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

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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_σ of transformer windings can be calculated by (1).

$$L_\sigma = \frac{\psi_\sigma}{i}. \tag{1}$$

Wherein, ψ_σ 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.

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

Here, μ_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.

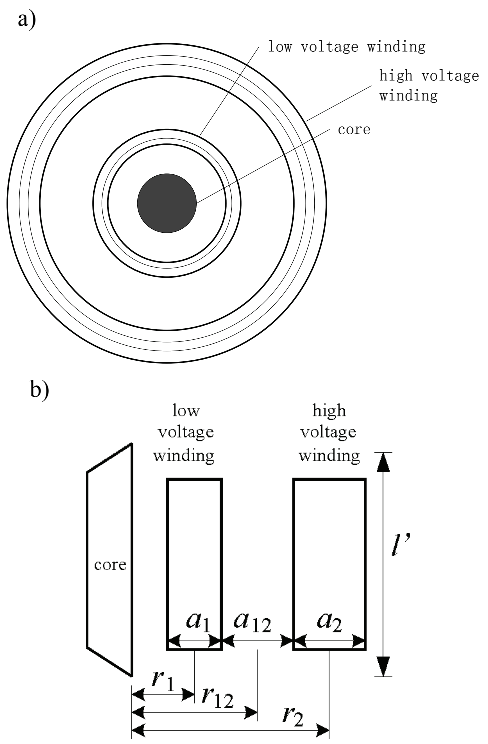


Fig. 1. The structure of a core type transformer

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_σ 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.

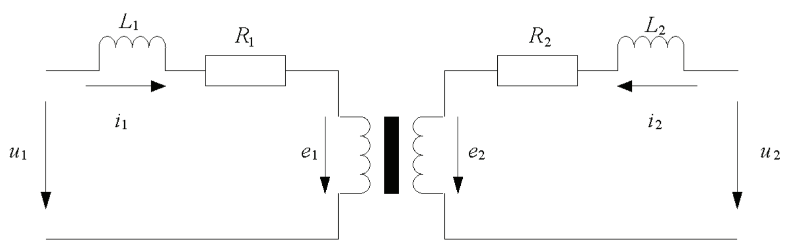


Fig. 2. A single phase two-winding transformer model

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:

$$\begin{cases} u_1 = L_1 \dfrac{di_1}{dt} + R_1 i_1 - e_1 \\ u_2 = L_2 \dfrac{di_2}{dt} + R_2 i_2 - e_2 \end{cases}. \tag{3}$$

Wherein,

$$e_1 = ke_2, \quad e_1 = N_1 \frac{d\phi}{dt}, \quad k = \frac{N_1}{N_2}$$

and Φ is the magnetic flux.

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

$$u_1 - ku_2 = L_1 \frac{di_1}{dt} + R_1 i_1 - kL_2 \frac{di_2}{dt} - kR_2 i_2. \tag{4}$$

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

$$\begin{gathered} \int_{t_0}^{t} (u_1 - ku_2) dt = L_1 (i_1(t) - i_1(t_0)) + \\ R_1 \int_{t_0}^{t} i_1 dt - kL_2 (i_2(t) - i_2(t_0)) - kR_2 \int_{t_0}^{t} i_2 dt \end{gathered} \tag{5}$$

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.

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

In (6), X is the coefficient matrix; Y is a constant matrix; and A contains the parameters to be identified; t_1, t_2,...... , 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.

$$\begin{cases} \omega_1 = \dfrac{X_0' Y_0}{\left\| X_0' Y_0 \right\|} = \dfrac{1}{\sqrt{\sum\limits_{j=1}^{5} r^2 \left(x_j, y\right)}} \begin{bmatrix} r(x_1, y) \\ \vdots \\ r(x_n, y) \end{bmatrix}, \\ g_1 = X_0 \omega_1 \end{cases} \tag{7}$$

$$\begin{cases} c_1 = \dfrac{Y_0' X_0}{\left\| Y_0' X_0 \right\|} \\ u_1 = Y_0 c_1. \end{cases} \tag{8}$$

In (7) and (8), $r(x_j, y)$ represents the correlation coefficient between x_j and y; ω_1 is the first axis component of X_0 and its modulus value $\left\| \omega_1 \right\|=1$; c_1 is the first axis component of Y_0 and $\left\| c_1 \right\|=1$.

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

$$\begin{cases} X_1 = X_0 - g_1 p_1' \\ Y_1 = Y_0 - g_1 r_1' \end{cases} \tag{9}$$

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

$$\begin{cases} p_1 = X_0' g_1 / \left\| g_1 \right\|^2 \\ r_1 = Y_0' g_1 / \left\| g_1 \right\|^2 \end{cases}. \tag{10}$$

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 $g_1, g_2, \ldots, g_h$. Then calculate the regression equation between Y_0 and $g_1, g_2, \ldots, g_h$, which can be shown as (11).

$$Y_0 = r_1 g_1 + r_2 g_2 + \cdots + r_h g_h. \tag{11}$$

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

$$Y_0 = X_0 (r_1 \omega_1^* + \cdots + r_h \omega_h^*). \tag{12}$$

In (12),

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

And I is the unit matrix.
Express α_j with

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

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

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

In (13), X_{0j} (j = 1, …, 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).

$$Y = \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_5 x_5. \tag{14}$$

In (14), β_j (j = 1, …, 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, …,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.

$$\begin{cases} S_h = \sum_{j=1}^{n} (y_j - \hat{y}_{hj})^2 \\ P_h = \sum_{j=1}^{n} (y_j - \hat{y}_{h(-j)})^2 . \\ Q_h^2 = 1 - \dfrac{P_h}{S_{h-1}} \end{cases} \tag{15}$$

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_σ can be calculated according to (16).

$$L_\sigma = L_1 + k^2 L_2. \tag{16}$$

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 $L_\sigma = \{L_{\sigma 1}, L_{\sigma 2}, \ldots, L_{\sigma m}\}$. Calculate the mean value $\overline{L}_\sigma$, the standard deviation $S_{L\sigma}$ and count the number m_1 in the interval $(\overline{L}_\sigma - S_{L\sigma}, \overline{L}_\sigma + S_{L\sigma})$. Then the value of P is calculated according to (17). Compare P with P_{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_{set}. According to the "3σ" criterion in normal distribution, P_{set} is set to be 0.683 in this paper.

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

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

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 ΔL_σ.

$$\begin{gathered}\Delta L_\sigma(l) = L_\sigma(l + 2 \bullet N_w) - L_\sigma(l) \\ (l = 1, \cdots, N_w).\end{gathered} \tag{18}$$

3) Calculate the probability density function of the ΔL_σ 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).

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

In (19), ms_j is the mean data of leakage inductance changes in the confidence interval of the j_{th} time window and ε_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 ε_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 $N_\text{w}/2$ 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 ε_1 is set according to (20) considering a margin coefficient.

$$\varepsilon_1 = k \bullet \max(|ms_1|, |ms_2|). \tag{20}$$

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 ε_1. When ms_j is equal to ε_1, the minimum change range δ can be got according to (21).

$$\delta = \varepsilon_1. \tag{21}$$

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_σ. 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_σ to 0. The winding deformation in future time windows can be detected.

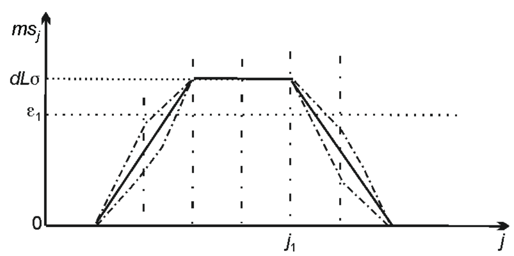


Fig. 3. Mean data of leakage inductance changes in different time windows

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).

$$M = d\,L_{\sigma}. \tag{22}$$

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 ± 2×2.5%/20 kV, and the short-circuit impedance percentage U_{d} is equal to 18%. The connection mode of the windings is YN, d11.

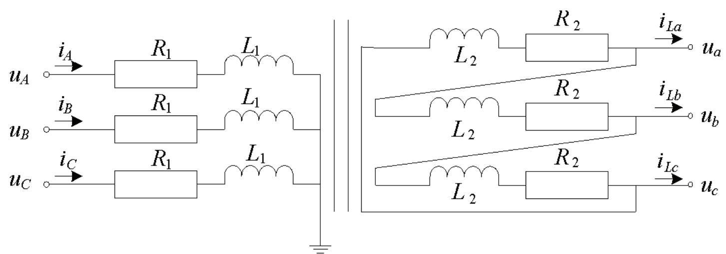


Fig. 4. A two winding three-phase transformer with Y/Δ connection

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

$$\begin{cases} N_1 \dfrac{d\Phi_{\mathrm{Aa}}}{dt} + L_1 \dfrac{di_{\mathrm{A}}}{dt} + R_1 i_{\mathrm{A}} = u_{\mathrm{A}} \\ N_1 \dfrac{d\Phi_{\mathrm{Bb}}}{dt} + L_1 \dfrac{di_{\mathrm{B}}}{dt} + R_1 i_{\mathrm{B}} = u_{\mathrm{B}} \\ N_2 \dfrac{d\Phi_{\mathrm{Aa}}}{dt} + L_2 \dfrac{d(i_{\mathrm{a}} + i_{\mathrm{p}})}{dt} + R_2 (i_{\mathrm{a}} + i_{\mathrm{p}}) = u_{\mathrm{a}} - u_{\mathrm{c}} \\ N_2 \dfrac{d\Phi_{\mathrm{Bb}}}{dt} + L_2 \dfrac{d(i_{\mathrm{b}} + i_p)}{dt} + R_2 (i_{\mathrm{b}} + i_{\mathrm{p}}) = u_{\mathrm{b}} - u_{\mathrm{a}}. \end{cases} \tag{23}$$

In (23), the i_p is the circular current; Φ_{Aa} and Φ_{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 Φ_{Aa}, Φ_{Bb} and i_p in (23).

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

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).

a) b)

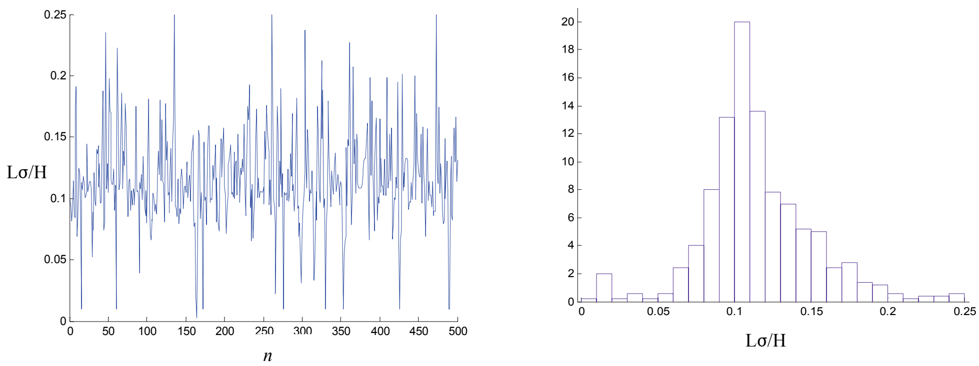
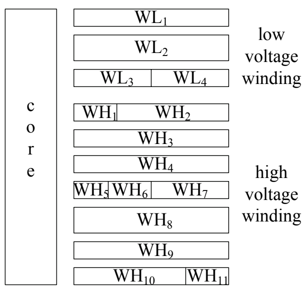


Fig. 5. Curve of leakage inductance L_σ and its distribution

Fig. 6. Wingding structure



Due to the environment and measurement errors, the calculated leakage inductance data fluctuates and follows normal distribution approximately. The mean value $\overline{L_\sigma}$ 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_1-WL_4 segments, and the high voltage winding is divided into WH_1-WH_{11} segments. The specific number of turns is shown in Table 1.

Table 1. Number of sub-wingding turns

Segments	Turns	Segments	Turns
WL_1	8	WH_5	8
WL_2	72	WH_6	8
WL_3	4	WH_7	16
WL_4	4	WH_8	192
WH_1	8	WH_9	64
WH_2	24	WH_{10}	24
WH_3	32	WH_{11}	8
WH_4	32		

In the experiment, the low-voltage windings are composed of WL_2 and WL_3. The high voltage winding is composed of WH_2, WH_3, WH_5, WH_6, WH_7, WH_9 and WH_{10}. 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 ε_1 and minimum detection range δ 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]
ε_1	0.00596
δ	0.00596

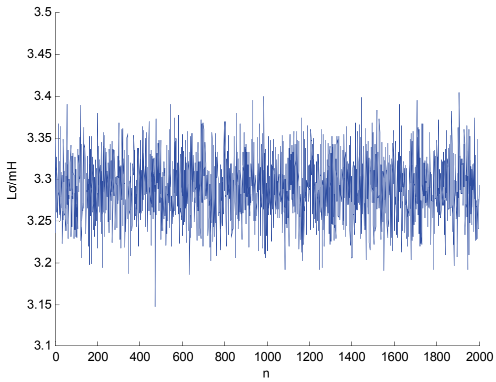


Fig. 7. The leakage inductance of transformer in normal operation

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 ε_1 in Table 2. The parameter DL_σ 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(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.

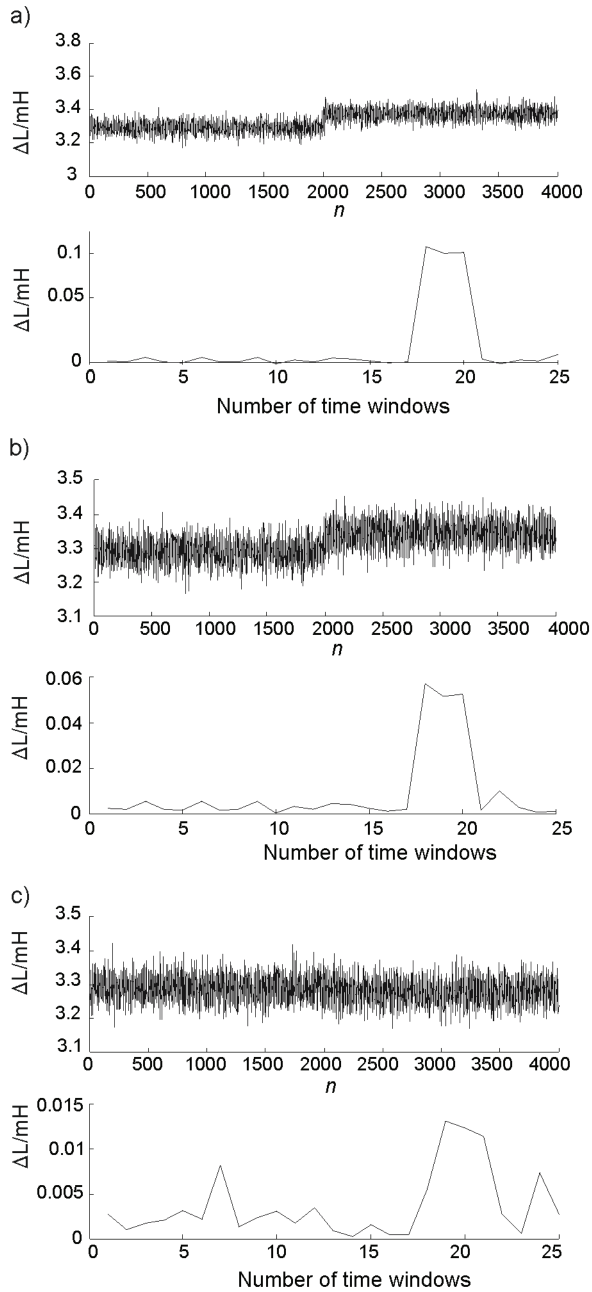


Fig. 8. Leakage inductance and the sum of changes

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.

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