

# A transformer winding deformation detection method based on the analysis of leakage inductance changes

LI JIANSHEG, TAO FENGBO, WEI CHAO, LU YUNCAI,  
WU PENG, ZHU MENGZHOU, YU MIAO

*Jiangsu Electric Power Company Research Institute, Nanjing 211103, China*  
*e-mail: lijiansheng86@hotmail.com*

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**Abstract:** The detection of transformer winding deformation caused by short-circuit current is of great significance to the realization of condition based maintenance. Considering the influence of environment and measurement errors, an online deformation detection method is proposed based on the analysis of leakage inductance changes. First, the operation expressions are derived on the basis of the equivalent circuit and the leakage inductance parameters are identified by the partial least squares regression algorithm. Second, the amount of the leakage inductance samples in a detection time window is determined using the Monte Carlo simulation thought, and then the samples in the confidence interval are obtained. Last, a criteria is built by the mean value changes of the leakage inductance samples and the winding deformation is detected. The online detection method considers the random fluctuation characteristics of the leakage inductance samples, adjust the threshold value automatically, and can quantify the change range to assess the severity. Based on the field data, the distribution of the leakage inductance samples is analyzed to obey the normal function approximately. Three deformation experiments are done by different sub-winding connections and the detection results verify the effectiveness of the proposed method.

**Key words:** condition-based maintenance, winding deformation, leakage inductance, partial least squares regression

## 1. Introduction

The traditional maintenance has some limitations in technical and economical aspects, which may lead to excessive or lack of overhaul. To realize condition based maintenance, the accuracy of equipment condition assessment is very important [1-4]. Therein, the detection of transformer winding deformation is one piece.

Because of the impact of short-circuit current, the axial and radial size of windings may change, which threatens the safe operation of transformers. According to the signal type, the transformer winding deformation detection researches can be divided into two classes, the detection method based on non-electrical information and the detection method based on electrical information. The former method is based on the vibration signal and needs extra

sensors [5-6]. The latter uses the frequency response or leakage inductance characteristics to detect winding deformation [7-14]. The frequency response analysis method is offline and the method based on the leakage inductance can be realized online, therefore the method based on the leakage inductance should be paid more attention to. In the existing researches, the leakage inductance is calculated by the least squares algorithm and the detection process is rough, causing the problem of misconvergence as well as tiny deformation detection difficulty. Based on the results obtained by the above analysis, the transformer may operate with defects, which threatens the grid operation.

To improve the winding deformation detection accuracy, a method based on the analysis of the leakage inductance changes is proposed. First, based on the equivalent circuit, the leakage inductance parameters are identified by the partial least squares regression algorithm. Second, the amount of the leakage inductance samples in a detection time window is determined on the basis of its probability distribution. Last, by comparing the mean data of the change samples in different confidence intervals with the threshold value, the winding deformation is detected. The method considers the parameter fluctuation characteristics and has high sensitivity and self-learning ability.

## 2. Leakage inductance identification based on the partial least squares regression algorithm

In this section, the relationship between the leakage inductance and the winding deformation is analyzed based on a single-phase two-winding transformer. And the leakage inductance is calculated by the partial least squares regression algorithm, which can avoid the abnormal phenomenon in the least square regression processes and ensure accurate and reliable results [15-19].

### 2.1. Leakage inductance analysis

According to the definition of inductance, the leakage inductance  $L_\sigma$  of transformer windings can be calculated by (1).

$$L_\sigma = \frac{\psi_\sigma}{i}. \quad (1)$$

Wherein,  $\psi_\sigma$  is the leakage flux linkage and  $i$  represents the current flowing through the winding.

In Figure 1, a single-phase two-winding transformer is shown and the leakage inductance can be derived from (2), which is relative with winding size and its location.

$$L_\sigma = \mu_0 N_1^2 \frac{2\pi}{l'} \left( \frac{a_1 r_1 + a_2 r_2}{3} + a_{12} r_{12} \right). \quad (2)$$

Here,  $\mu_0$  represents the air permeability,  $N_1$  is the primary winding turns,  $l'$  is magnetic line height,  $a_1$ ,  $a_2$ ,  $a_{12}$ ,  $r_1$ ,  $r_2$ ,  $r_{12}$  are the size and location parameters of transformer windings.

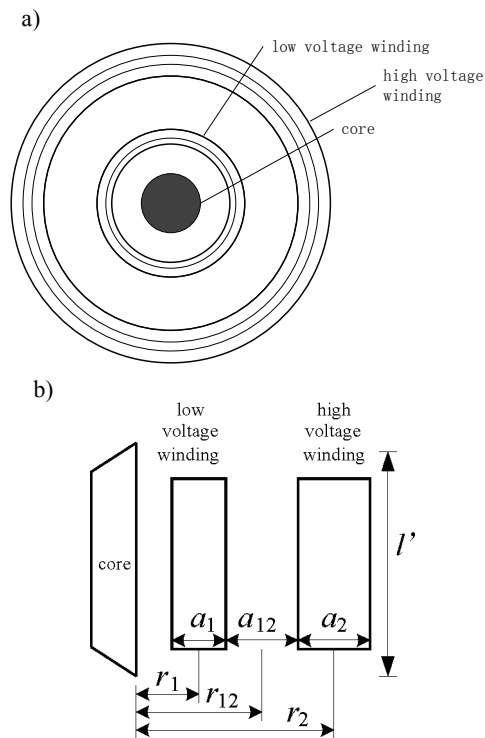


Fig. 1. The structure of a core type transformer

When the transformer winding deforms, the parameters  $a_1$ ,  $a_2$ ,  $a_{12}$ ,  $r_1$ ,  $r_2$  and  $r_{12}$  may change, which makes the leakage inductance  $L_\sigma$  change. Therefore, the accurate identification of the leakage inductance is an important point of detecting winding deformation.

## 2.2. Leakage inductance identification algorithm

In the leakage inductance identification, when the coefficient determinant is close to zero, the regression results got by the least square method will contain a serious rounding error and have poor accuracy. However, the partial least squares regression algorithm can solve this kind of problem.

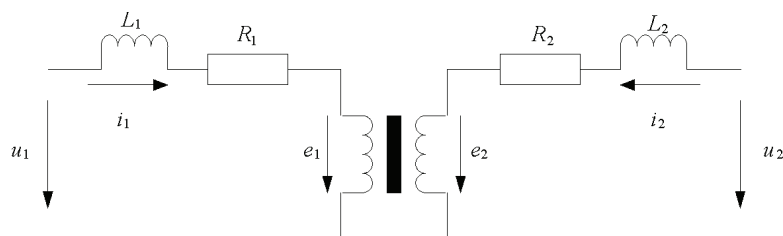


Fig. 2. A single phase two-winding transformer model

In Figure 2, a single-phase two winding transformer model is shown. Wherein,  $N_1, N_2$  represent the turns of primary and secondary winding;  $L_1, L_2$  are the leakage inductance and  $R_1, R_2$  are the leakage resistance respectively.

The electromagnetic transient process during the operation of the transformer can be expressed as:

$$\begin{cases} u_1 = L_1 \frac{di_1}{dt} + R_1 i_1 - e_1 \\ u_2 = L_2 \frac{di_2}{dt} + R_2 i_2 - e_2 \end{cases} \quad (3)$$

Wherein,

$$e_1 = k e_2, \quad e_1 = N_1 \frac{d\phi}{dt}, \quad k = \frac{N_1}{N_2}$$

and  $\Phi$  is the magnetic flux.

Eliminate  $e_1$  and  $e_2$ , the formula (4) is got.

$$u_1 - k u_2 = L_1 \frac{di_1}{dt} + R_1 i_1 - k L_2 \frac{di_2}{dt} - k R_2 i_2. \quad (4)$$

The integral expression of formula (4) is shown in (5).

$$\begin{aligned} \int_{t_0}^t (u_1 - k u_2) dt &= L_1 (i_1(t) - i_1(t_0)) + \\ &R_1 \int_{t_0}^t i_1 dt - k L_2 (i_2(t) - i_2(t_0)) - k R_2 \int_{t_0}^t i_2 dt \end{aligned} \quad (5)$$

Here,  $t_0$  is the initial time and  $t$  is the time of subsequent point. Put the data of different time into (5), and (6) can be got.

$$\begin{cases} XA = Y \\ X = \begin{bmatrix} \int_{t_0}^{t_1} u_2 dt & i_1(t_1) - i_1(t_0) & \int_{t_0}^{t_1} i_1 dt & i_2(t_1) - i_2(t_0) & \int_{t_0}^{t_1} i_2 dt \\ \int_{t_0}^{t_2} u_2 dt & i_1(t_2) - i_1(t_0) & \int_{t_0}^{t_2} i_1 dt & i_2(t_2) - i_2(t_0) & \int_{t_0}^{t_2} i_2 dt \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \int_{t_0}^{t_n} u_2 dt & i_1(t_n) - i_1(t_0) & \int_{t_0}^{t_n} i_1 dt & i_2(t_n) - i_2(t_0) & \int_{t_0}^{t_n} i_2 dt \end{bmatrix} \\ Y = [\int_{t_0}^{t_1} u_1 dt \int_{t_0}^{t_2} u_1 dt \cdots \int_{t_0}^{t_n} u_1 dt]' \\ A = [k \ L_1 \ R_1 \ kL_2 \ kR_2]'. \end{cases} \quad (6)$$

In (6),  $X$  is the coefficient matrix;  $Y$  is a constant matrix; and  $A$  contains the parameters to be identified;  $t_1, t_2, \dots, t_n$  represent  $n$  different moments; ' is the matrix transpose expression;

$k, L_1, R_1, L_2, R_2$  are the unknown parameters. Standardize the independent variables  $X$  and the dependent variable  $Y$  respectively, and  $X_0$  and  $Y_0$  can be got. Then the unknown parameters are identified by partial least squares regression algorithm following the following steps.

1) According to (7)-(8), extract the first component  $g_1$  and  $u_1$  from  $X_0$  and  $Y_0$ .

$$\left\{ \begin{array}{l} \omega_1 = \frac{X_0' Y_0}{\|X_0' Y_0\|} = \frac{1}{\sqrt{\sum_{j=1}^5 r^2(x_j, y)}} \begin{bmatrix} r(x_1, y) \\ \vdots \\ r(x_n, y) \end{bmatrix}, \\ g_1 = X_0 \omega_1 \end{array} \right. \quad (7)$$

$$\left\{ \begin{array}{l} c_1 = \frac{Y_0' X_0}{\|Y_0' X_0\|} \\ u_1 = Y_0 c_1. \end{array} \right. \quad (8)$$

In (7) and (8),  $r(x_j, y)$  represents the correlation coefficient between  $x_j$  and  $y$ ;  $\omega_1$  is the first axis component of  $X_0$  and its modulus value  $\|\omega_1\|=1$ ;  $c_1$  is the first axis component of  $Y_0$  and  $\|c_1\|=1$ .

2) Calculate the residual matrix  $X_1$  and  $Y_1$  of the regression equation by (9).

$$\left\{ \begin{array}{l} X_1 = X_0 - g_1 p_1' \\ Y_1 = Y_0 - g_1 r_1' \end{array} \right. \quad (9)$$

In (9), the regression coefficient vector  $p_1$  and  $r_1$  can be expressed as (10).

$$\left\{ \begin{array}{l} p_1 = X_0' g_1 / \|g_1\|^2 \\ r_1 = Y_0' g_1 / \|g_1\|^2 \end{array} \right. \quad (10)$$

3) Replace  $X_0$  and  $Y_0$  with  $X_1$  and  $Y_1$ , repeat the above steps until the cross validation principles meet.

4) After the above steps,  $h$  components can be got, which are expressed as  $g_1, g_2, \dots, g_h$ . Then calculate the regression equation between  $Y_0$  and  $g_1, g_2, \dots, g_h$ , which can be shown as (11).

$$Y_0 = r_1 g_1 + r_2 g_2 + \dots + r_h g_h. \quad (11)$$

Because  $g_1, g_2, \dots, g_h$  are the linear combination of  $X_0$ , (11) can also be expressed as (12).

$$Y_0 = X_0 (r_1 \omega_1^* + \dots + r_h \omega_h^*). \quad (12)$$

In (12),

$$\omega_h^* = \prod_{j=1}^{h-1} (I - \omega_j p_j^T) \omega_h.$$

And  $I$  is the unit matrix.

Express  $\alpha_j$  with

$$\alpha_j = \sum_{m=1}^h r_m \omega_{mj}^*,$$

and (12) can be changed to be (13).

$$Y_0 = \alpha_1 X_{01} + \alpha_2 X_{02} + \cdots + \alpha_5 X_{05}. \quad (13)$$

In (13),  $X_{0j}$  ( $j = 1, \dots, 5$ ) is the  $j$ th column of  $X_0$ .

5) By the inverse processes of standardization, the regression equation of  $Y$  on  $X$  can be expressed as (14).

$$Y = \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_5 x_5. \quad (14)$$

In (14),  $\beta_j$  ( $j = 1, \dots, 5$ ) is the regression coefficient.

In step 3), the components should meet cross validation principles. That is to say, there is no need to use all components in partial least squares regression algorithm and the number of components can be determined as follows.

In (15), suppose that the components are  $g_1, g_2, \dots, g_h$  and  $\hat{y}_{hj}$  is the value calculated by regression equation which is got using all samples. And  $\hat{y}_{h(-j)}$  is the fitting value of  $j_{gh}$  sample using the regression equation which is calculated except  $j_{gh}$  sample.

$$\left\{ \begin{array}{l} S_h = \sum_{j=1}^n (y_j - \hat{y}_{hj})^2 \\ P_h = \sum_{j=1}^n (y_j - \hat{y}_{h(-j)})^2 \\ Q_h^2 = 1 - \frac{P_h}{S_{h-1}} \end{array} \right. \quad (15)$$

Generally, if  $Q_h$  is larger than 0.0975, the contribution of the added component is significant and the component should be considered.

After the above processes, the five unknown parameters are calculated and the leakage inductance  $L_\sigma$  can be calculated according to (16).

$$L_\sigma = L_1 + k^2 L_2. \quad (16)$$

### 3. Adaptive detection of transformer winding deformation

In the traditional detection method, the uncertainty of leakage inductance caused by measurement errors is not concerned, which may cause wrong results and has low sensitivity.

In this paper, an adaptive algorithm is proposed to improve the accuracy of winding deformation detection.

### 3.1. Determination of the number of samples in a detection time window

To detect winding deformation, the sample number in a detection time window should be determined first, which should ensure the random characteristics be fully represented. Using the Monte Carlo thoughts, the number is determined through the analysis of distribution of the leakage inductance.

Suppose there are  $m$  leakage inductance samples in the detection time window, divide the time window into  $m$  intervals, construct Equation (6) using voltage and current data at different time and calculate the unknown parameters. Therefore, the leakage inductance sequence can be expressed as  $L_\sigma = \{L_{\sigma 1}, L_{\sigma 2}, \dots, L_{\sigma m}\}$ . Calculate the mean value  $\bar{L}_\sigma$ , the standard deviation  $S_{L_\sigma}$  and count the number  $m_1$  in the interval  $(\bar{L}_\sigma - S_{L_\sigma}, \bar{L}_\sigma + S_{L_\sigma})$ . Then the value of  $P$  is calculated according to (17). Compare  $P$  with  $P_{\text{set}}$  to determine the feasibility of the samples. If  $P < P_{\text{set}}$ , increase  $m$  and repeat the above processes until  $P$  is larger than  $P_{\text{set}}$ . According to the "3 $\sigma$ " criterion in normal distribution,  $P_{\text{set}}$  is set to be 0.683 in this paper.

$$P(\bar{L}_\sigma - S_{L_\sigma} < L_\sigma < \bar{L}_\sigma + S_{L_\sigma}) = \frac{m_1}{m}. \quad (17)$$

In (17),  $P$  is the cumulative probability of  $L_\sigma$  in the interval  $(\bar{L}_\sigma - S_{L_\sigma}, \bar{L}_\sigma + S_{L_\sigma})$ . The parameter  $m_1$  is the number that  $L_\sigma$  fall in the interval  $(\bar{L}_\sigma - S_{L_\sigma}, \bar{L}_\sigma + S_{L_\sigma})$ .

After the above calculation processes, the number  $N_w$  in a detection time window can be set to be larger than  $m_1$ , which can represent the stochastic characteristics of the leakage inductance.

### 3.2. Processes of transformer winding deformation detection

Suppose the voltage and current of a single-phase two-winding transformer are  $u_1$ ,  $u_2$ ,  $i_1$  and  $i_2$ , and there are  $N_w$  samples in a detection time window. The processes of winding deformation detection are as follows.

1) Divide the detection time window into  $N_w$  intervals, calculate the leakage inductance using voltage and current data at different moments by (6) based on the partial least squares regression algorithm.

2) According to (18), calculate the leakage inductance changes  $\Delta L_\sigma$ .

$$\Delta L_\sigma(l) = L_\sigma(l + 2 \bullet N_w) - L_\sigma(l) \quad (18)$$

$$(l = 1, \dots, N_w).$$

3) Calculate the probability density function of the  $\Delta L_\sigma$  samples in a time window, and estimate the bilateral confidence interval under a certain confidence, which have  $N_{w1}$  samples.

4) Construct the criteria to detect winding deformation, as shown in (19).

$$\begin{cases} ms_j = \left| \sum_{l=1}^{N_{w1}} \Delta L_{\sigma}(i) \right| / N_{w1} \\ D_{L\sigma}(j) = \begin{cases} 0, s_j < \varepsilon_1 \text{ or } s_{j-1} < \varepsilon_1 \text{ or } s_{j-2} < \varepsilon_1 \\ 1, s_j > \varepsilon_1 \text{ and } s_{j-1} > \varepsilon_1 \text{ and } s_{j-2} > \varepsilon_1 \end{cases} \end{cases} \quad (19)$$

In (19),  $ms_j$  is the mean data of leakage inductance changes in the confidence interval of the  $j_{th}$  time window and  $\varepsilon_1$  is the threshold value;  $N_{w1}$  represents the number of samples in the confidence interval. When the mean values in three consecutive time windows are larger than  $\varepsilon_1$ , the parameter  $D_{L\sigma}$  is equal to 1, which indicates that the winding deformed.

5) Move the time window at the interval of  $N_w/2$  data points, adjust the threshold value and repeat steps 1)-4) to detect the change of leakage inductance in new time windows.

In the detection method, the determination of the threshold value is the key point to influence the accuracy. In order to eliminate the subjectivity, the threshold value is determined using historical data adaptively.

According to (19), calculate the mean data of leakage inductance changes in history time windows. Analyze the mean data and get its changing range  $[ms_1, ms_2]$ . The threshold value  $\varepsilon_1$  is set according to (20) considering a margin coefficient.

$$\varepsilon_1 = k \bullet \max(|ms_1|, |ms_2|). \quad (20)$$

In (20),  $k$  is the margin coefficient and its value is equal to the ratio of largest and second largest data of the absolute value.

Therefore, the winding deformation can be detected by comparing  $ms_j$  and  $\varepsilon_1$ . When  $ms_j$  is equal to  $\varepsilon_1$ , the minimum change range  $\delta$  can be got according to (21).

$$\delta = \varepsilon_1. \quad (21)$$

In order to evaluate the severity of winding deformation, the leakage inductance change range is an important index. In normal operation process of transformers, the mean data calculated by (19) is about 0. After winding deformation, the mean data changes from 0 to a certain stable data  $dL_{\sigma}$ . The transition processes have three different forms according to the relationship between the deformation time and time window, as shown in Figure 3. With the moving of time window, the mean data of leakage inductance changes transits from  $dL_{\sigma}$  to 0. The winding deformation in future time windows can be detected.

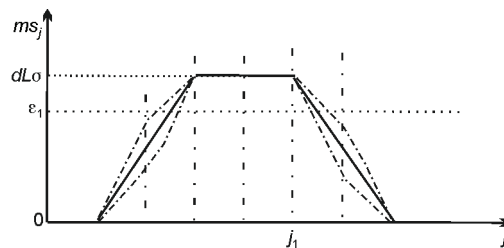


Fig. 3. Mean data of leakage inductance changes in different time windows



In Figure 3,  $j_1$  is the label of the time window whose  $D_{L\sigma}$  is equal to 1. The leakage inductance change range  $M$  can be calculated by (22).

$$M = dL_{\sigma}. \tag{22}$$

The detection method adjusts the threshold value and the margin coefficient based on historical data continuously, which can reduce the omission and error rate. The detection precision is high and the change range of leakage inductance can be obtained, which provides a reference for maintenance strategy.

### 4. Experiment analysis

In order to verify the method proposed in this paper, the stochastic characteristics of identified leakage inductance is analyzed and a two-winding transformer is built to simulate the winding deformation.

#### 4.1. Analysis of leakage inductance

In Figure 4, the diagram of a three-phase two winding transformer is illustrated. The type of the transformer is SFP10-370000/220, the rated capacity is 370 MVA, the voltage of two windings is  $242 \pm 2 \times 2.5\%/20$  kV, and the short-circuit impedance percentage  $U_d$  is equal to 18%. The connection mode of the windings is YN, d11.

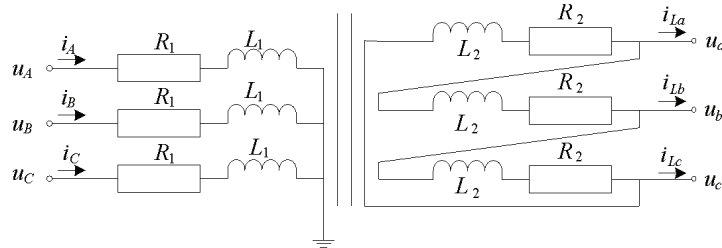


Fig. 4. A two winding three-phase transformer with Y/Δ connection

Suppose the three-phase windings of the transformer are symmetrical, the circuit equation of the transformer is expressed by (23).

$$\begin{cases} N_1 \frac{d\Phi_{Aa}}{dt} + L_1 \frac{di_A}{dt} + R_1 i_A = u_A \\ N_1 \frac{d\Phi_{Bb}}{dt} + L_1 \frac{di_B}{dt} + R_1 i_B = u_B \\ N_2 \frac{d\Phi_{Aa}}{dt} + L_2 \frac{d(i_a + i_p)}{dt} + R_2 (i_a + i_p) = u_a - u_c \\ N_2 \frac{d\Phi_{Bb}}{dt} + L_2 \frac{d(i_b + i_p)}{dt} + R_2 (i_b + i_p) = u_b - u_a \end{cases} \tag{23}$$

In (23), the  $i_p$  is the circular current;  $\Phi_{Aa}$  and  $\Phi_{Bb}$  are the flux in the windings;  $i_a, i_b$  and  $i_C$  are the current in the delta connection windings;  $k, L_1, R_1, L_2$  and  $R_2$  are the unknown parameters;  $u_A, u_B, u_C, u_a, u_b, u_c$  and  $i_A, i_B, i_C, i_{La}, i_{Lb}, i_{Lc}$  are the measured voltage and current data.

The formula (24) can be got after the elimination of the flux  $\Phi_{Aa}, \Phi_{Bb}$  and  $i_p$  in (23).

$$u_A - u_B - k(2u_a - u_b - u_c) = L_1 \frac{d(i_A - i_B)}{dt} + R_1(i_A - i_B) + kL_2 \frac{di_{La}}{dt} + kR_2 \cdot i_{La}. \tag{24}$$

According to the above method, the number of samples in a time window can be set 500. The leakage inductance calculated by partial least squares regression algorithm using electrical information is shown in Figure 5a). Count the number of leakage inductance samples in different sections and draw the distribution histogram, as shown in Figure 5b).

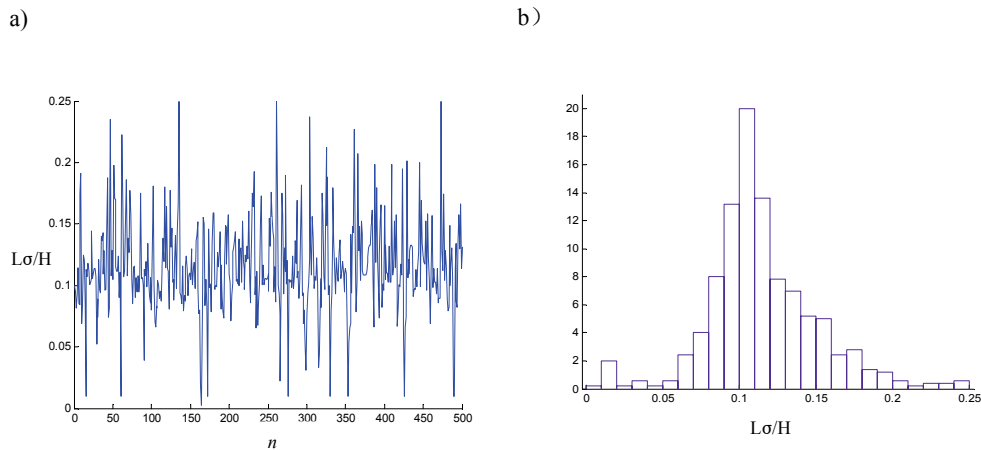


Fig. 5. Curve of leakage inductance  $L_\sigma$  and its distribution

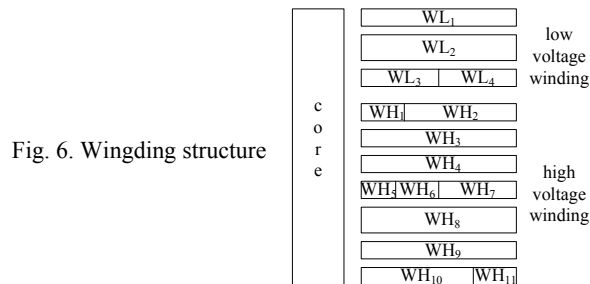


Fig. 6. Winding structure

Due to the environment and measurement errors, the calculated leakage inductance data fluctuates and follows normal distribution approximately. The mean value  $\bar{L}_\sigma$  and the standard deviation value  $S_{L_\sigma}$  are 0.11486 H and 0.036744.

#### 4.2. Winding deformation detection

To simulate the transformer winding deformation, a single-phase two winding transformer is established, as shown in Figure 6. The high and low voltage windings are arranged up and down. The low voltage winding is composed of 11 pies and its number of turns is 88. The high-voltage winding is composed of 13 pies, and there are 416 turns. By different taps, the low voltage winding is divided into WL<sub>1</sub>-WL<sub>4</sub> segments, and the high voltage winding is divided into WH<sub>1</sub>-WH<sub>11</sub> segments. The specific number of turns is shown in Table 1.

Table 1. Number of sub-winding turns

Segments	Turns	Segments	Turns
WL <sub>1</sub>	8	WH <sub>5</sub>	8
WL <sub>2</sub>	72	WH <sub>6</sub>	8
WL <sub>3</sub>	4	WH <sub>7</sub>	16
WL <sub>4</sub>	4	WH <sub>8</sub>	192
WH <sub>1</sub>	8	WH <sub>9</sub>	64
WH <sub>2</sub>	24	WH <sub>10</sub>	24
WH <sub>3</sub>	32	WH <sub>11</sub>	8
WH <sub>4</sub>	32		

In the experiment, the low-voltage windings are composed of WL<sub>2</sub> and WL<sub>3</sub>. The high voltage winding is composed of WH<sub>2</sub>, WH<sub>3</sub>, WH<sub>5</sub>, WH<sub>6</sub>, WH<sub>7</sub>, WH<sub>9</sub> and WH<sub>10</sub>. The voltage of the two windings is 220/95 V and the rated capacity is 2 kVA. The sample frequency is 5 kHz and the length of a time window is 0.2 s.

Collect the voltage and current signal in continuous 4 seconds, and add white noise to simulate the real operation conditions. The number of samples in a time window can be set 200 according to (17). Then the leakage inductance in 4 s identified by the partial least squares regression algorithm is shown in Figure 7.

Calculate the changes by (18) and set the confidence level to be 0.9. After the calculation of the probability density function of the changes in the time window, the samples in the confidence interval are determined. Analyze the calculated mean data and obtain the range [ $ms_1$ ,  $ms_2$ ]. Therefore, the threshold value  $\varepsilon_1$  and minimum detection range  $\delta$  can be calculated by (20) and (21), which are shown in Table 2.

Table 2. Number of leakage inductance in time window and threshold

$N_w$	200
$[ms_1, ms_2]$	[-0.00561, 0.00527]
$\varepsilon_1$	0.00596
$\delta$	0.00596

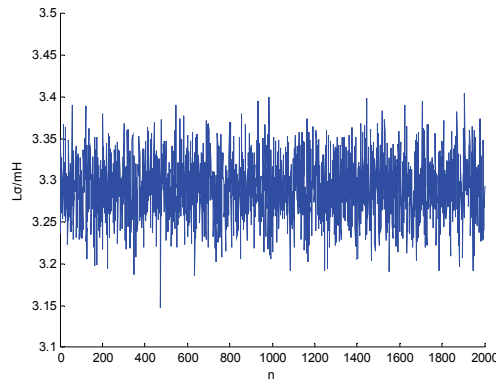


Fig. 7. The leakage inductance of transformer in normal operation

To simulate transformer winding deformation caused by short-circuit current, three experiments are designed through different winding connection: (1) The segment  $WH_3$  of high voltage winding is replaced by  $WH_4$ , which simulates winding axial downward displacement; (2)  $WH_5$  is replaced by  $WH_1$  to simulate axial displacement; (3) The segments  $WL_3$  of low voltage winding is replaced by  $WL_4$  to simulate winding radial deformation.

Analyze the 4000 leakage inductance samples in the three experiments, the sequence of the leakage inductance and the mean data of the leakage inductance changes are shown in Figure 8 (a), (b), (c).

Compare the mean data of leakage inductance changes in Figure 8 a), b), c) with the threshold value  $\varepsilon_1$  in Table 2. The parameter  $DL_\sigma$  is equal to 1 at 17th, 18th, 18th time window respectively, which shows that the winding deformation is detected and the effectiveness of the proposed method is verified. Especially in experiment (3), when the variation in the leakage inductance is about 0.5%, this method is still effective.

In Table 3, the range of leakage inductance changes  $M$  in the three experiments are shown.

Table 3. Calculated data of  $M$

	a)	b)	c)
$M(\text{mH})$	0.0846	0.0577	0.0133

## 5. Conclusion

To detect the transformer winding deformation, a method based on the leakage inductance considering the stochastic characteristics is proposed. The leakage inductance is identified by the partial least squares regression algorithm, which can ensure the accuracy of the results. According to the probability distribution characteristics of the leakage inductance, the number of samples is determined in the time window, which can show its fluctuation characteristics.

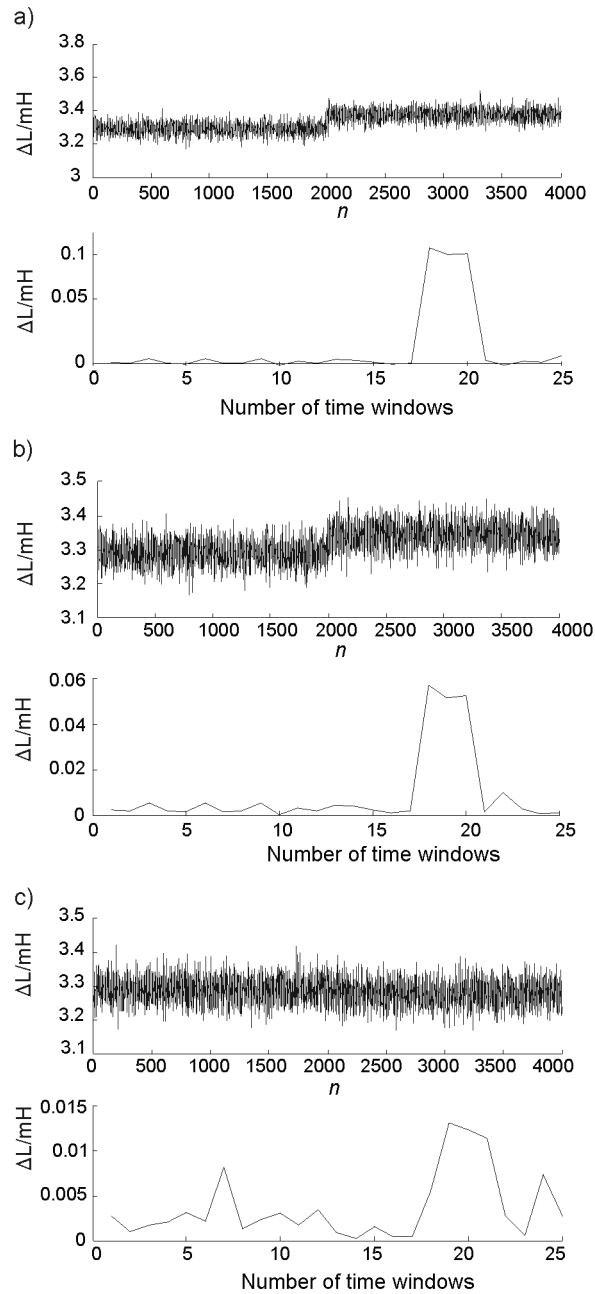


Fig. 8. Leakage inductance and the sum of changes

The threshold value can be adjusted automatically according to the historical data of leakage inductance changes and the detection sensitivity is high. The experimental results verify the effectiveness of the proposed method.

## References

- [1] Xu J., Wang J., Gao F., Shu H.C., *A survey of condition based maintenance technology for electric power equipments*. Power System Technology 24(8): 48-52 (2000).
- [2] Huang J.H., Quan L.S., *Current status and development of condition-based maintenance of high-voltage electric power equipment in substation*. Automation of Electric Power System 25(16): 56-61 (2001).
- [3] Zhang H.Y., Zhu S.L., Zhang Y. et al., *Research and implementation of condition-based maintenance technology system for power transmission and distribution equipments*. Power System Technology 33(13): 70-73 (2009).
- [4] Bagheri M., Naderi M.S., Blackburn T., *Advanced transformer winding deformation diagnosis: moving from off-line to on-line*. IEEE Transactions on Dielectrics and Electrical Insulation 19(6): 1860-1870 (2012).
- [5] Ma H.Z., Geng Z.H., Chen K. et al., *A new fault diagnosis method for power transformer winding deformation based on vibration*. Automation of Electric Power Systems 37(6): 89-95 (2013).
- [6] Xu J., Shao Y.Y., Wang F.H. et al., *Comparative research on behavior of vibration frequency response analysis and frequency response analysis in detection of transformer winding deformation*. Power System Technology 35(6): 213-218 (2011).
- [7] Gawrylczyk K.M., Banaszak S., *Modeling of frequency response of transformer winding with axial deformations*. Archives of Electrical Engineering 63(1): 5-17 (2014).
- [8] Mehdi B., Mehdi V., Ebrahim R., *Comparison of transfer functions using estimated rational functions to detect winding mechanical faults in transformers*. Archives of Electrical Engineering 61(1): 85-99 (2012).
- [9] Ebrahim R., Stefan T., *Fault diagnosis of actual large-power high-voltage winding using transfer function method*. Archives of Electrical Engineering 60(3): 269-281 (2011).
- [10] Secue J., Mombello E., Cardoso C.V., *Review of sweep frequency response analysis – SFRA for assessment winding displacements and deformation in power transformers*. Revista IEEE America Latina 5(5): 321-328 (2007).
- [11] William G., Hurley D.J., *Calculation of leakage inductance in transformer windings*. IEEE Transactions on Power Electronics 9(1): 121-126 (1994).
- [12] Li P., Zhang B.H., Hao Z.G., Chu Y.L., *Actuality and prospect of transformer winding deformation monitoring based on electric characteristic*. Electric Power Automation Equipment 26(2): 28-32 (2006).
- [13] Hao Z.G., Zhang B.H., Li P., Gao J., Wang Q., *Study on on-line detection of transformer winding deformation based on parameter identification of leakage inductance*. High Voltage Engineering 32(11): 67-70 (2006).
- [14] Deng X.L., Xiong X.F., Gao L., Fu Y., Chen Y.J., *Method on on-line monitoring of transformer winding deformation based on parameter identification*. Proceedings of the CSEE 34(28): 4950-4958 (2014).
- [15] Wang M.H., Bao J., Qi X., Zhang Z., *Online estimation of transmission line parameters based on PMU measurements*. Automation of Electric Power Systems 34(1): 25-27 (2010).
- [16] Chen J., Yan W., Lu J.G. et al., *A robust transformer parameter estimation method considering multi-period measurement random errors*. Automation of Electric Power Systems, 35(2): 28-33 (2011).
- [17] Wang M.H., Qi X., Niu S.Q., Han F.K., *Online estimation of transformer parameters based on PMU measurements*. Automation of Electric Power Systems 35(13): 61-65 (2011).
- [18] Wang W.S., Ding J., Zhao Y.L., Zhang X.M., *Study on the long term prediction of annual electricity consumption using partial least square regressive model*. Proceedings of the CSEE 23(10): 17-21 (2003).
- [19] Mao L.F., Jiang Y.C., Long R.H. et al., *Medium- and long- term load forecasting based on partial least squares regression analysis*. Power System Technology 32(19): 71-77 (2008).