Research Article

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Online Monitoring Technology of Power Transformer based on Vibration Analysis

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Abstract: This paper presents a method for the study of the influence of stability of a power transformer on the power system based on the vibration principle. Traditionally, the EMD and EEMD algorithms are employed to test the box vibration signal data of the power transformer under three working conditions. The proposed method utilizes a partial EMD screening along with MPEEMD method for the online monitoring of power transformer. A complete online monitoring system is designed by using the STM32 processor and LabVIEW system. The proposed system is compared with EMD and EEMD algorithms in terms of the number of IMFs obtained by decomposition, maximum correlation coefficient, and mean square error. The inherent mode correlation, when compared with the mean square error of the reconstructed signal, shows that the reconstruction error of MPEEMD algorithm is $4.762 \times 10^{-15}$ which is better than the traditional EMD algorithm. It is observed from the results that the proposed method outperforms both EMD and EEMD algorithms.

Keywords: power transformer, online monitoring, multiscale permutation entropy, empirical mode decomposition

1 Introduction

According to statistics, the average annual growth of electric power demand in China can reach 10% in the next few years. Therefore, it is necessary to carry out comprehensive real-time monitoring on all parts of the power grid system to timely investigate potential safety hazards, prevent failures, and ensure the safe and stable operation of the power grid. The power transformer is one of the most crucial equipment in the whole power network and the critical factor to ensure the safe operation of the power system.

In power transmission & distribution, the power transformer undertakes the essential tasks of voltage conversion and power distribution. Its regular operation will directly affect the stability of the power grid [1]. As the transformer functions continuously over long periods, the occurrence of faults and accidents is inevitable. However, when the transformer accident occurs, it will inevitably lead to power grid failure. When the fault is severe, it may affect a large-area with prolonged power failure, paralyzing traffic, interrupting communication, causing other inconvenience to people and shutdown of various industrial units.
Based on the real-time data of the power transformer in the operational state, the continuous monitoring of the transformer is carried out to obtain the signal data of vibration, current and voltage. The data are analysed and compared vertically and horizontally, combined with the historical data of the transformer and the data of the maintenance experiment. For determining the fault location, fault degree and development trend, effective measures should be taken to maintain the transformer before its performance drops to a specific level or before the fault occurs. This would enable to prevent the grid system failure caused by the power transformer, reduce the maintenance cost and prolong the service life of the transformer [2].

The method of online monitoring the surface vibration signal of the transformer’s oil tank and analysing the state of iron core and winding was commercially established in the mid-1980s. The early research work mainly focused on the following aspects [3]: Relationship between vibration signal amplitude and load current [4]; Joint modelling of the vibration signal, load current, temperature and other parameters of transformer [5]; Modelling of transformer winding vibration amplitude and load current to diagnose transformer winding state [6]; Study of the variation trend of valid value and frequency domain amplitude of power transformer vibration signal to achieve the purpose of separating noise interference in the signal [7].

With the improvement of science and technology and the improvement of safety awareness, many technologies, including computer technology and sensor technology, have made breakthroughs and innovations [4]. Aiming at the operation condition monitoring of power transformer, the methods are more diversified, the algorithm model is more mature, the real-time performance of condition monitoring is stronger, and the response speed is faster. This method has been applied to mechanical fault monitoring and diagnosis and has been applied to the field of power transformer vibration analysis in recent years. However, the end effect and mode aliasing of HHT in the process of EMD screening and processing complex power transformer vibration signal seriously interferes with the final decomposition effect, resulting in partial distortion of signal components and affecting the accuracy of algorithm processing [6].

In recent years, the task of observing the condition of power transformer has migrated from offline to online mode. Therefore, in this paper, the likelihood of applying vibration analysis method to online monitoring of power transformer is demonstrated. The main aim of this paper targets the existing problems in the screening process of EMD and thereby improving it. A multiscale permutation entropy ensemble average empirical mode decomposition (MPEEMD) algorithm replacing the traditional EMD algorithm is used to complete the signal screening process. The processing effect of the improved MPEEMD algorithm is compared using the intrinsic mode correlation of decomposition and mean square error of the reconstructed signal to validate the advantage of MPEEMD algorithm. Finally, a complete online monitoring system is designed by using the STM32 processor and LabVIEW system. The MPEEMD algorithm is accurate for screening both simple signal and complex power transformer vibration signals.

The rest of this article is organized as: Section 2 providing the literature review of the existing techniques in this domain. The research method has been highlighted in Section 3. Results and discussion are described in Section 4 followed by the conclusion in Section 5.

2 Literature review

In [8], the authors use property owners and utility engineering information to detect the transformer abnormality using the SMS system. A method to check the transformer health index depending upon the load data and various transformer tests was proposed in [9]. The fuzzy set theory was applied by the authors to compute the health index for eye-immersed transformers [10]. Furan analysis and Domain generated algorithms (DGA) were used in this method. A stable approach comprising of symmetric components before trouble shooting was proposed by the authors in [11]. An algorithm for calculating errors and rotating the line was proposed by [12]. It is investigated that in the case of high loads, an analysis based on no-load harmonics is not used because the current at this level is constant regardless of load [13]. To detect the presence of an inter-turn fault, the authors have examined the approaches demonstrating their applicability at no-load and very light load conditions [14].
The authors developed and implemented a transformer inter-turn fault detection system (TIFDS) for power transformers. This eliminates the need for current transformers on the secondary side and in this case, the load profile needs to be reorganized as a condition for determination of bend error [15]. The application of ultra-high frequency range for monitoring has been explored by the authors [16], which was considered good for transformer diagnosis. In [17], offline methods such as flow response and partial discharge analysis were used by the authors to analyse the condition of the transformer, but some of these are approaches to expert analysis. This requirement makes such methods expensive and is not suitable for the monitoring distribution system. In [18], the authors studied various faulty as well as non-faulty conditions of power transformers. Domain generation algorithms (DGA) were proved to be the most powerful diagnostic tools for determining the dielectric, thermal and chemical aging effects in the transformers.

The deep learning domain has also demonstrated its applicability in the vibration analysis and transformer fault detection field. Liu et al. [19] and Zhang, et al. [20, 21] addressed the non-stationary environment of electrical machines and bearings by recommending a CNN-based approach with a decomposed time-series signal. Pan, et al. proposed a multi-level semi-supervised fault-finding approach based on CNN using the unlabelled samples [22]. They used a transfer learning approach that initially trains the network on the base data set and eventually transfers the learned characteristics to the destination network. Another transferable deep CNN model was presented by Yosinski, et al. [23] with specifically dedicated layers that transfer characteristics of distant functions compared to randomization by weight.

Through the research of relevant published papers and conducting field experiments, we found that processing the vibration signal from the existing power transformer faces two problems. On the one hand, the shortcomings of many traditional algorithms could lead to the problems of low accuracy of the information and consequent misjudgement. On the other hand, traditional technologies such as sensor technology and embedded technology are maturing with time. The emerging Internet of Things and cloud computing could provide a solution. However, the existing data acquisition hardware and software systems are obsolete for adopting IoT and cloud computing. Given these two problems, a set of lumped average empirical mode decomposition MPEEMD algorithm based on multiscale permutation entropy needs to be constructed. This paper aims to analyse the characteristics of the vibration signal caused by the core and winding of the power transformer. A comprehensive monitoring system based on the vibration signal analysis of power transformer, assisted by the signal acquisition of current, voltage and temperature are designed to realize online monitoring of power transformer core and winding, improve the accuracy of data acquisition, analyse the performance of the power transformer, and provide reference data for fault diagnosis [24–30].

The objective of this paper: Targeting the existing problems in the screening process of EMD, the permutation entropy principle is combined with the improvement, and the screening effect is observed by replacing the traditional EMD process with MPEEMD. The accuracy and application of the online monitoring system using MPEEMD algorithm are verified by comparing the intrinsic mode correlation of decomposition and mean square error of reconstructed signal. MPEEMD algorithm is accurate for screening both simple signal and complex power transformer vibration signals. The Hilbert spectrum effect after the screening is clear.

3 Research methods

3.1 Design of improved algorithm

With the advancement of science and technology and safety awareness, many technologies, including computer and sensor technologies, have made breakthroughs and innovations. There are various advantages of using online monitoring of power transformer such as the methods are more diversified, the algorithm model has been more mature, the real-time performance of condition monitoring is better, and the response speed is faster. This method to monitor and diagnose mechanical faults of power transformer vibration has been in use for some years now. However, the end effect and mode aliasing of HHT during the process of EMD screening
and processing of complex power transformer vibration signals interfere with the final decomposition effect. It results in partial distortion of signal components and affecting the accuracy of the algorithm.

To solve the problems mentioned above this paper proposes improved multiscale permutation entropy ensemble average empirical mode decomposition (MPEEMD). To reduce the reconstruction error of the original signal $s(T)$, a pair of opposite sign white noises $(n_i)$ and $(-n_i)$, are added to the target signal $s(T)$, where $N_i(T)$ is the added white noise signal; $a_i$ is the amplitude of the white noise signal; $I = 1, 2, \ldots, NE$ is the logarithm of the white noise added.

Notably, the root mean square value of the added white noise signal should be similar to the internal noise of the signal to be decomposed. If the internal noise of the signal cannot be known, then the root mean square value of the added white noise should not be greater than 0.2 times of the signal to be decomposed.

The corresponding IMF component sequence is obtained by EMD decomposition
\[
\{I_i^+(t)\} \text{ and } \{I_i^-(t)\}, \ i = 1, 2, \ldots, NE
\]

The above components are integrated and averaged using the following formula;
\[
I_1(t) = \frac{1}{2NE} \sum_{i=1}^{NE} [I_i^+(t) + I_i^-(t)]
\]

According to the scale factor $\tau$, the $I_1(T)$ obtained by the ensemble average is coarsened from 1 to $\tau$ scales, and the entropy values of each arrangement after coarsening are calculated.

The average permutation entropy $\theta$ of each permutation entropy is calculated. If the set threshold is greater than the permutation entropy $\theta_0$ (the empirical value is generally (0.5-0.6), then it is determined that the signal is abnormal, otherwise, the signal is considered to be approximately stable $\theta_0$. The value is 0.6.

Get the decomposed abnormal signal component separated from the original signal.
\[
r(t) = S(t) - \sum I_i(t)
\]

After separation, the residual signal $r(t)$ is decomposed by EMD again, and all IMF components are obtained according to the order of frequency from high to low.

### 3.2 Design of integrated platform

The comprehensive monitoring platform of power transformer based on LabVIEW realizes the vibration state of power transformer through online monitoring of the changes of the vibration signal, current signal, voltage signal, temperature and humidity signal of power transformer box. The upper computer system needs two panels in the overall design; the program panel and the display panel. The program panel is used to write the basic program, block diagram and statements. The display panel is used to display the performance parameters of the power transformer. The communication mode between the upper and the lower computers is through wireless serial communication. The serial communication configuration of the upper computer includes the selection of serial port number, baud rate, data bit, check bit and stop bit. During the normal working condition of the serial port, the upper and the lower computers complete the communication, and the indicator light is green. However, when the serial port fails to open or the communication is abnormal, then the indicator light turns red. The design interface of integrated platform is depicted in Figure 1.

The main interface includes vibration signal display diagram, start and stop buttons, serial port setting, baud rate setting, status indicator, data saving and reading. The first step of Hilbert Huang transformation is to decompose the fluctuation or trend of different scales in the signal, in a step-by-step mode and high-to-low sequence. Therefore, in the analysis module of the program, MPEEMD subroutine is designed and concluded. By calling the subroutine, the collected signal is decomposed into corresponding IMFs components, and then the corresponding spectrum diagram is drawn to realize the analysis of the data signal.

The signal is then decomposed to Hilbert spectrum. The Hilbert spectrum is drawn using HHT transformation improved by MPEEMD algorithm. The frequency component of the vibration signal of the power
transformer box can be monitored through the spectrum diagram. By observing the change of frequency component in the spectrum diagram, the state of the inner iron core and winding of the power transformer can be monitored to provide reference data for possible hidden dangers and faults.

For feasibility and efficiency of LabVIEW, the integrated monitoring platform provided the front panel, program flow chart and icon connection port, and designs the display interface of the whole platform. Combined with the actual test data, the operation process of the whole system is explained in the following section.

### 4 Experimental results and discussion

In this paper, MATLAB simulation software was used to generate analog signals and the traditional EMD, EEMD and the improved MPEEMD algorithms were used for processing the signals. Then, the simulation test results were analysed. Two thousand forty-eight sampling points were selected in MATLAB simulation with the sampling time of 1s.
The signal decomposed by EMD was transformed into Hilbert transform, and the final Hilbert spectrum was obtained. The simulation signal was generated by MATLAB simulation software. The traditional EMD algorithm, EEMD algorithm and improved MPEEMD algorithm were used to process the signal, and the simulation test results were analysed. The correlation coefficient of IMFs obtained by the three algorithms was calculated. The correlation coefficient obtained was, as shown in Figure 2. When compared using the correlation coefficient distribution diagram, the correlation between the IMFs decomposed by MPEEMD algorithm and the original signal was observed to be stronger than that from the other two algorithms. However, the correlation of the IMFs decomposed by the EEMD algorithm with noise was the weakest, which also proved that the EEMD algorithm aimed at the improvement of the end effect. The method of adding mode was minimal to deal with the noise.

The mean square error (i.e. reconstruction error) between the reconstructed signal and the original signal was obtained by signal reconstruction of IMFs, as shown in Table 1.

<table>
<thead>
<tr>
<th>Algorithm name</th>
<th>Mean square error ($10^{-15}$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>EMD algorithm</td>
<td>6.387</td>
</tr>
<tr>
<td>EEMD algorithm</td>
<td>8.233</td>
</tr>
<tr>
<td>MPEEMD algorithm</td>
<td>4.762</td>
</tr>
</tbody>
</table>

The larger the mean square error between the reconstructed signal and the original signal, the more is the mean square error of the reconstructed signal. It is desirable to obtain the least mean square error value. The vibration of the power transformer under normal working conditions primarily originates from the core vibration caused by magnetostriction and the vibration caused by magnetic leakage when the load current passes through the winding. The vibration frequency is distributed in the double frequency (100Hz) of the load voltage and load current with a higher harmonic component. The vibration signal at 112 positions on the sidewall of the power transformer during the regular operation was selected in this experiment.

The corresponding frequency domain diagram of the vibration signal was plotted and the frequency distribution was observed. The frequency-domain diagram is shown in Figure 3.

![Figure 3: Spectrum Vibration Diagram (a) Raw signal (b) Spectrum Diagram](image)

It can be seen from Figure 3 that the frequency band of power transformer vibration signal under normal working conditions was mainly concentrated between 100-400 Hz. Also, it has been noticed from Figure 3(b) that the amplitude of the harmonic component is 250 mV and 275 mV at 100 Hz and 300 Hz, respectively.
EMD, EEMD and MPEEMD were used to decompose the vibration signal. The number of decompositions, correlation and mean square error are shown in Table 2. The Hilbert spectra of the three algorithms have been drawn and compared.

Table 2: Comparison of decomposed parameters

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>The number of IMFs obtained by decomposition</th>
<th>Maximum correlation coefficient</th>
<th>Mean square error ((10^{-15}))</th>
</tr>
</thead>
<tbody>
<tr>
<td>EMD</td>
<td>10</td>
<td>0.773</td>
<td>8.064</td>
</tr>
<tr>
<td>EEMD</td>
<td>12</td>
<td>0.659</td>
<td>12.257</td>
</tr>
<tr>
<td>MPEEMD</td>
<td>7</td>
<td>0.912</td>
<td>6.489</td>
</tr>
</tbody>
</table>

The number of IMFs and correlation coefficients obtained from decomposition were compared with the mean square error after reconstruction. The results showed that the number of IMFs and the correlation coefficient obtained by using MPEEMD algorithm were less, which improved the overall calculation efficiency of the program. The mean square error was the smallest, which indicated that the algorithm could suppress the generation of false IMFs in signal processing, and the deviation degree between the reconstructed signal and the original signal was the lowest.

To simulate the fault state of the power transformer, the test loosened the fastening bolts of the power transformer manually, resulting in the loosening of the transformer core. The vibration signals of 112 positions on the sidewall of the box were collected. The frequency domain diagram of the vibration signal under the loose iron core state has been shown in Figure 4, to observe the frequency distribution.

![Figure 4: Spectrum of vibration signal of the iron core fault](Image)

(a) Raw signal (b) Spectrum Diagram

It is depicted from Figure 4 that, when compared with the frequency spectrum of vibration signal in normal working state, the vibration signal of power transformer under loose iron core produced 500-900 Hz harmonic component in addition to 100-400 Hz frequencies. It is also noticed from Figure 4(b) that the harmonic amplitudes are much higher having values of 350 mV, 375 mV and 360 mV at 200 Hz, 400 Hz and 700 Hz, respectively.

This indicated that the vibration signal in that state had changed. Similarly, the three algorithms were used to decompose the signal and the parameters compared as shown in Table 3.

The IMFs obtained by MPEEMD algorithm were still less. Although the signal contained complex information, its decomposition efficiency was still well guaranteed. Besides, the calculated correlation coefficient and
Table 3: Comparison of decomposition parameters

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>The number of IMFs obtained by decomposition</th>
<th>Maximum correlation coefficient</th>
<th>Mean square error (10^{-15})</th>
</tr>
</thead>
<tbody>
<tr>
<td>EMD</td>
<td>14</td>
<td>0.508</td>
<td>12.384</td>
</tr>
<tr>
<td>EEMD</td>
<td>15</td>
<td>0.441</td>
<td>21.060</td>
</tr>
<tr>
<td>MPEEMD</td>
<td>10</td>
<td>0.897</td>
<td>10.593</td>
</tr>
</tbody>
</table>

The mean square error were still the best among the three algorithms. It showed that the information contained in the signal was effectively retained and accurately reflected in the decomposition process, and the authenticity of the screened data was effectively guaranteed.

In this paper, EMD algorithm, EEMD algorithm and MPEEMD algorithm have been used to compare the performance index and Hilbert spectrum of box vibration signals of simple simulation signal, power transformer’s normal working state, iron core loose fault state and winding deformation fault state. In the analysis of simple simulation signal, correlation coefficient and mean square error of IMFs screening were obtained by comparison algorithm. Also, three kinds of EMMMD algorithms were used to eliminate the distortion of the signal, and the EMMD algorithm could eliminate the noise distortion of the signal. Finally, the frequency distributions of the three working conditions were compared. It was observed that there were apparent differences in vibration signals under different conditions, which could be used as a valid basis for monitoring hidden dangers or faults of the transformer’s core and winding.

Figure 5 represents the comparison of different state-of-the-art methods for vibration analysis of power transformers.

In Figure 5, CEEMD stands for complementary ensemble empirical mode decomposition method [31] and CEEMAN represents complete ensemble empirical mode decomposition with adaptive noise [32]. All these methods are the state-of-the-art methods in this field and it was observed that the proposed MPEEMD method yields the best results among all its counterparts in terms of both correlation coefficient and mean square error parameters.

The improved MPEEMD algorithm was found to have a better decomposition effect for non-stationary and nonlinear vibration signals of power transformer, the correlation of IMFs after the screening was higher, and the deviation between the reconstructed signal and the original signal was found to be smaller. This work is dedicated to the online monitoring of power transformer using a more diversified approach designed using two main strategies: the STM32 processor and LabVIEW system to support the online capability of the technologies.
It provides the real-time performance of condition monitoring at faster response speed. The advantage of the MPEEMD approach over the conventional EMD and EEMD is that, it introduces the concept of Multiscale Permutation Entropy (MPE) ensemble in the IMFs so that noise signal can be interpreted and excluded from the target signals. This proposed approach is far better than the traditional EMD and EEMD techniques in terms of calculation ability as they do not assemble or average all the IMFs and decomposes only fewer number of IMFs. Therefore, MPEEMD improves the calculation ability of the algorithm greatly improving the IMFs accuracy, providing fast calculation speed of the algorithm as well as improved robustness.

The various advantages of MPEEMD which were clear from the simulation and comparison are:

- The MPEEMD algorithm replaced the traditional EMD algorithm to complete the signal screening process.
- This method uses the combination of EMD and EEMD algorithms to test the box vibration signal data of power transformer under three working conditions.
- The processing effect of the improved MPEEMD algorithm was comprehensively compared, to validate the superiority of MPEEMD algorithm.
- A complete online monitoring system was designed by using the STM32 processor and LabVIEW system.

5 Conclusions

A complete online monitoring system was designed based on MPEEMD algorithm replacing the traditional EMD algorithm. The system has been designed by using the STM32 processor and LabVIEW system. The working principle, structure, vibration mechanism and transmission path of the power transformer have been explored in-depth. The feasibility of applying the vibration analysis method to the online monitoring of power transformers has been demonstrated. The theory of HHT time-frequency analysis method and permutation entropy method was combined with the vibration characteristics of the transformer in different states along with a series of problems existing in the traditional HHT implementation process. The performance of the proposed system has been compared with EMD and EEMD algorithms. The reconstruction error of MPEEMD algorithm ($4.762 \times 10^{-15}$) is found to be better than the traditional EMD and EEMD algorithms.


References
