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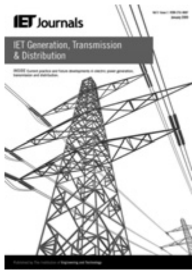

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Online monitoring of transformer winding axial displacement and its extent using scattering parameters and *k*-nearest neighbour method

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Abstract: The online monitoring of the transformer winding using scattering parameters fingerprint is presented. As a test object, a simplified model of transformer is used. The winding axial displacement is modelled on this test object. The scattering parameters of the test object are calculated using the high-frequency simulation software and measured using a network analyser. Two indices are defined based on the magnitude and phase of scattering parameters for the detection of the axial displacement. A new algorithm for the estimation of the axial displacement extent is presented using the proposed indices and high-frequency modelling of the transformer. To detect this mechanical defect and its extent, the *k*-nearest neighbour (*k*-NN) regression is suggested.

1 Introduction

The mechanical forces, mainly due to short circuits, can cause axial displacement and/or radial deformation of the transformer winding. These mechanical deformations and displacements may not cause a quick failure of the transformer, but the ability of the transformer to resist against future dielectric and mechanical stresses may be highly decreased [1, 2].

There are several transformer monitoring and diagnostic methods for different type of problems [3, 4]. Several offline methods such as short-circuit (SC) test method [1], low voltage impulse (LVI) method [5] and frequency response analysis (FRA) method [3] for the detection of the winding deformation have been proposed.

In the short-circuit test method, the short-circuit reactance is measured. In this method, the sensitivity of the reactance to the winding displacement is very low, and the type and the location of the mechanical damage in the winding cannot be determined [3]. FRA method is based on comparison, which can be performed: time-based, type-based, construction-based and model-based. This method can be used offline and online [6, 7].

In the offline method, the transformer is switched on and off on the high voltage side (HV-side). The transformer is disconnected from the power network on the low voltage side (LV-side) [6]. The well-known FRA method has been carried out offline [8].

In the online method, it is suggested that switching and lightning over-voltages could be used to determine the transfer function. This method does not require the switching of the transformer, but it is faced due to different problems as follows [9, 10]:

1. non-linear behaviour due to external/internal surge,
2. multiphase excitation of the transformer because of the electromagnetic coupling between phases,
3. the limited bandwidth of the recorded signal,
4. difficulty in distinguishing between excitation and response signals and
5. different reflections from different configurations of the substation [10].

The online FRA method is in the research phase and has not been applied to any practical transformer yet. The advantage of an online monitoring method to the offline methods is the prediction of the important fault before its occurrence [8].

A new online monitoring method based on the measured scattering parameter of the winding is proposed in this paper. This method, which is named *S*-parameters method, is also based on the comparison of measurement results with a reference curve. The simulations have shown that the scattering parameter of the winding can be used as a fingerprint for the detection of winding axial displacement or radial deformation [11, 12]. In another research, the effect of the antenna position for the online monitoring of transformer winding axial displacement using scattering parameters has been studied [13]. It is shown that changing the antenna position can affect the results of the simulated scattering parameters.

All our previous publications are just reporting the simulations results using the high-frequency simulation software (HFSS), but in this paper, both the simulation results of the scattering parameter of a simplified model of a transformer and the measurements using a network analyser are reported. Also, two indexes are suggested for the detection of the axial displacement of the winding. It is shown that the winding displacement extent can be determined by using the k-nearest neighbour (k-NN) regression [14].

2 Mechanical defects monitoring based on scattering parameters

In the S-parameters method, the transformer is considered as an N-port microwave network as shown in Fig. 1. The power can be injected or absorbed from the N anetnnas in the transformer tank. As a result, there are N incoming waves and N outgoing waves [15].

The N incoming waves are usually designated by a vector of N complex quantities, V_N^+ and the N outgoing waves are designated by a vector of N complex quantities, V_N^-, which are related as follows

$$\begin{bmatrix} V_1^- \\ V_2^- \\ \cdot \\ \cdot \\ V_N^- \end{bmatrix} = \begin{bmatrix} S_{11} & S_{12} & \cdot & \cdot & \cdot & S_{1N} \\ S_{21} & S_{22} & \cdot & \cdot & \cdot & S_{2N} \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ S_{N1} & S_{N2} & \cdot & \cdot & \cdot & S_{NN} \end{bmatrix} \begin{bmatrix} V_1^+ \\ V_2^+ \\ \cdot \\ \cdot \\ V_N^+ \end{bmatrix} \tag{1}$$

In (1), the $N \times N$ matrix with complex elements is the scattering matrix. The elements of this frequency-dependent matrix, which are termed 'S-parameters', determine the behaviour of the network.

The principle of the proposed S-parameters method is based on the comparison of the magnitude and phase of scattering parameters measured by ultra-high frequency (UHF) antennas. The reflected wave from the inside of the transformer can be received by the antennas. These antennas can be placed inside or outside the tank. If an antenna is placed outside the tank, then it should have a dielectric window which forms an electrical aperture for sending and receiving very high frequency electromagnetic waves. An externally mounted UHF sensor can be seen on the tank of a transformer shown in Fig. 1 [16].

The UHF sensors have been used for partial discharge detection inside the transformer and the antenna works in the receiving mode. In this paper, the idea is the application of the existing UHF band antennas in both transmitting and receiving modes for the detection of the mechanical defects. The data of the normal condition, that is, the new installed transformer, can be stored in a database as a base case. Then, the data can be measured in specified intervals and compared with the base case (scattering parameter), which is defined as the fingerprint of the transformer. Then, an expert system can be used to determine the occurrence, the type and the extent of mechanical defects.

The proposed S-parameters method is a new method to determine the mechanical defect of the transformer. The S-parameters method is based on comparisons like the FRA method that compares the measured transfer function with a reference one [3]. It should be noted that the proposed S-parameters method can be used online without disconnecting the transformer. For offline applications, detailed information about the setup, test procedure and the antenna position is needed to reproduce comparable results. It is because some parameters like changing the antenna position can alter the results [13].

In this paper, the comparison approach of scattering parameters is time-based. This approach is also the most accurate one in FRA results comparisons [16]. In this approach, the measured parameters are compared with the latest measurements. In the proposed S-parameters method, the time-based comparison can be accurately used, since the S-parameters method can be used online and the timing intervals between measurements can be decreased to have more information from the same transformer.

3 High-frequency simulation of transformer and measurement

For the detection of partial discharge using UHF sensors, the transformer has been modelled in the ultra-high-frequency band using finite-difference time-domain (FDTD) method [17]. The core and windings have been modelled using a unified metal structure. Fig. 2 shows the cylinders, which are the model of HV and LV windings. It is assumed that waves cannot enter the hole between disks and travel outside the winding.

In this research, a simplified model of the transformer has been simulated by HFSS as shown in Fig. 3. The model is based on an ideal metallic cylinder in a metallic box, as a

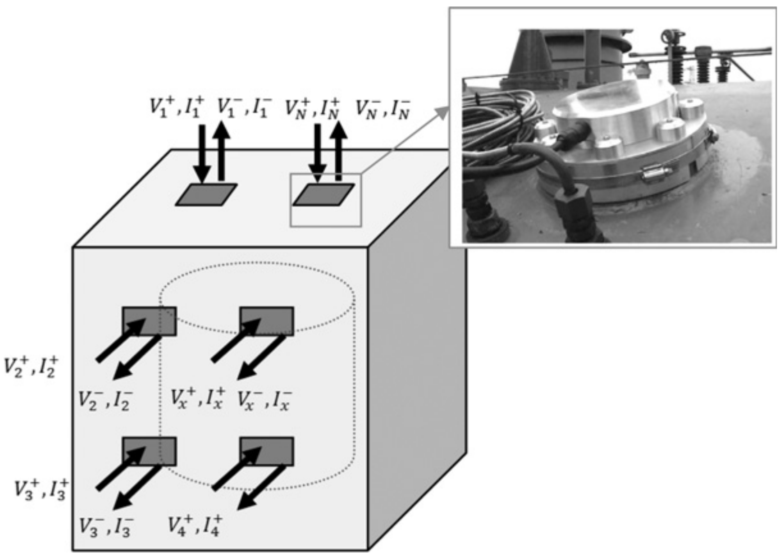

Fig. 1 *N-port network*

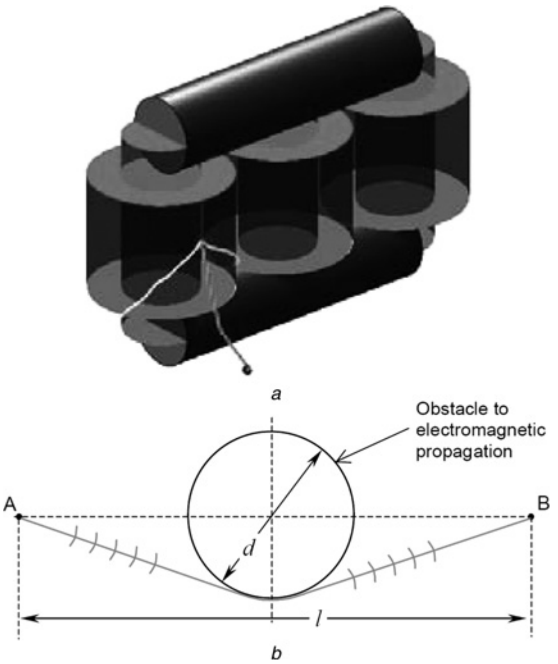

Fig. 2 *Simulated model of transformer using FDTD method*

a Three-dimensional view
b Top view of one phase [16]

first step of modelling. The inner metallic cylinder represents the LV winding, whereas the outer metallic cylinder represents the HV winding. The same as real transformer, the LV winding is slightly higher than the HV winding.

The sensitivity of the *S*-parameters method to the mechanical defects depends on the ratio of λ/(defect size). Therefore, if we use a higher operating frequency, more accurate results would be obtained in finding the mechanical defects. Although increasing the frequency can improve the accuracy of detection, the high-frequency electromagnetic waves may not propagate in the transformer oil. As the propagation of UHF band signals, resulted from the partial discharge, has been studied and verified in the transformer oil ambient, the frequency of the excitation in this research has been selected in the UHF band.

Building a model with mechanical defects in the size of a real transformer is very expensive and difficult, so the dimensions of the model and the defect sizes have been selected to be 20 times smaller than a real transformer as presented in Fig. 3. As a result, the excitation frequency should be 20 times higher than the UHF band (i.e. λ is 20 times smaller) for the simulation of the behaviour of UHF antennas in a real transformer. In this way λ/(defect size) ratio will become the same and the sensitivity to the mechanical defect will remain the same as the case with the dimensions of a real transformer.

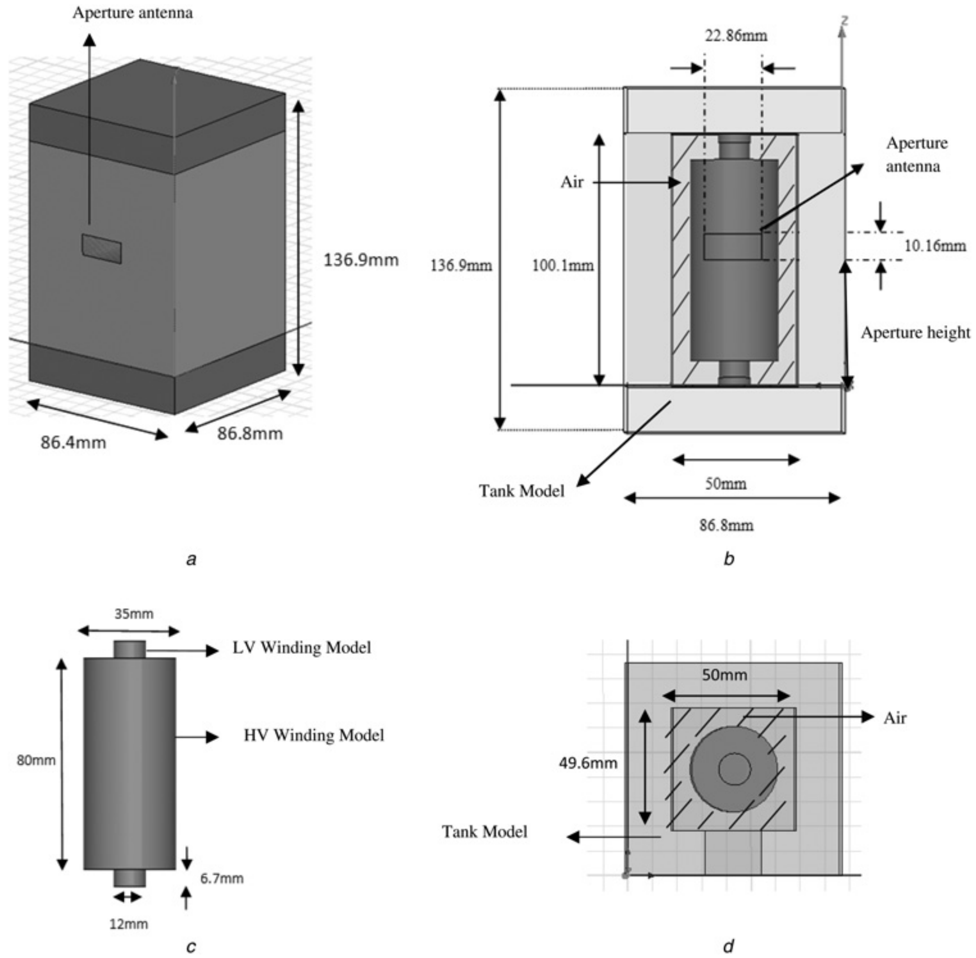

Fig. 3 *Simulated model of transformer*

a Three-dimensional view
b Side view of transformer model
c Side view of winding model
d Top view of transformer model

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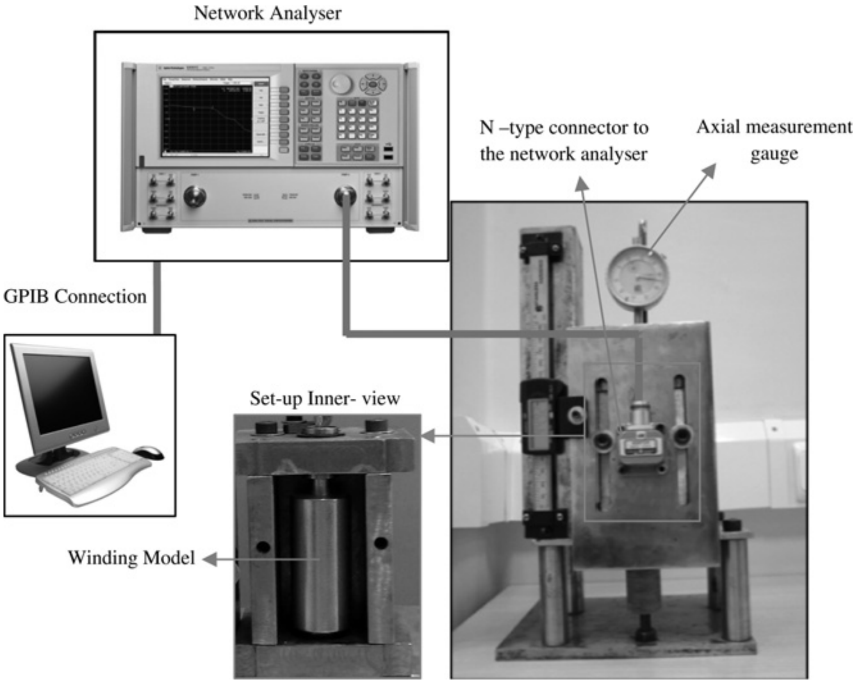

Fig. 4 *Measurement set-up and network analyser*

In this model, there is only one rectangular aperture. As a result, the S-matrix dimension is 1×1. The single element of the S-matrix is easily determined by the following equation

$$S_{11} = \frac{V_1^-}{V_1^+} \tag{2}$$

This equation can be written in the following simple form

$$|S_{11}| = \sqrt{\frac{P_{\text{ref}}}{P_{\text{in}}}} \tag{3}$$

where $|S_{11}|$ is the amplitude of the scattering parameter, P_{in} is the transmitting power and P_{ref} is the receiving power of the antenna.

The antenna, used in the model, is a rectangular aperture with the dimensions of a standard X-band waveguide (WR90). To make the results comparable, the antenna position for both measurements and simulations should be the same [13]. The excitation frequency should be between the first and second cut-off frequencies (i.e. 6.6 and 14.7 GHz, respectively) to have a single mode of propagation. In the real transformer, the disks have been separated by spacers. Although the distance between disks seems to be like a wave channel for wave propagation, but it can be modelled like a unified surface to decrease the simulation time. This simplification is based on this fact that the width of the gap between windings is less than 0.1 of the wavelength (i.e. $\lambda = 31$ mm in the middle of the frequency band) and the wave cannot enter the gap. It means that the excitation frequency is not high enough for penetrating in the gap between the high voltage disks; therefore the entire incident wave is reflected back from the surface and the winding can be modelled as a unified metal structure.

The scattering parameters have been calculated by using the HFSS software and measured by using a network analyser. The network analyser is an HP 8510 automatic vector network analyser [18]. It should be mentioned that the tests can be performed by any type of network analyser

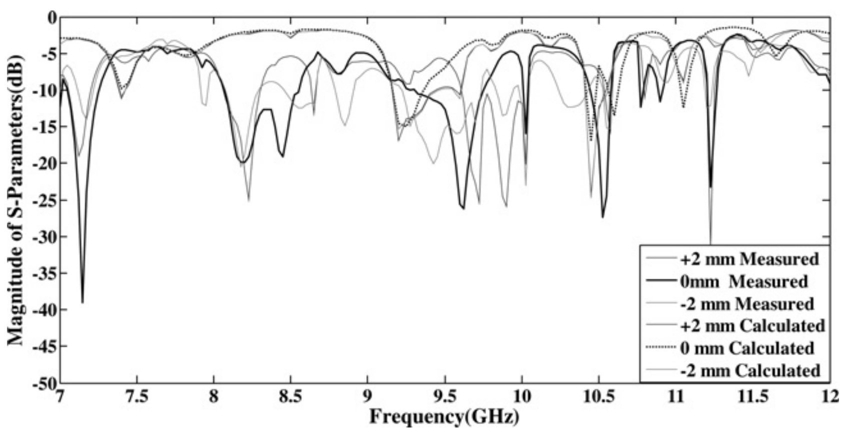

Fig. 5 *Calculated and measured magnitude of S-parameters against frequency for normal, upward and downward displacements*

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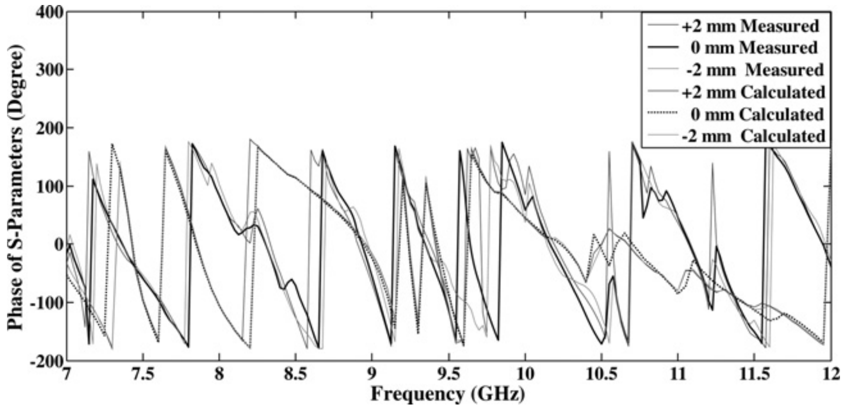

Fig. 6 *Calculated and measured phase of S-parameters against frequency for normal, upward and downward displacements*

that is capable of running tests from 7 to 12 GHz in 250 MHz steps. The model transformer is connected to the network analyser through a waveguide/coax connector and the network analyser cable. The results can be easily transmitted to a PC by using a GPIB connector. Fig. 4 shows the measurement set-up and the network analyser.

It should be mentioned again that the dimensions are 20 times larger in a power transformer. As a result, the frequency of the excitation should be 20 times smaller, that is, in the UHF frequency band. The cylinder is axially shifted in 0.1 mm steps for 94 different axial positions. In each position, the magnitude and phase of scattering parameters are measured and stored. The feature vector, used for the classification, contains both the magnitude and the phase at $n = 201$ frequencies (points). Figs. 5 and 6 show the calculated and measured magnitude and phase of scattering parameters over the frequency band for the reference position (normal condition) and for two other positions, respectively. The displacement is equal to 2.5% of the transformer height (a cylinder displacement of 2 mm in upward and downward directions). The detection accuracy of the axial winding displacement depends on the transmitter frequency, that is, decreasing the wavelength enhances the sensitivity to the displacement.

4 Detection and determination of winding axial displacement

In this paper, two approaches have been used for the detection and determination of the axial displacement. The first approach is based on the suggested displacement indices calculated by using the magnitude and phase of the scattering parameters. The second method is the k-NN method, which can exactly determine the axial displacement using a database of scattering parameters for different axial positions.

4.1 Displacement indices

Two indexes for the detection of the axial displacement are proposed. These indexes are based on the cross-correlation concept, which is a measure of similarity of two waveforms. The first index is the correlation of the S-parameters magnitude (CSM) defined as follows

$$\mathrm{CSM}(x, 0) = \mathrm{corr}(|S_x|, |S_0|) = \frac{\sum_{i=1}^{N}(|S_x(f_i)| - |\bar{S}_x|)(|S_0(f_i)| - |\bar{S}_0|)}{\sigma_1\sigma_2 N} \quad (4)$$

where σ_1 and σ_2 are defined as follows

$$\sigma_1 = \left(\frac{\sum_{i=1}^{N}(|S_x(f_i)| - |\bar{S}_x|)^2}{N}\right)^{(1/2)} \quad (5)$$

$$\sigma_2 = \left(\frac{\sum_{i=1}^{N}(|S_0(f_i)| - |\bar{S}_0|)^2}{N}\right)^{(1/2)} \quad (6)$$

In (4), CSM $(x, 0)$ is the cross-correlation of the S-parameters magnitude of x mm displacement ($|S_x|$) with the reference position ($|S_0|$), $|S_x(f_i)|$ and $|S_0(f_i)|$ are the S-parameter magnitude at frequency f_i in the position x and the reference position, respectively. N is the number of frequency axis points, $|\bar{S}_x|$ and $|\bar{S}_0|$ are the average of S-parameters magnitude over N for the position x and the reference position, respectively.

The second index is the correlation of the S-parameters phase (CSP) defined as follows

$$\mathrm{CSP}(x, 0) = \mathrm{corr}(\angle S_x, \angle S_0) = \frac{\sum_{i=1}^{N}(\angle S_x(f_i) - \angle\bar{S}_x)(\angle S_0(f_i) - \angle\bar{S}_0)}{\sigma_1\sigma_2 N} \quad (7)$$

where σ_1 and σ_2 are defined as follows

$$\sigma_1 = \left(\frac{\sum_{i=1}^{N}(\angle S_x(f_i) - \angle\bar{S}_x)^2}{N}\right)^{(1/2)} \quad (8)$$

$$\sigma_2 = \left(\frac{\sum_{i=1}^{N}(\angle S_0(f_i) - \angle\bar{S}_0)^2}{N}\right)^{(1/2)} \quad (9)$$

In (7), CSP$(x, 0)$ is the cross-correlation of the S-parameters phase of x mm displacement ($\angle S_x$) with the reference position ($\angle S_0$), $\angle S_x(f_i)$ and $\angle S_0(f_i)$ are the S-parameter phases at frequency f_i in the position x and the reference position, respectively. $\angle\bar{S}_x$ and $\angle\bar{S}_0$ are the average of S-parameters phases over N for the position x and the reference position, respectively. Figs. 7 and 8 show the calculated CSM and CSP against displacement at 201 frequency points (from 7 to 12 GHz) for the measured and calculated S-parameters. It is assumed that the central position of the cylinder is the reference position and the cylinder has a positive or negative (upward or downward, respectively) axial displacement.

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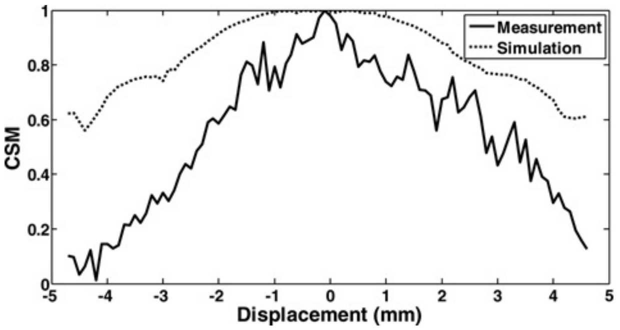

Fig. 7 *CSM against axial displacement (mm) for measured and simulated S-parameters*

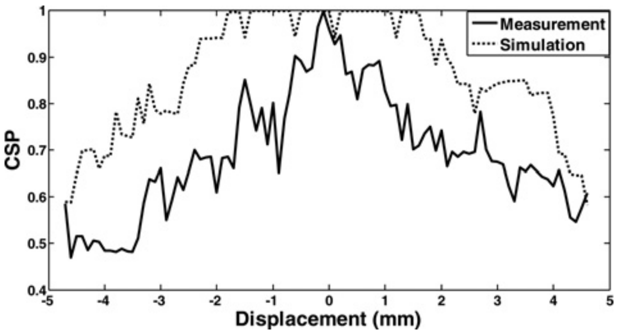

Fig. 8 *CSP against axial displacement (mm) for measured and simulated S-parameters*

The following points can be drawn from in these figures:

- These indices are inversely proportional to the increase of the axial displacement. As a result, they can be used as an index to detect the axial displacement and estimate the displacement extent, approximately.
- These indices cannot discriminate between the upward and downward displacements, that is, CSM and CSP are even functions of the displacement.
- The measurement results show the same trend as simulated results.
- CSM curve is more linear than the CSP curve.

It should be mentioned that the cross-correlation (CC) index has also been used for the interpretation of FRA test results [19]. To compare the *S*-parameters method with the FRA method, sensitivity of CC indexes to the axial displacement is calculated as follows

$$\text{Sensitivity} = \frac{\Delta\text{Cross} - \text{correlation Index}(\%)}{\Delta x(\%)} \tag{10}$$

where ΔCross-correlation Index(%) is the absolute of increment in the cross-correlation indices and Δx(%) is the absolute of change in the winding axial position (mm).

Table 1 lists the result of the calculation. It is obvious that the proposed method detects the axial displacement with a higher sensitivity compared to the FRA method.

The displacement detection and determination algorithm, which is shown in Fig. 9, can be summarised as follows:

Step 1: The measurement of scattering parameters of the specified type of the transformer in normal condition.
Step 2: Developing a databank for *S*-parameters in the specified axial displacements of the transformer winding. This databank can be generated by high-frequency modelling of the transformer winding in the specified positions.
Step 3: Calculating the CSM and CSP for the measured axial displacements of the databank.
Step 4: Application of CSM and CSP curves to estimate an unknown axial displacement occurrence and its extent in a sister unit transformer.

4.2 k-Nearest neighbour method

Nearest neighbour classifier (NNC) is a simple, popular and efficient classification algorithm, which assumes that the class label of an unknown pattern is the same as that of its nearest neighbour. When the number of neighbours is more than one, it extends to *k*-nearest neighbour (*k*-NN) classifier [20].

The *k*-NN classifiers have been widely used in pattern recognition, mainly because of its conceptual simplicity [21]. If the number of the training data is fixed, the error of NNC changes with the dimensionality of training data [20, 22].

The data are divided into two sets: training set and testing set. The training set is stored and used for classification, while the testing set is used to determine the classification accuracy. The performance of the classifier is determined according to the classification accuracy [20]. The training samples are denoted by *n*-dimensional numeric attributes. The *k*-NN algorithm searches the *k* training samples that are adjacent to the unknown sample given for the classification process. The closeness is measured in terms of Euclidean distance (ED) and can be calculated as follows

$$\text{ED}(z, y) = \sqrt{\sum_{i=1}^{n} (z_i - y_i)^2} \tag{11}$$

The unknown sample is classified according to the most occurring class among *k*-NNs. In a special case, if $k = 1$, it simply classifies the unknown sample to its nearest neighbour. The *k* values are chosen as odd numbers in the case of binary classification, so as to avoid the tied votes [23]. The best choice of *k* is dependent upon the data; usually, larger values of *k* decrease the effect of noise on the classification, but make the boundaries between classes ambiguous [24]. In [25], for instance, the distance between the unlabelled sample and each of its *k*-nearest training

Table 1 Comparison of *S*-parameters method with FRA method

	S-parameters method				FRA method
minimum detectable axial displacement (%)	0.125				0.5
cross-correlation Index	CSM		CSP		CC
	measurement	simulation	measurement	simulation	
sensitivity	0.2	0.1	0.18	0.15	0.001

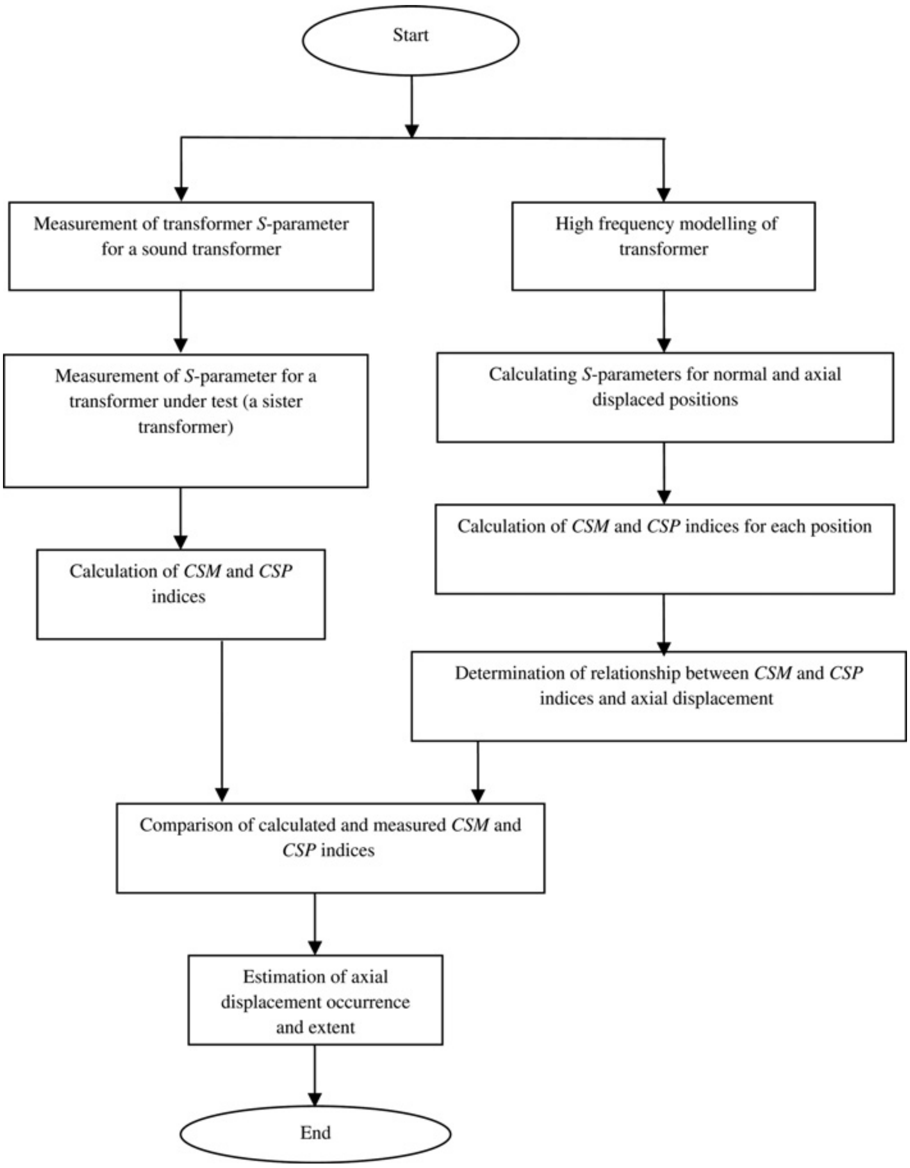

Fig. 9 *Algorithm of estimation of axial displacement extent*

samples is computed and then used as a weight to influence the global decision process. Other variants make use of fuzzy set and Dempster–Shafer theories to better exploit information conveyed by the set of k-nearest training samples [26, 27]. The k-NN error varies with the value of k, when the number of training patterns is fixed. Therefore the combination of multiple k-NNs with different k may improve the accuracy of the whole system [28].

The estimation of the axial displacement of the winding, which is a continuous parameter, is a regression problem. In this paper, a k-NN regression algorithm has been used for the estimation of the axial displacement by simply averaging the values of its k-NNs. It can be useful to weight contributions of neighbours, so that nearer neighbours contribute more to the average than the more distant ones. The proposed method can be summarised as follows:

Step 1: Store the pattern $S_x (1 \le x \le n)$ with the class label $l(S_x)$ into the training database, where S_x is the magnitude of scattering parameters and n is the number of training tests.
Step 2: Give a query pattern S_q, which is the scattering parameter magnitude of an unknown axial position, to be classified.
Step 3: Compute $\mathrm{ED}(S_q, S_x)$, which is the Euclidean distance between the query pattern S_q and each pattern S_x in the training database.
Step 4: Select the k-NN, that is, $\{S_{x1}, S_{x2}, \ldots, S_{xk}\}$, and its relating class label matrix $l(S_x) = \{l(S_{x1}), l(S_{x2}), \ldots, l(S_{xk})\}$ according to the Euclidean distance.
Step 5: Compute the weighting matrix according to (12)

$$W = \{1/\mathrm{ED}(S_q, S_{x1}), 1/\mathrm{ED}(S_q, S_{x2}), \ldots, 1/\mathrm{ED}(S_q, S_{xk})\} = \{W_1, W_2, \ldots, W_k\} \tag{12}$$

Step 6: Compute the class label of the query pattern by (13)

$$l(S_q) = \frac{\sum_{j=1}^{k} W_j l(S_{x_j})}{\sum_{j=1}^{k} W_j} \tag{13}$$

The class label of the query pattern, $l(S_q)$, is not necessarily limited to the class labels of the database and can change continuously according to the weighting matrix. As a result,

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Table 2 Test results of k-NN regression (d and d_e are real and estimated displacements, respectively)

d (mm)	k-NN regression									
	$k=3$		$k=5$		$k=7$		$k=9$		$k=11$	
	d_e, mm	Error, %	d_e, mm	Error, %	d_e, mm	Error, %	d_e, mm	Error, %	d_e, mm	Error, %
−4.3	−4.5	0.25	−4.4	0.125	−4.3	0	−4.2	0.125	−4.2	0.125
−3.9	−4.0	0.125	−4.0	0.125	−4.1	0.25	−4.0	0.125	−4.0	0.125
−3.3	−3.6	0.375	−3.6	0.375	−3.6	0.375	−3.5	0.25	−3.4	0.125
−2.9	−2.9	0	−2.8	0.125	−2.7	0.25	−2.7	0.25	−2.7	0.25
−2.3	−2.5	0.25	−2.4	0.125	−2.4	0.125	−2.3	0	−2.4	0.125
−1.9	−1.9	0	−1.8	0.125	−1.8	0.125	−1.8	0.125	−1.9	0
−1.3	−1.4	0.125	−1.5	0.25	−1.4	0.125	−1.5	0.25	−1.4	0.125
−0.9	−1.1	0.25	−0.7	0.25	−0.4	0.625	−0.1	1	−0.2	0.875
−0.3	−0.4	0.125	−0.3	0	−0.2	0.125	−0.3	0	−0.4	0.125
0.1	−0.1	0.25	−0.1	0.25	−0.2	0.375	−0.3	0.5	−0.2	0.375
0.7	1.0	0.375	0.9	0.25	0.9	0.25	0.8	0.125	0.7	0
1.1	1.0	0.125	1.0	0.125	1.1	0	0.9	0.25	0.8	0.375
1.7	1.5	0.25	1.3	0.5	1.3	0.5	1.4	0.375	1.4	0.375
2.1	2.1	0	1.9	0.25	2.0	0.125	1.8	0.375	1.7	0.5
2.7	2.8	0.125	2.7	0	2.6	0.125	2.2	0.625	2.2	0.625
3.1	3.2	0.125	3.2	0.125	3.3	0.25	3.4	0.375	3.3	0.25
3.7	3.7	0	3.7	0	3.6	0.125	3.5	0.25	3.6	0.125
4.1	4.2	0.125	4.1	0	4.1	0	4.0	0.125	4.0	0.125
4.7	4.4	0.375	4.3	0.5	4.2	0.625	4.1	0.75	3.5	1.5

Table 3 Comparison of average error per cent of k-NN method with different values of k

Method	k-NN ($k=3$)	k-NN ($k=5$)	k-NN ($k=7$)	k-NN ($k=9$)	k-NN ($k=11$)
Average error, %	0.171	0.184	0.230	0.309	0.322

this method can give a continuous estimation of the axial displacement.

The measured scattering parameters for the different axial position of the winding have been divided to the test and training data. The unknown positions of the test data have been calculated using the k-NN regression method and compared with the actual displacements. Table 2 lists the test results of the k-NN regression for unknown positions. The per cent of error is calculated by the following equation

$$\text{Error}(\%) = \frac{\text{Absolute Error}}{\text{Winding Height}} \times 100 \tag{14}$$

The average error per cent of the proposed method with different values of k is presented in Table 3.

The minimum detectable axial displacement is very important, because the tolerances are very fine for the transformer and displacements more than 1% can cause serious damages to the winding. So, it is important to detect the displacements below 1%. The minimum detectable axial displacement using the S-parameters fingerprint is 0.125% of the winding height, that is, 0.1 mm. But, this minimum displacement in the FRA method is 0.5% of the transformer winding height [19]. In [29], the minimum detectable axial displacement using the FRA method is 4% of the winding height. This shows higher sensitivity of S-parameters method compared to FRA method.

5 Conclusions

In this paper, the online monitoring of the transformer winding by using scattering parameters has been presented. In this research, the scattering parameter of a simplified model of transformer has been calculated using a HFSS and measured by using a network analyser in different axial positions. Two indices have been defined by using the magnitude and phase of scattering parameters to detect the axial displacement. The results show that these indices can be used to detect the winding displacement and present information about the approximate amount of the displacement. A new method for the detection of the axial displacement extent has been proposed by using the k-NN method, too. It has been shown that the method has great accuracy in finding the unknown displacement of the winding and can discriminate between upward and downward displacements.

The proposed S-parameters method has the following advantages:

- In the S-parameters method, there is no electrical connection to the windings and the transformer tank. Therefore neither the high voltage nor the low voltage windings of the transformer should be disconnected from the network. As a result, the S-parameters method is an online method.
- The S-parameters method cannot be affected by the power factor of the load and loading conditions because the antennas are isolated electrically from the winding and transformer tank.

- The S-parameters method can be used for offline applications, too.
- Transformers can be monitored in specific intervals or continuously.
- The axial displacement can be detected and determined using the proposed S-parameters method.
- The sensitivity of the proposed method to axial displacements is higher than the FRA method, because of measurement at higher frequencies.

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7 References

1 Xu, D.K., Huang, J.H., Li, Y.M.: 'Online monitoring of winding deformation of power transformer'. Proc. 2001 Int. Symp. Electrical Insulating Materials, 2001 (ISEIM 2001), 2001, pp. 853–856
2 Morched, A.S., Marti, L., Brierley, R.H., Lackey, J.G.: 'Analysis of internal winding stresses in EHV generator step-up transformer failures', *IEEE Trans. Power Deliv.*, 1996, **11**, (2), pp. 888–894
3 Christian, J., Feser, K.: 'Procedures for detecting winding displacements in power transformers by the transfer function method', *IEEE Trans. Power Deliv.*, 2004, **19**, (1), pp. 214–220
4 Rahimpour, E., Christian, J., Feser, K., Mohseni, H.: 'Transfer function method to diagnose axial displacement and radial deformation of transformer windings', *IEEE Trans. Power Deliv.*, 2003, **18**, (2), pp. 493–505
5 Chen, W., Sun, C., Yun, Y., Xie, Z.: 'Study on the recognition of transformer winding deformation by using wavelet transform in the LVI method'. Proc. Int. Conf. Power System Technology 2002, PowerCon2002, 2002, vol. 3, pp. 1966–1969
6 Leibfried, T., Feser, K.: 'Monitoring of power transformers using the transfer function method'. IEEE Winter Meeting Power Engineering Society 1999, 31 January–4 February 1999, vol. 2, p. 1046
7 Leibfried, T., Feser, K.: 'Off-line- and on-line-monitoring of power transformers using the transfer function method'. IEEE Int. Symp. on Electrical Insulation, 16–19 June 1996, vol. 1, pp. 34–37
8 Tenbohlen, S., Stirl, T., Bastos, G., *et al.*: 'Experience-based evaluation of benefits of on-line monitoring systems for power transformers'. CIGRE Session 2002, paper 12-110, Paris, 2002
9 Leibfried, T., Feser, K.: 'On-line monitoring of transformers by means of the transfer function method'. IEEE Int. Symp. on Electrical Insulation, Pittsburgh, PA, USA, 5–8 June 1994
10 Wimmer, R.: 'Die Ermittlung der Übertragungsfunktion von Grosstransformatoren mittels on-und offline-Messungen'. Dissertation, Stuttgart University, 2010
11 Hejazi, M.A., Gharehpetian, G.B., Mohammad, A.: 'Characterization of on-line monitoring of transformer winding axial displacement using electromagnetic waves'. 15th Int. Symp on High Voltage Engineering, ISH 2007, Ljubljana, Slovenia, 27–31 August 2007
12 Hejazi, M., Gharehpetian, G.B., Mohammadi, A.: 'On-line monitoring of the radial deformation of transformer winding using radar cross section'. 15th Int. Symp. on High Voltage Engineering, ISH 2007, Ljubljana, Slovenia, 27–31 August 2007
13 Hejazi, M.A., Choopani, M., Dabir, M., Gharehpetian, G.B.: 'Effect of antenna position of transformer winding axial displacement measurement using electromagnetic waves'. Second IEEE Int. Conf. Power and Energy 2008 (PECon 2008), Johor Bahru, Malaysia, 1–3 December 2008
14 Denoeux, T.: 'A k-nearest neighbor classification rule based on Dempster-Shafer theory', *IEEE Trans. Syst. Man Cybern.*, 1995, **25**, (5), pp. 804–813
15 Pozar, D.M.: 'Microwave engineering' (Wiley, 2005, 3rd edn.)
16 Judd, M.D., Yang, L., Hunter, I.B.B.: 'Partial discharge monitoring of power transformers using UHF sensors. Part I: sensors and signal interpretation', *IEEE Electr. Insul. Mag.*, 2005, **21**, (2), pp. 5–14
17 Judd, M.D., Yang, L., Craddock, I.J.: 'Locating partial discharges using UHF measurements: a study of signal propagation using the finite-difference time-domain method'. Proc. XIVth Int. Symp. on High Voltage Engineering, Tsinghua University, Beijing, China, 25–29 August 2005
18 www.agilent.com
19 Nirgude, P.M., Ashokraju, D., Rajkumar, A.D., Singh, B.P.: 'Application of numerical evaluation techniques for interpreting frequency response measurements in power transformers', *IET Sci. Meas. Technol.*, 2008, **2**, (5), pp. 275–285
20 Wang, L.J., Wang, X.L., Chen, Q.C.: 'GA-based feature subset clustering for combination of multiple nearest neighbors classifiers'. Proc. 2005 Int. Conf. Machine Learning and Cybernetics, August 2005, vol. 5, pp. 2982–2987, see also pp. 18–21
21 Cover, T., Hart, P.: 'Nearest neighbor pattern classification', *IEEE Trans. Inf. Theory*, 1967, **13**, (1), pp. 21–27
22 Jain, A.K., Chandrasekaran, R.: 'Dimensionality and sample size considerations in pattern recognition practice', in Krishnaiah, P.R., Kanal, L.N. (Eds.): 'Handbook of statistics, v2, classification, pattern recognition, and reduction of dimensionality' (North-Holland, New York, 1982), pp. 835–855
23 Panigrahi, B.K., Pandi, V.R.: 'Optimal feature selection for classification of power quality disturbances using wavelet packet-based fuzzy k-nearest neighbour algorithm', *IET Gener. Transm. Distrib.*, 2009, **3**, (3), pp. 296–306
24 Parveen, P., Thuraisingham, B.: 'Face recognition using multiple classifiers'. 18th IEEE Int. Conf. Tools with Artificial Intelligence, ICTAI '06, November 2006, pp. 179–186
25 Dudani, S.A.: 'The distance-weighted k-nearest-neighbor rule', *IEEE Trans. Syst. Man Cybern.*, 1976, **SMC-6**, (4), pp. 325–327
26 Keller, J.M., Gray, M.R., Givens, J.A.: 'A fuzzy k-nearest neighbor algorithm', *IEEE Trans. Syst. Man Cybern.*, 1985, **15**, (4), pp. 580–585
27 Zhu, H., Basir, O.: 'An adaptive fuzzy evidential nearest neighbor formulation for classifying remote sensing images', *IEEE Trans. Geosci. Remote Sens.*, 2005, **43**, (8), pp. 1874–1889
28 Wang, L.J., Wang, X.L., Chen, Q.C.: 'Combination of multiple k-NNCS by fuzzy integral'. Int. Conf. Machine Learning and Cybernetics', August 2006, pp. 1774–1778
29 Karimifard, P., Gharehpetian, G.B., Tenbohlen, S.: 'Determination of axial displacement extent based on transformer winding transfer function estimation using vector-fitting method', *Eur. Trans. Electric Power (ETEP)*, 2008, **18**, (4), pp. 423–436

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