Research on Vibration Signal Analysis Method of Transformer Winding Based on Wavelet Packet Transform and LMD Algorithm

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Abstract. Power transformer is an important equipment in power system, and its operation status has an important impact on the safe and stable operation of power system. However, most of the existing methods are off-line detection, which can not meet the requirements of engineering practice. Therefore, how to monitor and analyze the operation status of transformer based on the on-line measured vibration signal has become a research hotspot in this field. Therefore, this paper introduces a wavelet packet transform and local mean decomposition (LMD) decomposition method based on EMD. In this method, wavelet packet transform is used to denoise the vibration signal of transformer winding, and then it is adaptively decomposed into a series of product function (PF) components by LMD, so as to reveal the signal characteristics and realize on-line monitoring and analysis of transformer winding. Finally, the feasibility and effectiveness of the analysis method in this paper is verified by combining theory with simulation.

1. Introduction

These guidelinesPower transformer is an important equipment of power network. Its normal operation is closely related to the safe and stable operation of the whole power system. In actual operation, faults are inevitable. The research shows that among the numerous faults of power transformer, the probability of mechanical faults such as core looseness and winding deformation is very high \cite{1-2}. Therefore, how to realize on-line monitoring and fault diagnosis of transformer operation state has attracted many scholars' attention\cite{3-5}.

In reference [5], an analysis method using wavelet transform to extract the characteristics of transformer vibration signal is proposed. In this method, the original signal is decomposed into nine levels by db4 wavelet, and the energy of each layer in high frequency and low frequency is calculated, and the operation state of transformer is monitored through the energy distribution of different frequency bands. Although wavelet transform has variable time-frequency window and can obtain high time-frequency resolution, it is mechanical segmentation of time-frequency plane like window Fourier transform, which is not suitable for processing non-stationary vibration signal in essence.

Therefore, a new algorithm combining wavelet transform and LMD decomposition is introduced into transformer fault diagnosis. Because the vibration signal directly measured contains a lot of noise, in order to fully extract useful information, the original sampling signal is decomposed by Meyer wavelet packet, and the wavelet coefficients of each layer are processed by threshold value, and then
the signal is reconstructed. In this way, the noise can be filtered effectively and the mechanical segmentation of the signal can be avoided as in reference [5]. The reconstructed vibration signal is decomposed by LMD, and the PF components reflecting the dynamic process of transformer operation are obtained. The fault diagnosis of transformer is realized by changing the frequency and amplitude of each component. Finally, the simulation results show that the algorithm proposed in this paper not only has high accuracy and strong anti noise ability, but also has smaller endpoint effect and no false component compared with EMD decomposition, so it has a good application prospect in transformer early fault diagnosis [6-10].

2. Construction of transformer winding vibration model and vibration information collection

2.1. Construction of mathematical model of winding vibration

According to the structural characteristics of transformer winding, the winding can be simplified as a spring mass system.

According to Biot Savart law, the electromagnetic force acting on the coil is directly proportional to the square of the current.

$$F = bi^2$$

(1)

$$\omega$$ is the grid frequency and the stable current of transformer, as shown in formula (2):

$$i = I_m \cos \omega t$$

(2)

Combine the above two formulas, and the axial force is as shown in formula (3):

$$F_y = b_i I_m^2 \left( \frac{1}{2} + \frac{1}{2} \cos 2\omega t \right)$$

(3)

Then, by solving the mass motion equation (4) of each turn, the relationship $Y=f(t)$ is the function of the displacement of any point of the coil to time (5), and finally the force expressing the relationship is the product of stiffness coefficient and displacement.

$$\begin{align*}
    m \frac{d^2Y}{dt^2} + C_i \frac{dY}{dt} + K_i Y + K_{iy} (Y_i - Y_i) &= F_{yi} + mg \\
    m \frac{d^2Y}{dt^2} + C_i \frac{dY}{dt} + K_i (Y-Y_i) &= F_{yi} + mg \\
    m \frac{d^2Y}{dt^2} + C_i \frac{dY}{dt} + K_i (Y-Y_i) &= F_{yi} + mg \\
    \vdots \\
    m \frac{d^2Y}{dt^2} + C_i \frac{dY}{dt} + K_i (Y_{n+1} - Y_i) &= F_{yn} + mg
\end{align*}$$

(4)

Where $Y_n$ is the displacement of the original position of the nth unit phase with respect to the axial direction itself; $C_i$ is the friction coefficient; $mg$ is the mass of the coil unit; $K_{ii}, K_{yi}, K_{ii}$ are the stiffness coefficient; $K_{yi} Y_i$ is the elastic force of the nth unit of the coil insulation.

$$\begin{align*}
    C_i' &= \sum_i C_i = nC_i \\
    K_i' &= K_a + K_{iy} \\
    M &= \sum_i m = nm \\
    F_{yi} &= \sum_i F_{iy}
\end{align*}$$

(5)

The force on the limb plate of iron clip and the motion law of the whole coil are shown in the following formula:

$$M \frac{d^2Y}{dt^2} + C_i' \frac{dY}{dt} + K_i' = F_y + Mg$$

(6)

The amplitude of winding vibration acceleration signal is as follows:
\begin{equation}
\alpha_t = -\alpha_0^2 A e^{2\omega t} \sin(\omega_0 t + \alpha) - 4\omega^2 C t \sin(2\omega t + \beta) \tag{7}
\end{equation}

Where \( A, \alpha \) and \( \beta \) are constants, and \( \omega_0 t \) is the axial natural vibration frequency.

Since the elastic coefficient \( K_y \) of insulation pad is not a constant, it is related to the degree of insulation compression. The change under different compression force will reflect the amplitude and frequency changes of acceleration signal obtained by winding vibration monitoring.

2.2. Extraction of vibration signal

Under normal conditions, the grounding requirements of power transformer oil tank are very strict, but due to the influence of surrounding environment, electromagnetic interference cannot be avoided. Therefore, the mechanical vibration signal generated on the surface of oil tank has vibration frequency amplitude of 0.4-50 \( \mu \)m and 20-2000 Hz.

In the process of collecting the sensor output signal with the data acquisition card, it is often necessary to filter, amplify, A/D conversion and other signal conditioning processes of the sensor output signal, and then send it to the acquisition card, and then the data collected by the acquisition card will be sent to the computer for analysis and processing.

3. Wavelet packet principle and LMD principle and algorithm

3.1. Principle of wavelet packet

The frequency window of the basis function of wavelet transform increases as the scale decreases, and the change of the time-frequency window width decreases as the scale \( j \) decreases. Orthogonal wavelet transform, the time-frequency distribution law of large-scale small-frequency window and small-scale large-frequency window is suitable for analyzing signals of any scale. Sometimes, we only need to extract the information of specific frequency and time point, because we only care about some undetermined frequency or time period signals. The main factor is that the multiresolution decomposition of orthogonal wavelet transform only decomposes the fixed \( V \) (scale) space, and does not further optimize the decomposition of \( W \) (wavelet) space. \( W_j \) can be optimally decomposed by wavelet packet transform, and the spectrum window widened by orthogonal wavelet transform with \( j \) increasing becomes smaller, and the optimal basis or time-frequency window that is most suitable for the signal to be analyzed can be found.

3.2. Principle and algorithm of LMD

3.2.1 LMD principle

The LMD method decomposes a complex multi-component signal into several instantaneous frequency meaningful product functions (PF). The PF component is obtained by multiplying an envelope signal with a pure FM signal. The envelope signal is the instantaneous amplitude of PF, and the instantaneous frequency can be obtained from pure FM signal. The time-frequency distribution of the original signal is obtained by combining the instantaneous frequency and amplitude of all PF components. The PF component is a single component FM-AM signal.

3.2.2 LMD algorithm

All local extremum points \( n_i \) of signal \( y(t) \) are determined, and calculate the mean \( m_i \) of all adjacent extreme points:

\begin{equation}
m_i = (n_i + n_{i+1}) / 2 \tag{8}
\end{equation}

Connect all adjacent \( m_i \) with a straight line, and then perform a moving average process to obtain the local mean function \( m_{11}(t) \).

The envelope estimate of signal \( y(t) \) can be given by the following formula:

\begin{equation}
a_i = |n_i - n_{i+1}| / 2 \tag{9}
\end{equation}
Get the local envelope function \( a_{11}(t) \) in the same way as above. Separate the local mean function from \( y(t) \) to get:
\[
h_{11}(t) = y(t) - m_{11}(t)
\]
(10)
Divide \( h_{11}(t) \) by the envelope function \( a_{11}(t) \) to realize the demodulation of \( h_{11}(t) \), and get:
\[
s_{11}(t) = h_{11}(t) / a_{11}(t)
\]
(11)
If the envelope estimation function \( a_{12}(t) \) of \( s_{11}(t) \) is 1, then \( s_{11}(t) \) is already a pure FM signal; otherwise, repeat the above process until \( a_{1n+1}(t)=1 \), that is, \( s_{1n}(t) \) is a pure FM signal.
The first PF component envelope estimation function can be obtained by multiplying all envelope estimation functions to obtain \( y(t) \):
\[
a_{1}(t) = \prod_{q=1}^{n} a_{q}(t)
\]
(12)
The first PF component can be expressed as:
\[
PF_1 = a_{1}(t)s_{in}(t)
\]
(13)
PF1 contains the highest frequency in \( y(t) \) as a single-component FM-AM signal, the instantaneous amplitude is \( a_{1}(t) \), and the instantaneous frequency can be obtained by \( s_{in}(t) \) by the following formula:
\[
f_{1}(t) = \frac{1}{2\pi} \frac{d[\arccos(s_{1n}(t))]}{dt}
\]
(14)
Let \( u_{1}(t)=y(t)-PF_{1}(t) \), repeat the above process \( k \) times for \( u_{1}(t) \) until \( u_{k}(t) \) is a monotonic function.
then:
\[
y(t) = \sum_{i=1}^{k} PF_{i}(t) + u_{k}(t)
\]
(15)

4. Simulation analysis of winding vibration signal
In order to verify the anti-noise performance and decomposition accuracy of the algorithm proposed in this paper, the simulation signal \( y(t) \) is constructed as shown in the following formula:
\[
y(t) = 10 + (1 + 0.3\cos(9\pi t))\cos(200\pi t + 2\cos(10\pi t)) + (2 + 0.5\cos(5\pi t))\cos(600\pi t + 2\cos(5\pi t))
\]
(16)
It is composed of 2 AM and FM signals and DC component.
(1) When \( y(t) \) does not contain noise, it is directly decomposed by LMD, \( \epsilon \) is taken as 0.001, and the moving average step length is taken as the maximum value between adjacent extreme points of the signal. In order to reduce the end effect during decomposition, this paper implements signal extension by adding a virtual pole at both ends of the signal.

Figure 1. The instantaneous frequency and instantaneous amplitude of the first PF component

Figure 2. The instantaneous frequency and instantaneous amplitude of the second PF component

It can be seen from Figure 1 and Figure 2 that the decomposition results of the two PF correspond to the two FM-AM components of the simulation signal, and \( u_{2}(t) \) corresponds to the DC component of the simulation signal. The decomposition results reflect the inherent nature of the signal. Compared with the EMD decomposition result (as shown in Figure 3), there is no false component. The reason is that the LMD algorithm estimates the signal envelope and mean value function through moving
average, and there is no overshoot phenomenon when using cubic spline function interpolation. At the end point, the moving average can effectively offset the error introduced to the signal pole extension, which can well suppress the end effect and improve the signal resolution accuracy.

Figure 3. EMD decomposition diagram of simulation signal

(2) Add 0.5 (signal-to-noise ratio of approximately 10dB) Gaussian white noise to $y(t)$. In order to prevent noise from adversely affecting the accuracy of LMD and EMD decomposition, first use meyer wavelet packet transform to perform $y(t)$ Pretreatment. Then perform LMD and EMD decomposition of $y(t)$ after noise reduction. The decomposition results are shown in Figure 4 and Figure 7:

Figure 4. LMD decomposition result of noisy simulation signal $y(t)$ after wavelet packet filtering

Figure 5. The instantaneous frequency and instantaneous amplitude of the first PF component

Figure 6. The instantaneous frequency and instantaneous amplitude of the second PF component
Comparing Figure 4 and Figure 7, it can be found that the algorithm proposed in this paper can still obtain high-precision decomposition results when the noise is relatively strong. However, under strong noise, although $y(t)$ is preprocessed by wavelet, false components still appear in EMD decomposition, and it is more serious than when there is no noise. It can be seen that the LMD algorithm is more suitable for processing non-linear and non-stationary signals such as frequency modulation and amplitude modulation than the EMD algorithm. Theoretical analysis shows that when the transformer is deformed, the amplitude and phase modulation are generated. Therefore, the algorithm in this paper is introduced into the analysis of the transformer vibration signal, and the PF components that reflect the operating state of the transformer can be obtained, thereby providing online monitoring and fault monitoring of the transformer. Diagnosis provides a solid foundation.

5. Summary
Through the analysis method combining theory and simulation, the following conclusions can be obtained:

- The algorithm in this paper has strong anti-noise performance, and can still obtain accurate decomposition results under low signal-to-noise ratio (10dB);
- The algorithm in this paper can suppress the end effect well. Under low signal-to-noise ratio (10dB), there will be no false components, and the algorithm is simple and effective;
- The algorithm in this paper can adaptively decompose the various PF components that reflect the intrinsic nature of the signal. It is especially suitable for processing nonlinear and non-stationary AM-FM signals. It provides a new idea for transformer operating status monitoring and fault diagnosis.

References
[1] Hu Yong, Cheng Lei. Statistical analysis of faults in large power transformers. Power Safety Technology, 2003, Vol.5(1): 20-22.
[2] Wang Mengyun. Statistical analysis of transformer accidents of 110 kV and above in 2004. Electric Power Equipment, 2005, 6(11): 31-37.
[3] Ji Shengchang, Li Yanming, Fu Chenzhao. Application of load current method in monitoring transformer core condition based on vibration signal analysis method. Proceedings of the Chinese Society for Electrical Engineering, 2003, 23(6): 254-157.
[4] Yan Qiurong, Liu Xin, Shui Yunlong, et al. Development of Transformer Condition Monitoring System Based on Virtual Instrument Technology. High Voltage Technology, 2005, 31(8): 39-41.
[5] Yan Qiurong, Liu Xin, Yin Jianguo. Research on characteristics of power transformer vibration signal based on wavelet theory. High Voltage Technology, 2007, 33(1): 165-168.
[6] Wang Mengyun, Ling Han. Statistics and analysis of short-circuit accidents of large power transformers. Transformer, 1997, 34(10): 12-17.

[7] C. Bengtsson. Status and Trend in Transformer Monitoring. IEEE Transactions on Power Delivery, 1996, 11(3): 1379-1384.

[8] Zhang Tan. Application of winding deformation test on power transformer. Transformer, 2007, 44(5): 35-37.

[9] Yao Senjing, Ouyang Xudong, Lin Chunyao. Diagnosis and analysis of power transformer winding deformation. Automation of Electric Power Systems, 2005, 29(18): 95-98.

[10] Wang Hongfang, Wang Naiqing, Li Tongsheng. Research on Axial Nonlinear Vibration of Large Power Transformer Windings. Power System Technology, 2003, 24(3): 42-45.