Fault Diagnosis of On-load Tap-changer Based on Vibration Signal

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Abstract. On-load tap-changer (OLTC) is an important part of large-scale load transformers, and its fault will directly affect the reactive power flow regulation of the power system and the stability of the load center voltage. In this paper, a fault state diagnosis method based on vibration signal is proposed for fault diagnosis of tap changer. The vibration signals are decomposed by wavelet packet transform and calculated energy entropy to obtain the state information of the tap changer. The experimental data shows that the state characteristics are obvious under different faults, which lays a foundation for in-depth study of fault diagnosis.

1. Introduction

The transformer is one of the core equipment in the power system, and the on-load tap-changer (OLTC) is the only operating component of the power transformer. It plays an important role in regulating the reactive power flow and stabilizing the load center voltage. Once a tap changer fails, it will directly affect the stability and safety of the transformer and power system.

Vibration occurs during the OLTC action process. Different states of the switch have different effects on the vibration, that is, the state information of the OLTC is included in the vibration signals. Some scholars have proposed to use the vibration to diagnose the tap changer fault. Kang et al.1-3 used wavelet analysis to extract the time-domain features such as amplitude, time interval and wavelet ridge obtained from the envelope, and compared the normal and fault characteristics by self-organizing mapping method. Rivas et al.4-6 used the wavelet transform to decompose the vibration signals. According to the information of the peak time and amplitude of the vibration signal, the characteristics of the normal and typical faults of the OLTC model were compared, and the evaluation criteria of the typical working state of the OLTC were obtained. Zhao Tong et al.7 reconstructed the original signal in high-dimensional space according to the chaotic characteristics of the vibration signal during the OLTC switching process, and defined the phase point spatial distribution coefficient to identify the normal and fault state of OLTC. Zhang Huifeng8 proposed using the Hilbert-Huang transform algorithm to analyze the vibration signal in the time-frequency domain, and combined with the frequency change to diagnose the typical fault of OLTC.

In this paper, the vibration sensor is installed at the appropriate position of the OLTC to obtain the vibration signal, and the signals are analyzed to obtain the characteristic information from the aspects of timing, spectrum and energy entropy. The experimental results show that the state characteristics are obvious under different faults, which provides a condition for further fault diagnosis.

2. Signal acquisition and preprocessing
The accelerometer is mounted on the OLTC end cap, and the signal is transmitted to the data acquisition device via the cable. Finally, the vibration data will be transferred to the PC for storage and processing. Because the experimental site environment and electromagnetic environment are relatively harsh, and most of the vibration signals are weak, it is necessary to analyze and preprocess the vibration signals. The signal acquisition system and preprocessing flowchart is shown in Figure 1.

Figure 1. signal acquisition system and preprocessing flowchart

When the signals are sampled synchronously, the vibration sensors are installed at different positions such as the side wall and the top of the on-load tap-changer. After the preliminary analysis and comparison of the signals, the position with stronger vibration signal is selected as the measurement point of this experiment.

As we know that the vibration signal is mainly concentrated in the low frequency 500Hz and below from the spectrum analysis of the signal. The electromagnetic environment of the experimental site is complex, so that it is often necessary to filter the sampled data. In the paper, the wavelet algorithm is used for filtering and noise reduction processing, which can reduce the high-frequency random noise mixed into the vibration signal, while the low-frequency vibration signal information and the characteristic parameters of vibration signal are retained.

In the process of sampling the vibration signal of the on-load tap-changer, the vibration signals are unaligned due to human operation habits and other factors. In order to facilitate subsequent analysis and processing, the vibration signal data needs to be translated and aligned.

Through the principle of the tap-changer and the vibration signal analysis of the normal situation, it is found that the whole vibration signal can be clearly divided into two stages, namely the preparing section and the in-position section, as shown in the following figure. The preparing section is mainly the motor running, driving the mechanical structure to store the spring energy, and the vibration signal is relatively stable at this stage. The in-position section is a segment that the tap-changer works in a predetermined order and the transition resistance is pre-switched to realize the gear shift operation. The vibration signal is abruptly changed, and there are three signal peaks.
Figure 2. Vibration signal segmentation and signal amplification
Because there are obvious differences between the two stages, it is necessary to divide the whole process into the preparing section and the in-position section, and perform wavelet packet decomposition and calculate energy entropy to extract state features of OLTC.

3. Wavelet packet decomposition and IMF energy entropy extraction

3.1. Signal decomposition and energy entropy calculation introduction
The traditional Fourier transform is suitable for signals that are more stable over a long period of time. The signal after orthogonal decomposition of the wavelet packet has the characteristics of independent signal and energy conservation in each frequency band, and is more suitable for time-frequency analysis and energy spectrum analysis of vibration signals. Therefore, the wavelet packet transform is applied to the fault diagnosis of the tap changer. By selecting the appropriate wavelet basis function, the vibration signal is decomposed into several sub-components by wavelet packet, and then the energy value of each sub-component is calculated. After normalization, the energy entropy vector is constructed as the vibration feature. The process is as follows:
(1) Vibrations signals are preprocessed, including filtering, alignment, and segmentation.
(2) The j-layer wavelet packet decomposition is performed on the vibration signal data S. Taking j=4 as an example, \( M = 2^4 \) sub-band signals are obtained on the fourth layer. The wavelet packets coefficients corresponding to the \( k (k = 1, 2, \ldots, 16) \) subband is \( d (j, k) \).
(3) Calculate the energy value of each sub-band of the bottom layer, and the energy on the k-th sub-band is:
\[
E( j, k) = \frac{1}{N} \sum_{i=1}^{N} |d_i(j, k)|^2
\]
where N is the length of the k-th subbandsignal. Then the total energy of the signal is:
\[
E = \sum_{j=1}^{M} E_i(j, k)
\]
If \( \varepsilon(i) = \frac{E_i}{E} \), then \( \sum_i \varepsilon(i) = 1 \).
(4) Defining the wavelet packet energy entropy is:
\[
H_{jk} = -\sum_{i=1}^{N} \varepsilon_{jk}(i) \log |\varepsilon_{jk}(i)|
\]
Where \( H_{jk} \) is the k-th sub-band wavelet packet energy entropy of the j-layer.
The energy entropy of each wavelet packet of the bottom layer is obtained by equation (3). Taking 4 layers as an example, the energy entropy eigenvector is recorded as:
\[
T = [H_{41}, H_{42}, \ldots, H_{415}, H_{416}]
\]
If \( H = \sqrt{\sum_{k=1}^{16} |H_k|^2} \), then the energy entropy feature vector can be normalized to:
\[
T' = [H_{41}, H_{42}, \ldots, H_{415}, H_{416}]
\]
3.2. Wavelet packet decomposition of the preparing section and the in-position section in the normal state of 5-6 gear

After the vibration signal is filtered and noise-reduced, the wavelet packet decomposition transform described above is used. Select ‘db3’ as the basis function to perform four-layer wavelet packet decomposition on the vibration data. The result is shown in Figure 3.

![Figure 3. Four-layer wavelet packet decomposition of vibration signal](image-url)
3.3. Energy entropy calculation and distribution
On the basis of the wavelet packet decomposition, the energy entropy of each component is further calculated and normalized. In the same way, the vibration signals under the fault conditions such as switching-late and spring-breakage, etc. are also processed and decomposed. Then the energy entropy of each sub-band is obtained. The comparison result by the histogram is shown in Figure 4.

It can be seen from the comparison of the Figure 4 that the fault occurs mainly in the in-position segment. Comparing the switching-late state with the normal state, the energy entropy distribution in the in-position section are significantly different in Figure 4b. These feature information can be used as the eigenvector of the support vector machine. While the energy entropy distribution of the preparing sections in Figure 4a is basically the same, consistent with the actual physical process.
It can be seen from the figure that the spring break will affect the normal energy storage of the preparing section and even affect the gear shifting action of the in-position section. In Figure 4a, the energy entropy distribution under the fault of spring-break is obviously different from the normal state. The energy entropy of wavelet component 1 is relatively large, and the other components also account for a considerable proportion. In the normal state, except the wavelet component 1, the rest of the wavelet The entropy of energy is much smaller and can even be ignored. In Figure 4b, the gear shifting action is also affected and the vibration signal waveform is weak due to spring breakage. The energy entropy distribution is different from the others.

4. Conclusions

The research shows that the vibration signal can be used to diagnose the working state of the tap changer. In this paper, the vibration signal of the tap-changer are filtered and divided into the preparing section and an in-position section. Then the vibration signals are decomposed by wavelet packet transform to obtain each vibration signal component, and the energy entropy of each signal components are calculated. The statistical data shows that there are significant differences in the energy entropy distribution of the tap changer in different states (such as switching too late, spring break), which can be used as the basis for discriminating the normal state and the fault state.

In further research, the energy entropy of these vibration signals will be used to construct the feature vector of SVM to verify the feasibility of this method in OLTC fault diagnosis applications. At the same time, the vibration signal of this paper is measured under the light load condition of OLTC, and it is still to be verified under the actual load condition.

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