "New fault diagnosis of circuit breakers", *IEEE Transactions on Power Delivery*, vol. 18, 454-459.

[3] G. Z. Xu, J. R. Zhang, J. L. Qian, 2000, *Principle and application of high voltage circuit breakers*, Press of Tsinghua University, Beijing, China, 439-452.

[4] H. K. Hoidalen, and M. Runde, 2005, "Continuous monitoring of circuit breakers using vibration analysis", *IEEE Transactions on Power Delivery*, vol. 20, 2458-2465.

[5] Z. W. Liu, H. R. Cao, and X. F. Chen, 2013, "Multi-fault classification based on wavelet SVM with PSO algorithm to analyze vibration signals from rolling element bearings", *Neurocomputing*, vol. 99, 399-410.

[6] X. Y. Zhang, and Y. L. Guo, 2009, "Optimization of SVM parameters based on PSO algorithm", *The Fifth International Conference on Natural Computation*, TIANJIN, CHINA, vol. 1, 536-539.

[7] T. Thelaidjia, and S. Chenikher, 2013, "A new approach of pre-processing with SVM optimization based on PSO for bearing fault diagnosis", *The 13th International Conference on Hybrid Intelligent Systems*, GAMMARTH, TUNISIA, 319-324.

[8] N. T. Huang, H. J. Chen, S. X. Zhang, 2015, "Mechanical fault diagnosis of high voltage circuit breakers based on wavelet time-frequency entropy and one-class support vector machine", *Entropy*, vol. 18, 1-17.

[9] C. Noppadol, S. Thanapong, and B. Teratam, 2012, "Vibration signal analysis for condition monitoring of puffer-type high-Voltage circuit breakers using wavelet transform", *IEEJ Transactions on Electrical and Electronic Engineering*, vol. 7, 13-22.

[10] Y. P. Meng, S. L. Jia, and M. Z. Rong, 2004, "Condition monitoring of vacuum circuit breakers using vibration analysis", *The 21st International Symposium on Discharges and Electrical Insulation in Vacuum*, YALTA, UKRAINE, vol. 2, 341-344.

[11] L. J. SUN, X. G. Hu, 2006, "A new method of fault diagnosis for high-voltage circuit breakers based on vibration signals", *Proceeding of the CSEE*, vol. 26, 157-161.

[12] M. Kezunovic, Z. F. Ren, and G. Latisko, 2005, "Automated monitoring and analysis of circuit breaker operation", *IEEE Transactions on Power Delivery*, vol. 20, 1910-1918.

[13] M. S. Silva, J. A. Jardini, and L. C. Magrini, 2004, "Determination of the circuit breaker operation times using the wavelet transform", *IEEE Power Engineering Society General Meeting*, vol. 2, 1214-1219.

[14] L. J. Sun, X. G. Hu, and Y. CH. Ji, 2007, "Fault diagnosis for high voltage circuit breakers with improved characteristic entropy of wavelet packet", *Proceeding of the CSEE*, vol. 27, 103-108.

[15] C. L. Huang, C. J. Wang, 2006, "A GA-based feature selection and parameters optimization for support vector machines", *Expert Systems with Applications*, vol. 31, 231-240.