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MECHANICAL FAULT DIAGNOSIS FOR HV CIRCUIT BREAKER WITH OPERATIONAL VIBRATION SIGNAL

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Abstract

The high-voltage (HV) circuit breakers are one of the most important controlling and protecting equipments in power system, and then safe and reliable operation is of great significance. In this paper, a fault diagnosis method is proposed which is based on the measurement of vibration signal during operation of the HV circuit breaker. The characteristics of the vibration signal are analyzed firstly. Then the feature extraction and fault pattern recognition of the measured operational vibration signal are carried out by wavelet packet analysis and support vector machine theory. The mechanical fault diagnosis platform for HV circuit breaker is developed by using LabVIEW and MATLAB tools. Finally, the experiments are carried out to validate the proposed fault diagnosis method and algorithm.

Introduction

The high-voltage (HV) circuit breaker plays a very important role in modern power system. First of all, it can control electrical equipments and circuits to put into use, out of operation, switch to spare or maintenance present condition according to power grid operation status. Secondly, it removes faulty equipments and circuit from the power grid quickly and protects rest parts of the power grid once abnormal in grid is occurred. As the increasing of automation degree, voltage levels and installed capacity in power grid, the requirement of reliability for main equipments such as HV circuit breakers in power grid becomes higher and higher. Relevant data indicates that the average power losses resulted from HV circuit breakers failure reach to millions of kilowatt hours in China, which have significant impact on the national economy. Thus, it is of great important to realization of accurate fault diagnosis for HV circuit breakers [1,2].

The closing or opening operation of the HV circuit breakers produces mechanical vibration which contains a large amount of equipment condition information. By installing accelerometer on the HV circuit breaker to monitor operational vibration signal, a mechanical fault diagnosis system might be realized, which does not involve with electric parameters measurement (higher cost and risk in high voltage apparatus) and have no effect on the normal operation of the breakers. The vibration signal analysis to monitor the health condition of the circuit breaker is a useful way and has been put forward for many years [2-6]. However, it is more difficult if we need to know the faulty parts and location in circuit breakers. The modern fast developing technologies on information and computer science may give engineers more chances to fulfill this goal.

Characteristics of Vibration Signal

Vibration signal of the circuit breaker is a rich information carrier, containing a plenty of equipment condition information, and even some small changes on mechanical system can be found in vibration signal, which consist of a series of transient waveforms. Actually each transient waveform is a reflection of internal event during operation of the circuit breakers. Especially when faults occur like mechanical jam, displacement, deformation, damage, loose, trip failure and valve body slowing, the vibration monitoring can reflect the failures in time. Then the monitoring of vibration signal can give us fully knowledge of the health condition about the circuit breakers, which is of great significance to online monitoring for the HV circuit breakers.

In vibration theory, it shows the vibration signal maintains a relatively stable as long as vibration and vibration propagation do not change. The experiment also shows that the same type of circuit breaker generates similar vibration signals, which makes it possible to detect faulty circuit breaker from the same type of different circuit breakers by comparing their vibration signal.

A. Operational Vibration Signal

Mechanical vibration is caused by change of impact force or movement. In circuit breaker, the operation action is generally driven by the actuator (solenoid, liquid/gas drive cylinder or energy storage spring) through the linkage mechanism to push the moving contact system close or open. In a single operation, there are a series of movement of mechanism with starting, braking and impacting. These movements cause several shock vibration in its structure. After vibration waveform goes through structural parts and is transmitted, attenuated, measured in the measurement site, it shows a series of attenuating acceleration waveform.

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B. Characteristics

The circuit breaker is in stationary state at the normal position. It is only in the implementation of the closing or opening operation that conducts the fast action, resulting in a strong vibration. The vibration signal of the circuit breaker has the characteristics of high acceleration, high-strength impaction, they are

(1) The vibration signal is an instantaneous nonstationary signal, which is not periodic, usually between tens of milliseconds and hundreds of milliseconds.

(2) The vibration signal is caused by the impacting of the operation mechanism components and changes of the movement. In single operation, a series of components in accordance with a certain logical order put into starting, moving forward and braking. One vibration wave, along a certain propagation path, eventually arrives at the sensor with superposition of other attenuated vibration waves. Obviously different mechanisms and different motion characteristics will produce different superimposed waveforms.

(3) The relationship of the mechanism and vibration transmission is very complex. The location of impaction and sensor will significantly affect the monitoring signal of the vibration acceleration [6].

Vibration Signal Processing

The vibration signal collected in operation of the HV circuit breakers is a transient, non-stationary signal, and the commonly used time domain or frequency domain analysis methods are not feasible. For non-stationary signals, the joint distribution in the time-frequency domain may be studied. This can not only understand the overall signal information, but also study local non-stationary of the signal in-depth, which is beneficial to the extraction of feature information.

A. Discrete Wavelet Transform

Wavelet analysis (WT) is a time-scale (time-frequency) analysis method for the signal, which has multi resolution and the ability to characterize the local characteristics of the signal in both time and frequency domain. It is a time-frequency localization analysis method whose window size is fixed but its shape can be changed. That is, it has a higher frequency resolution and a lower time resolution in the low frequency part while a higher time resolution and lower frequency resolution in the high frequency part. It is suitable for detecting the transient anomaly signal in normal signal and analyzing its composition, so it is known as the microscope of the signal analysis [8-10].

In practical applications, we often use Wavelet Packet Analysis. It can conduct multi-level division of frequency bands. It also can conduct the further decomposition and resolution of the high frequency part in high frequency refinement in multi-resolution analysis method, adaptive select the corresponding frequency band. As a result it has a good time-frequency positioning characteristics and the adaptability for the signal, which means effective decomposition for the various time-varying signal. Fig. 1 shows a signal S is treated in three-level wavelet packet decomposition, and the signal S can be expressed as

$$\begin{aligned} S = {} & AAA_3 + DAA_3 + ADA_3 + DAA_3 + \\ & AAD_3 + DAD_3 + ADD_3 + DDD_3 \end{aligned} \tag{1}$$

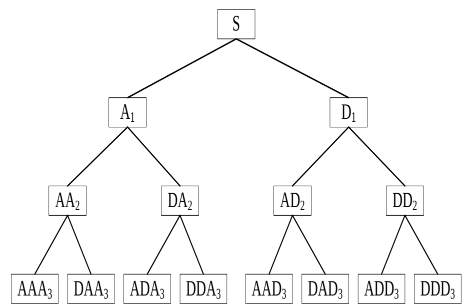

Fig. 1 Discrete wavelet transform diagram

When the failure occurs in circuit breakers, it will have a greater impact on the energy of the sampling points in each frequency band. So the energy element is used to construct the eigenvector [11]. E_j^* is the energy of the reconstructed sequence of the wavelet, which is expressed as

$$E_j^* = \sum_{k=1}^{N} \left| d_j^k \right|^2, \; j = 1, 2, \cdots, 2^n \tag{2}$$

where d_j^k is the k_{th} component of the j_{th} wavelet packet reconstruction sequence, N is the number of components in the sequence d_j, n is the number of wavelet packet decomposition layers. Set the energy value of each band in n-level wavelet packet decomposition as

$$E^* = (E_0^*, E_1^*, E_2^*, \cdots, E_{2^n}^*) \tag{3}$$

The Feature vector can be obtained by normalizing the vector

$$\begin{aligned} E &= (E_0^*/\Sigma, E_1^*/\Sigma, E_2^*/\Sigma, \cdots, E_{2^n}^*/\Sigma) \\ &= (E_0, E_1, E_2, \cdots, E_n) \end{aligned} \tag{4}$$

where $\Sigma = E_0^* + E_1^* + E_2^* + \cdots + E_n^*$.

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B. Support Vector Machine Theory

Support Vector Machine (SVM) is a general learning algorithm with the principle of structural risk minimization, which is suitable for the classification of small sample data [12]. The basic idea is shown in Fig. 2. In Fig. 2, the dots and square points represent two types of training samples, H is the classification line that completely separates the two types of samples. H_1 and H_2 are the straight lines passing through the classification line and paralleling to the classification line. The margin between them is the classification margin and the online sample point is the support vector. The optimal surface not only separates the two types of samples, but also makes the classification margin the largest. The former minimizes the risk of experience, while the latter makes the real risk of the problem the smallest.

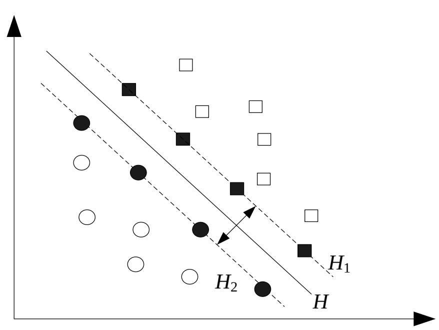

Fig. 2 SVM classification diagram of two types of samples

Assuming the training sample set is

$$(x_1, y_1)\cdots(x_i, y_i), i=1,2,\cdots,n \tag{5}$$

where $x_i \in R^l$ is the sample input, l is the input space dimension, $y_i \in\{-1,1\}$ is the sample output. Supposing φ is the non-linear mapping of the original space to the high-dimensional feature space. In the feature space, the optimal classification hyperplane problem is transformed into the following optimization problem by using the principle of structural risk minimization and the maximization of classification margin

Minimize $\quad \varphi(\omega,\varepsilon)=\frac{1}{2}\|\omega\|^2+C\sum_{i}^{n}u_i\varepsilon_i$

Subject to $\quad y_i[(\omega\cdot x_i)+b]\geq 1-\varepsilon_i \quad \varepsilon_i\geq 0, i=1,2,\cdots,n \qquad (6)$

where ω and b are the weights and offsets of the classifying hyperplane, respectively. ε_i is the nonnegative relaxation variable. C> 0 is the penalty coefficient in order to maintain the balance between the maximum margin of classification and the classification error.

In order to solve the above constrained optimization problem, a Lagrange function is introduced

$$L=\frac{1}{2}\|\omega\|^2+C\sum_{i=1}^{n}\varepsilon_i-\sum_{i=1}^{n}a_i[y_i(x_i\cdot\omega+b)-1+\varepsilon_i]-\beta_i\varepsilon_i \tag{7}$$

where $a_i \geqslant 0$, $\beta_i \geqslant 0$ is the Lagrange coefficient. The optimization problem (6) can be transformed into an equivalent dual programming problem by computing L on ω, b and ε_i partial derivatives, and making them equal to zero, respectively

Minimize $\quad W(\alpha)=\sum_{i=1}^{n}a_i-\frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}a_i a_j y_i y_j K(x_i,x_j)$

Subject to $\quad \sum_{i=1}^{n}a_i y_i=0 \quad 0\leq a_i\leq C, i=1,2,\cdots,n \qquad (8)$

where $K(x_i,y_j)=(\varphi(x_i),\varphi(x_j))$ is the kernel function. By solving the optimization problem, the optimal decision function is obtained as

$$f(x)=\mathrm{sgn}((\omega\cdot x)+b)=\mathrm{sgn}(\sum_{i=1}^{n}y_i a_i K(x_i\cdot x)+b) \tag{9}$$

where a_i, ω, and b are the optimal solutions for the optimization problem.

C. Signal Processing Flow

Vibration signal analysis and fault identification is the key points of fault diagnosis for the HV circuit breaker, in which the most important issue is to adopt appropriate processing methods to analyze the acquisition signal. If the signal processing is not good, it will be difficult to extract the right eigenvector and could not perform fault identification. Based on the above signal processing principle, the flow chart of signal processing for vibration signal during closing operation is put forward in Fig. 3. The specific content is as follows:

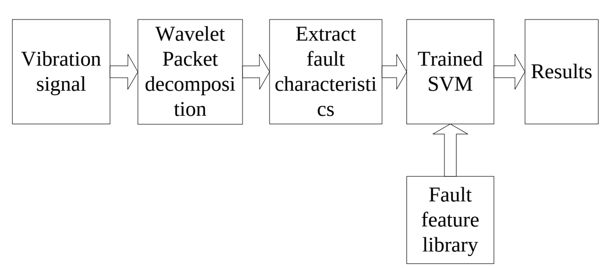

Fig. 3 Signal processing flow chart

(1) Establishing closing operation vibration database for sample circuit breaker by collecting vibration signal data. This database includes operational vibration data under healthy condition and different kinds of mechanical failure in corresponding sample circuit breaker;

(2) Collecting the closing operation vibration signal on the target circuit breaker and processing as follows: Firstly, the

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fault feature is extracted by the discrete wavelet decomposition. Then the fault feature vector is extracted by normalizing the fault features.

(3) Inputting the fault feature vector to the trained SVM classifier for realization of fault identification and fault diagnosis.

Experiment Validation

A. Experimental Platform

To establish a sufficient sample database for HV circuit breakers is very important in fault identification. It should be noted that the mechanism of the HV circuit breakers is complex and involves many parts. At present, the research on the failure mechanism of the HV circuit breakers there is not sufficient, which involves interdisciplinary knowledge. The model-based fault diagnosis method, which starts from the structure and operation mechanism of the HV circuit breakers, uses inductive reasoning, and then obtains the fault sample database, is difficult to realize. In this paper, the experimental method as an alternative is used to setup the fault sample database, where the corresponding fault vibration signal is detected and processed by certain algorithm, and then the fault feature vector is extracted. In on-line fault diagnosis, the feature vector is extracted from the measured vibration signal and compared with the existing data in the fault sample database to obtain the fault recognition result.

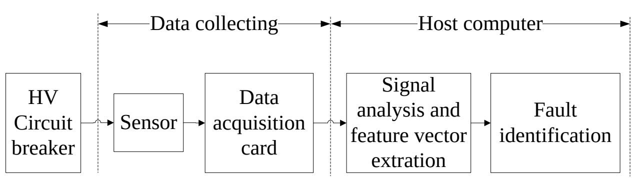

Fig. 4 The structure of the fault diagnosis system

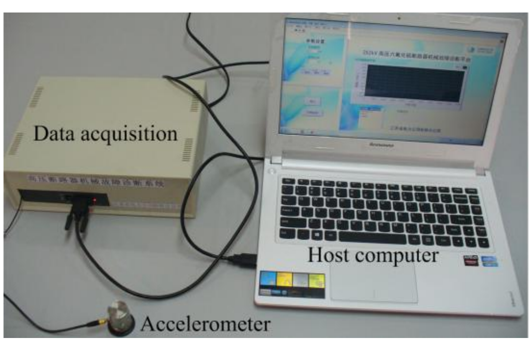

Fig. 5 The experimental platform

By taking the experiment based comparative analysis method, the structure of the fault diagnosis system is shown as Fig. 4. Where the vibration signal of closing operation is collected by the sensor, inputs to the data acquisition card for AD conversion, and then transfers the data into the host computer. In the host computer, graphical programming software LabVIEW is used for interface design, and MATLAB Script node calls MATLAB algorithm for signal processing and fault identification, to achieve the fault diagnosis results. Fig. 5 shows the experimental platform.

B. Feature Extraction

A SF6 HV circuit breaker with rated voltage 220 kV is used in this research, and the vibration sensor (accelerometer) is installed on the outer wall of the HV circuit breaker operating mechanism. In no-load state for the HV circuit breaker, following mechanical failures are simulated: abnormal spring output failure and pin loose failure. Fig. 6 shows the simulated mechanical failure, where in the first case the spring for fulfilling of closing operation is treated by removing two gaskets, while in second case the antifriction sleeve in pin hole is removed to make a loose connection in the linkage mechanism. Using the experimental platform to collect vibration signals during the closing operation, where healthy condition and two mechanical failure conditions are included. In three conditions, totally 30 data sets are measured during the closing operation of the circuit breaker. 15 selected data sets are training in the support vector machine to obtain the fault feature vector, and the remaining 15 data sets are used to detect the faulty parts. Then the effectiveness of the diagnostic method will be validated in the experiment. The typical measured original vibration signal is shown in Fig. 7, where they are measured in healthy condition, spring output abnormal condition, pin loose condition. The sampling frequency and sampling time set in the experiment are 150 kHz and 100 ms, respectively.

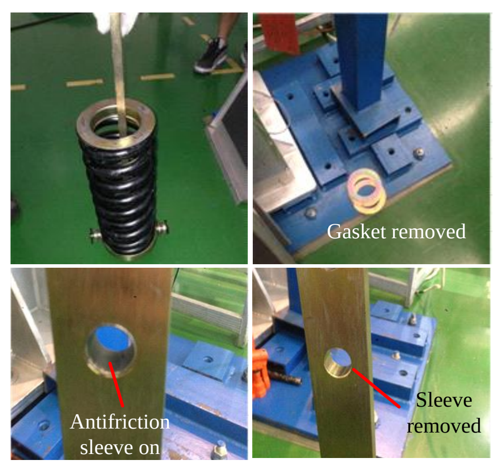

Fig. 6 Simulated mechanical failures

The db6 wavelet base is selected for noise reduction of the collected vibration signal. The reconstruction results of the vibration signal after noise reduction is shown in Figure 6.

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Three-level wavelet packet decomposition on the data after noise reduction is carried out and the same db6 wavelet is used as a wavelet basis function. The extracted energies from the eight nodes of the third layer by using equation (2) and (4) are the element to build eigenvectors. The normalized results of the node energy value extracted form part of signal are shown in Table 1.

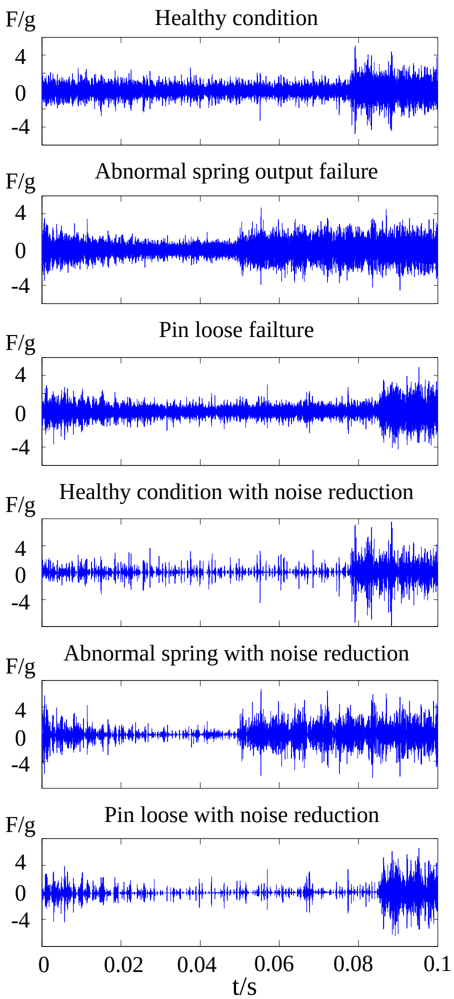

Fig. 7 Vibration signal acquisition and processing

As it can be seen from Table 1, significant differences in energy distribution of the vibration signal are shown as the circuit breaker is in different conditions. The low frequency energy of the vibration signal under the abnormal spring output failure is significantly lower than that under other two conditions. The energy of the vibration signal under pin loose failure condition in the frequency band 6 is higher than that under other two conditions. The energy distribution of the vibration signal under healthy condition is relatively uniform. This shows that the energy distribution of each band under the fault condition is obviously disturbed compared with the healthy condition. Therefore, the fault feature extraction method with the energy as the element can reflect the working conditions of the HV circuit breaker very well, and it can be further used for the subsequent fault identification algorithm.

C. Fault Recognition

The on-line condition monitoring could give the condition status of the HV circuit breakers. However, it is difficult for the operators to decide when the circuit breaker should exit operation if the detailed fault information is not provided. This may be the cause that why on-line fault monitoring technology is still not popular in industry in so many years. In this paper, based on the condition status analysis results, the fault identification is studied by using SVM technology. The SVM toolbox of MATLAB environment is used to reduce the programming labor. Three support vector machines are constructed by incorporating the samples in the single state with other states. The final classification results were determined by the SVM with largest classification distance. It is shown in Table 2 that the input of SVM is a 8×15 (in Table 1) matrix, training target matrix is 15×3. Defining the result is +1 that means the output is true and -1 that means false. The test results of SVM are given in Table 2. It is shown in the Table 2 that the SVM can accurately classify the fault type of the circuit breakers.

Conclusions

The HV circuit breakers play an important role in operation of power grid and the health condition of the HV circuit breakers has a direct impact on the safety of power grid. Therefore, it is very important to realize on-line condition monitoring and fault diagnosis for the HV circuit breakers. This paper gives an on-line monitoring and fault diagnosis system for the HV circuit breakers which based on the virtual instrument LabVIEW software and MATLAB. The wavelet packet decomposition and SVM classification are adopted to process the operational vibration signal for the HV circuit breakers. The experiments are carried out and the experiment results verify the proposed method well. The main conclusions of this paper are as follows:

(1) Based on the study of the mechanical fault diagnosis of the circuit breakers, the vibration signal of the circuit breakers during the operation is analyzed and the characteristics of the vibration signal of the circuit breakers are obtained;

(2) Based on the study of signal processing, a method based on wavelet packet decomposition and SVM classification is proposed for vibration signal processing of the HV circuit breaker;

(3) An experimental platform with LabVIEW and MATLAB Script node are fulfilled. The platform may meet

requirements of friendly human-machine interface and powerful data processing capability.

Table 1. The feature vector table of each vibration signal

		Band1	Band2	Band3	Band4	Band5	Band6	Band7	Band8
Healthy status	1	0.1621	0.0042	0.0482	0.0434	0.1401	0.1912	0.1749	0.2359
	2	0.1497	0.0038	0.0563	0.0375	0.1527	0.2103	0.1720	0.2178
	3	0.1659	0.0017	0.0558	0.0431	0.1431	0.1812	0.1752	0.2340
	4	0.1676	0.0023	0.0459	0.0374	0.1474	0.1845	0.1691	0.2458
	5	0.1625	0.0002	0.0451	0.0443	0.1401	0.1797	0.1698	0.2583
Spring output abnormal	1	0.1158	0.0197	0.1338	0.0986	0.1196	0.1627	0.2013	0.1486
	2	0.1106	0.0231	0.1400	0.1081	0.1175	0.1546	0.1849	0.1612
	3	0.1047	0.0295	0.1234	0.1012	0.1129	0.1618	0.2091	0.1574
	4	0.1190	0.0335	0.1435	0.1135	0.1090	0.1636	0.1730	0.1448
	5	0.1041	0.0103	0.1337	0.0836	0.1263	0.1831	0.1950	0.1639
Pin loose	1	0.1564	0.0062	0.0592	0.0450	0.1394	0.2082	0.1414	0.2442
	2	0.1525	0.0001	0.0530	0.0372	0.1134	0.2468	0.1483	0.2487
	3	0.1515	0.0001	0.0328	0.0239	0.1373	0.2624	0.1691	0.2229
	4	0.1297	0.0327	0.0292	0.0257	0.1357	0.2716	0.1407	0.2348
	5	0.1328	0.0008	0.0323	0.0283	0.1226	0.2802	0.1554	0.2476

Table 2. Test results of the SVM

Output	Health	Health	Health	Health	Health	Fault1	Fault1	Fault1
y1	1	1	1	1	1	-1	-1	-1
y2	-1	-1	-1	-1	-1	1	1	1
y3	-1	-1	-1	-1	-1	-1	-1	-1
Output	Fault1	Fault1	Fault2	Fault2	Fault2	Fault2	Fault2	
y1	-1	-1	-1	-1	-1	-1	-1	
y2	1	1	-1	-1	-1	-1	-1	
y3	-1	-1	1	1	1	1	1	

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