A method of fault detection of casing lead based on CEEMDAN-LMD

Chenggang Hao¹, Woye Sun¹, Jiguo Zhang¹, Kai Li¹, Xin Wang ²

¹ Siping Power Supply Company Jilin Electric Power Co., Ltd, Siping, Siping, Jilin, 136000, China
² Center of Electrical and Electronic Technology, Shanghai Jiao Tong University, Shanghai, 200240, China

*Corresponding author’s e-mail: wangxin26@sjtu.edu.cn

Abstract. The existing regular inspection tests for the deformation faults of the bushing lead have the problem of offline detection and poor sensitivity. In order to effectively extract the high frequency components of vibration for diagnosis and analysis, a new fault diagnosis method for the transformer bushing lead is proposed. This method decomposes the time-domain waveform of the collected ultrasonic echo signal through CEEMDAN, and reconstructs its high-frequency components according to the entropy weight method to obtain a denoising signal, and then performs LMD decomposition of the denoised signal, and decomposes the denoised signal. The PF component is analyzed as the input feature component. The method of ultrasonic inspection of casing lead in this article has good adaptability, can obtain lead fault location results with high precision and good reliability, low hardware cost, and good application prospects.

1. Introduction

As an important part of the power system, the transformer bushing lead plays an important role in the connection between the transformer and the power grid. However, since the bushing is subjected to electromotive force or heat during long-term operation, it will cause deformation and damage of the internal leads. If the location of the fault is not detected in time and repaired, it is very easy to interfere with the normal operation of the power grid [1]. In addition, considering that the lead is inside the bushing, traditional power transformer fault detection methods, such as partial discharge detection, infrared detection and high-voltage dielectric loss detection, can hardly detect the true working state of the lead [2-3]. Therefore, this article uses ultrasonic detection technology to realize the judgment of the state of the lead in the casing. The collection quality of the ultrasonic echo signal is an important factor that affects the detection of the casing.

In the process of using ultrasonic to detect the inner bushing lead of the transformer, it is very susceptible to the influence of environmental factors, which results in the interference of noise in the received ultrasonic echo signal, which affects the accuracy of the detection. Especially at the echo signal collected at the beginning, the amplitude of the ultrasonic signal is smaller than the amplitude of the noise signal, which causes the truly effective signal to be covered. Therefore, in view of the noise problem in ultrasonic detection, it is necessary to adopt a reasonable and efficient denoising method to improve the signal-to-noise ratio in the echo signal, thereby improving the accuracy of ultrasonic ranging. Currently, the widely used denoising methods include wavelet transform denoise [4], empirical
mode decomposition (EMD) [5], singular value decomposition [6] and adaptive filtering [7]. The ultrasonic signal will have a certain denoising effect, but there are still shortcomings.

The complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) is an improved method based on EEMD. The CEEMDAN method can effectively decompose the vibration signal into a series of accurate high and low frequency IMF components. It can improve the accuracy of traditional wavelet denoise and lay a foundation for the extraction and reconstruction of high-frequency signals.

Aiming at the shortcomings of casing vibration signal preprocessing, feature extraction and fault identification, this paper proposes a method for transformer fault diagnosis based on CEEMDAN algorithm denoising, combined with LMD algorithm analysis.

2. CEEMDAN
The complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) of adaptive white noise is an improved algorithm proposed on the basis of M.A.Colominas [8] EMD. It adaptively adds Gaussian at each stage of decomposition. For white noise, the modal components of each order are obtained by calculating a unique margin signal. The decomposition process is complete and there is almost no reconstruction error, so it overcomes the defects of low decomposition efficiency of EEMD and incomplete signal reconstruction [9].

Add the white noise of the standard normal distribution \( \omega^i(n) \) to the signal to be decomposed \( x(n) \):

\[
x^i(n) = x(n) + \gamma^i \omega^i(n) (i = 1, ..., I)
\]

(1) For the first time, the EMD method is used to obtain the mean value of the Intrinsic Mode Function \( IMF_1(n) \) and the residual signal \( r_1(n) \):

\[
IMF_1(n) = \frac{1}{I} \sum_{i=1}^{I} IMF_1^i(n)
\]

(2) \( r_1(n) = x(n) - IMF_1(n) \) (3)

Define \( E_k \) as the k-th IMF component of the EMD decomposition of the signal, for the sequence \( r_1(n) + \gamma_1 E_1[\omega^i(n)] \), the second IMF component and the remaining component can be obtained:

\[
IMF_2(n) = \frac{1}{I} \sum_{i=1}^{I} E_1[r_1(n) + \gamma_1 E_1[\omega^i(n)]]
\]

(4) \( r_2(n) = r(n) - IMF_2(n) \)

(5)

By analogy, the k-th residual component and the k+1-th IMF component are,

\[
r_k(n) = r_{k-1}(n) - IMF_k(n)
\]

(6)

\[
IMF_{k+1}(n) = \frac{1}{I} \sum_{i=1}^{I} E_k[r_k(n) + \gamma_k E_k[\omega^i(n)]]
\]

(7)

The termination condition of CEEMAN decomposition is that the solved residual signal cannot be EMD decomposed. Assuming that K-order modal components are finally decomposed, the final residual signal \( R(t) \) is,

\[
R(n) = x(n) - \sum_{i=1}^{K} IMF_k(n)
\]

(8)

3. LMD method
After using the LMD method, a multi-component signal is represented as a set of product functions (PFs), each of which is the product of an envelope signal and a purely frequency modulated signal. For a signal \( x(t) \), the procedure of its decomposition process is described as follows[10]:

(1) Find out all the local extrema \( n_i \) and calculate the mean of two successive extrema \( n_i \) and \( n_{i+1} \).
The i-th mean value \( m_i \) is then given by
\[
m_i = \frac{n_i + n_{i+1}}{2}
\] (9)

Connect all the average values \( m_i \) with a straight line, and then use the moving average method to smoothly change to obtain the continuous local mean function \( m_{11}(t) \).

(2) Calculate the local envelope function and use the local extreme point \( n_i \) to get the envelope estimated value \( a_i \), namely
\[
a_i = \frac{|n_i - n_{i+1}|}{2}
\] (10)

Similarly, all envelope estimation values \( a_i \) are connected with a straight line, and the moving average method is used for smooth change processing to obtain the envelope estimation function \( a_{11}(t) \).

(3) Subtracting the local mean function \( m_{11}(t) \) from the original signal \( x(t) \), the resulting signal \( h_{11}(t) \) is given by:
\[
h_{11}(t) = x(t) - m_{11}(t)
\] (11)

Then divide \( h_{11}(t) \) by the envelope estimation function \( a_{11}(t) \), demodulate \( h_{11}(t) \) to get \( s_{11}(t) \), that is
\[
s_{11}(t) = \frac{h_{11}(t)}{a_{11}(t)}
\] (12)

If the envelope function \( a_{12}(t) \) of \( s_{11}(t) \) equals to 1, the procedure stops and \( s_{11}(t) \) is a purely frequency modulated signal. If not, regard \( s_{11}(t) \) as the original signal and repeat the above steps until \( s_{1n}(t) \) is a purely frequency modulated signal, namely, the envelope function \( a_{1(n+1)}(t) \) of \( s_{1n}(t) \) equals to 1. Therefore
\[
\begin{align*}
h_{11}(t) &= x(t) - m_{11}(t) \\
h_{12}(t) &= s_{11}(t) - m_{12}(t) \\
\vdots \\
h_{1n}(t) &= s_{1(n-1)}(t) - m_{1n}(t)
\end{align*}
\] (13)

where,
\[
\begin{align*}
s_{11}(t) &= h_{11}(t)/a_{11}(t) \\
s_{12}(t) &= h_{12}(t)/a_{12}(t) \\
\vdots \\
s_{1n}(t) &= h_{1n}(t)/a_{1n}(t)
\end{align*}
\] (14)

(4) An envelope signal is derived by multiplying together the successive envelope estimates obtained during the iterative process described above,
\[
a_1(t) = a_{11}(t)a_{12}(t)\cdots a_{1n}(t) = \prod_{q=1}^{n} a_{1q}(t)
\] (15)

This final envelope signal is then multiplied by the frequency modulated signal to form the first product function \( PF_1(t) \), which is a mono-component amplitude-modulated and frequency-modulated signal.
\[
PF_1(t) = a_1(t)s_{1n}(t)
\] (16)

The first PF component contains the highest frequency part of a given signal. \( PF_1(t) \) is a single-component AM and FM signal. Its instantaneous amplitude is the envelope signal \( a_1(t) \), and its instantaneous frequency \( f_1(t) \) can be derived from pure FM signal \( s_{1n}(t) \), namely
\[
f_1(t) = \frac{1}{2\pi} \frac{\text{d} \arccos(s_{1n}(t))}{dt}
\] (17)

(5) \( PF_1(t) \) is then subtracted from the original signal \( x(t) \), resulting in a new signal \( \mu_1(t) \). Repeat the above steps \( k \) times until \( \mu_k(t) \) is a constant or monotonic.
\[\begin{align*}
\mu_1(t) &= x(t) - PF_1(t) \\
\mu_2(t) &= \mu_1(t) - PF_2(t) \\
\vdots \\
\mu_k(t) &= \mu_{k-1}(t) - PF_k(t)
\end{align*}\] (18)

As a result, the signal \(x(t)\) is represented as the sum of \(k\) production functions, \(PF_1, \ldots, PF_k\) and a monotonic function

\[x(t) = \sum_{p=1}^{k} PF_p(t) + \mu_k(t)\] (19)

The moving average method used in local mean decomposition is an important step in the decomposition process. At the extreme points of the signal, the value of the local mean function is the mean value of the left and right end points. The envelope function generated in this way is smoothed by the moving average method. The step size of the moving average is generally selected as the maximum local average step size. One part, the envelope function is moved and smoothed using the moving average method until the values of the two consecutive points of the envelope function are different.

4. Simulation analysis

By using the method of simulation experiment, the ultrasonic echo signal is simulated and the echo arrival time is set, the simulated environmental noise is added to the original signal, and after denoising by CEEDAN decomposition, the characteristic value is extracted by the LMD algorithm for analysis.

Set the signal model of the ultrasonic echo as:

\[f(t) = U e^{-\sigma (t - t_0)^2 \cos(2\pi \varphi (t - t_0) + \theta)}\] (20)

Among them, \(U\) is the signal amplitude, \(\sigma\) is the bandwidth coefficient, \(t_0\) is the echo arrival time, \(\varphi\) is the center frequency of the signal, and \(\theta\) is the phase.

| Parameters                        | Analog value | Units |
|-----------------------------------|--------------|-------|
| Sampling frequency                | 100          | Hz    |
| Signal amplitude \(U\)            | 5.52         | mV    |
| Bandwidth coefficient \(\sigma\)  | 40           | -     |
| Echo arrival time \(t_0\)         | 2.15         | s     |
| Center frequency of the signal \(\varphi\) | 5.1         | Hz    |
| Phase \(\theta\)                 | 0.97         | rad   |
| Sampling point \(N\)              | 500          | -     |
The ultrasonic echo signal of the lead wire of the transformer bushing is usually interfered by high-frequency noise signals and unstable white noise, but it mainly shows the characteristics of Gaussian white noise. CEEMDAN decomposition is performed on the noise-stained echo signal, and Gaussian white noise that obeys the normal distribution $N(0, 0.0095)$ is added to the analog signal. After multi-scale decomposition, the IMF components and residual components $R$ of each order of natural modes arranged in sequence from high to low are obtained.
Figure 3. CEEMDAN exploded view of ultrasonic echo signal

It can be seen from the figure that $IMF_5$ and $IMF_6$ show obvious Gaussian noise interference. From the signal amplitude analysis, $IMF_3$ and $IMF_4$ have larger signal energy and are similar to the echo signal waveform, while the remaining IMF components are similar to sine waves and have a smaller total energy. Since casing lead echo signals are generally difficult to visually divide the high and low frequency boundaries through the exploded diagram, it is impossible to directly select the high frequency IMF components for threshold noise reduction, so it is necessary to calculate the IMF components of each order of natural mode and the relevance of the ultrasonic echo signal to verify and filter the data.

Table 2. Correlation between IMF component and original signal

| IMF  | Correlation coefficient | IMF  | Correlation coefficient |
|------|-------------------------|------|-------------------------|
| IMF_1 | 0.5355                  | IMF_6 | 0.1045                  |
| IMF_2 | 0.7047                  | IMF_7 | 0.0518                  |
| IMF_3 | 0.8194                  | IMF_8 | 0.0579                  |
| IMF_4 | 0.7382                  | IMF_9 | 0.0458                  |
| IMF_5 | 0.3384                  |      |                         |

It can be obtained after denoising and reconstructing the ultrasonic signal, and the obtained signal waveform is shown in the figure below. It is difficult to systematically extract the changing laws and characteristic parameters of ultrasonic signals based on only the time-domain waveform diagram, and further features need to be extracted for algorithm fault identification.
After the denoised ultrasonic echo signal is decomposed by LMD, 3 PF components are obtained, as shown in the figure below,

![Graph showing the reconstruction of ultrasonic echo signal after denoising.](image1)

Figure 5. The denoised ultrasonic echo signal is decomposed into each PF component by LMD

### 5. Conclusion

This paper proposes a signal decomposition based on CEEMDAN as a preprocessing method of ultrasonic echo signals. Noise reduction processing for the collected signals, ultrasonic signal denoising in casing lead deformation detection, and decomposition technology. By analyzing the LMD decomposition as a characteristic component, the following conclusions can be drawn:

1. The CEEMDAN algorithm can adaptively process non-stationary ultrasound signals. By CEEMDAN decomposition of the ultrasonic detection signal of the transformer bushing lead, the
correlation coefficient of each component can be calculated to accurately locate the boundary point between the signal and the noise dominant mode, and it can effectively filter out the influence of Gaussian white noise in the ultrasonic detection.

(2) Aiming at the non-stationary and non-steady characteristics of the ultrasonic vibration signal of the transformer, LMD is used to decompose it, which solves the problems of modal aliasing and end effect of the traditional empirical mode decomposition method. Because of its high sensitivity to changes in the amplitude of the vibration signal, it can accurately extract signal features;

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