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A new method for evaluation of transformer drying process using transfer function analysis and artificial neural network

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Abstract: Since a few years ago, there is an increasing interest for utilization of transfer functions (TF) as a reliable method for diagnosing of mechanical faults in transformer structure. However, this paper aims to develop the application of TF method in order to evaluate the drying quality of active part during the manufacturing process of transformer. To reach this goal, the required measurements are carried out on 50 MVA 132 KV/33 KV power transformer when active part is placed in the drying chamber. Two different features extracted from the measured TFs are then used as the inputs to artificial neural network (ANN) to give an estimate for required time in drying process. Results show that this new represented method could well forecast the required time. The results obtained from this method are valid for all the transformers which have the same design.

Key words: transformer, drying process, transfer function, artificial neural network

1. Introduction

Power transformers are one of the most important and expensive equipments in electrical power transmission system or in an electrical distribution system. Therefore, any defect into them directly will increase the maintenance costs and reduce the network reliability. Also, it may lead to pay notable penalty to consumers due to network outage. Therefore, many techniques in monitoring and diagnosing several faults have been considered by electrical energy suppliers. Each technique can be applied for a specific type of problem and has its own merits. Among these methods, transfer function (TF) method which is generally known frequency response analysis (FRA), is increasingly being used to detect winding physical damages [1-7].

The TF method can be briefly described as following: Any power transformer may be represented by a complex network of resistances, inductances and capacitances. These electrical elements depend on mechanical geometry inside the transformer, as well as the electrical properties of the insulating materials used in the construction. Any change in these values will result in a measurable shift in the frequency response of transformer in comparison to reference response. In fact, TF analysis is basically a comparative method, in which one performs the frequency measurements over a wide frequency range and compares the result with a fingerprint measurement [8-10]. The TF method is usually applied as an on-site fault diagnostic method.

Beside above discussion, this paper represents a new application of TF which is used for assessment of the transformer drying quality during manufacturing stages. Because the electrical elements of windings in their equivalent circuits are affected by moisture content, this idea is occurring to the mind that the changes in the form of TF in high frequency ranges can be used as an index for degree of insulation dryness. As a result, TF analysis based on ANN is used as a reliable method to evaluate drying quality of power transformers.

In order to better understanding of author's idea, the drying process is described in the following. Drying process is one of the most important stages in transformers manufacturing stages which its quality is directly proportional with transformer lifetime [11]. If drying process is done well, the failure of this equipments will also greatly reduced. At the manufacturing site of power transformers when active part is formed, it must be dried in drying chamber under high vacuum and temperature. Its takes even a few days depend on the voltage level and the insulation quality of the transformer. So, this stage of manufacturing is a bottleneck in the production line. During the drying process the released water are collected and according to the rate of absorbed water the sufficiency of drying and consequently the time period that the active part must remain in the furnace is controlled. This open-loop control strategy has some disadvantages and causes the drying process to last more than the time actually required or before a sufficient dryness due to a failure in drying procedure, the process being terminated. To solve the problem a direct measurement of insulation dryness is needed while the active part is in the drying chamber. It is evident that measurement of moisture content of the active part insulation particularly under the environmental condition of the furnace is not a simple task.

Based on above discussion, with respect to long time duration in drying stage and furnaces limitation in factory, obtaining an estimation of required time in drying process can be very valuable and economical. In this regard, a new application of TF analysis is proposed which has the following advantages:

1) An intelligent method is introduced to evaluation of drying quality of transformers. For this purpose ANN is used, which is very popular classification method.
2) Two well-known algorithms are presented to compare the TFs for a proper extraction of features for training and validation of ANN. Moreover, these methods are compared with each other.
3) The results of the proposed method are verified. This verification shows that this new represented method could well forecast the required time in drying process.

2. Description of the ANN Employed

Two processing capabilities, its parallel distributed structure and its ability to learn, make it possible for the neural networks to solve complex and large scale problems. Design of ANN includes a set of inputs, outputs, network topology and weighted connection of nodes. Extraction of input features is the first and also important step. These features are extracted very carefully because they must correctly reflect the characteristics of the problem. Another major task of the ANN design is to choose network topology. This is done experimentally through a repeated process to optimize the number of hidden layers and nodes according to training performance and prediction accuracy. Weighted connection of node in the ANN is achieved by training algorithm. For many years there was no theoretically sound algorithm for training multi layer feed forward ANN, hence, the applications of the ANN were limited for different aspects. The invention of back propagation algorithm has played a vital role in the resurgence of interest in the ANN. Back propagation is a systematic method for training multi layer ANN. It has a strong mathematical foundation [15].

The proposed neural network is constructed as three layer feed-forward structure with the input, hidden, and output layers. The numbers of input layers depend on the size of input matrixes. Also, two hidden layers, with 5 nodes in each layer, were used. Each of the hidden nodes accumulates a sum of inputs presented at the input layer multiplied by a weighting factor for each connection. The output node accumulates the sum of the outputs of the 5 hidden nodes (second hidden layer). According to this fact that output matrix has only one dimension, output layer has only 1 neuron.

In this work, an ANN which is available in MATLAB toolbox [16] is used to estimate the required time in transformer drying process. For this purpose, the ANN is trained using the Back-propagation learning algorithm. This algorithm consists of repeatedly passing the training sets through the neural network until its weights and biases minimize the output error. The initial learning rate is assumed one ($\eta = 1$). And the training error limit is 0.00001 (0.2%) which is obtained in approximately 30000 training epochs. If the calculated performance error is below the training error limit, the training of the neural network ends. Activation functions of the input layer and hidden layers are the “sigmoid” function, and that of the output layer is the “pure-line” function.

3. Test objects and measurements

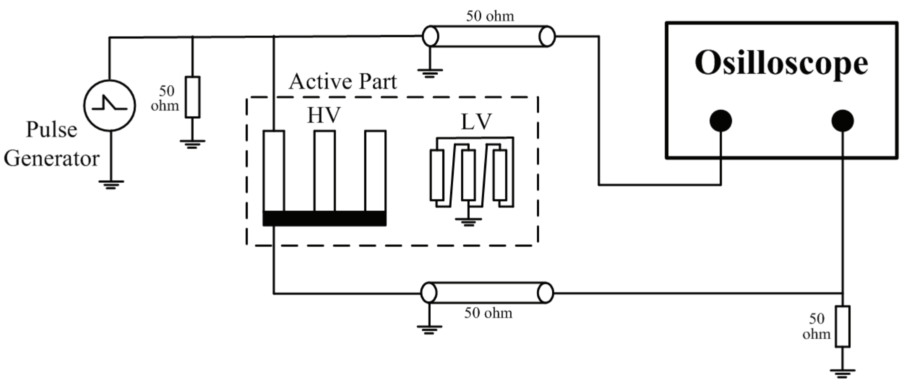
One of the methods of measuring the transformer winding TF is impulse voltage method. In this method, a steep impulse or step voltage is applied to the winding as input and simultaneously the voltage or current at the other terminal is measured as output. If the input signal involves enough frequency components to excite all desired oscillatory modes of the winding, the frequency behavior or TF can be extracted accurately.

In this paper, TF measurements have been performed for the active part of a 50 MVA 132 KV/33 KV power transformer while the active part had been placed in drying chamber in different time intervals during drying process.

Figure 1a and Figure 1b show a view of implemented instrumentation system and its schematic diagram, respectively. Using the pulse generator, a suitable step pulse with a rise-time of 100 nsec and the amplitude of 140 V is applied to the high voltage winding of a phase and the current is measured at the end of coil via a pure 50 Ω resistor shunt. The input and output signals were sampled with 500 Msps using a digital storage oscilloscope. These two time domain signals stored were converted into ASCII data and transferred to the computer for further processing.

The converted sampled data are zero padded to avoid spectral leakage. Also in order to obtain lower frequency range in the frequency response curves, exponential window is applied to the new time domain data before transforming in the frequency domain. Finally, the TF between applied voltage and response current is computed by dividing their spectra in the frequency domain employing fast Fourier transform (FFT) technique. Using the established setup, 30 measurements are performed while the active part was under drying process in drying chamber for about 66 hours. Note that because of low vacuum degree in furnace, the maximum applied voltage should not be more than 300 V.

a) A view of test object in high voltage laboratory



b) Schematic of measurement circuit

Fig. 1. Transformer under test in high voltage laboratory

4. Transfer functions comparison

Every transformer has a unique TF which is independent of input waveform shape. The FRA method is used to compute the transfer characteristic between the applied voltage and response current by dividing their frequency spectra in the frequency domain employing FFT technique.

The measured results in this contribution show that the enhancement of drying time affects the TFs and modify them, differently. Variations of measured TF for different times during early hours of process is significant rather than last hours of drying process. For instance, Figure 2 indicates the variations of TF for three different time intervals during early hours of process. Also, Figure 3 shows the variations of TF for three different time intervals during end hours of drying process. The measured TF at the end of drying process, is considered as a reference TF and the other TFs (in different time intervals) are compared against the reference one. Sound features extracted from these TFs can easily lead to valid time estimation.

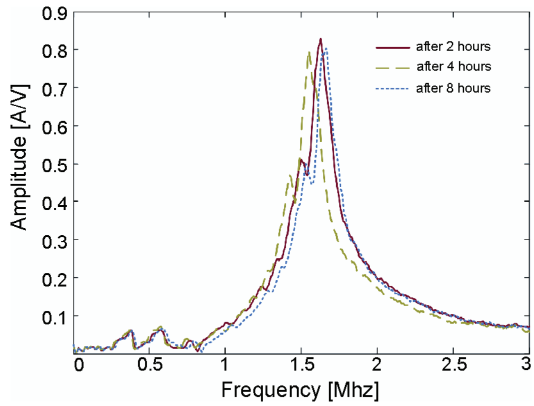


Fig. 2. The measured TFs for three different time intervals (2, 4, and 8 hours) during early hours of process

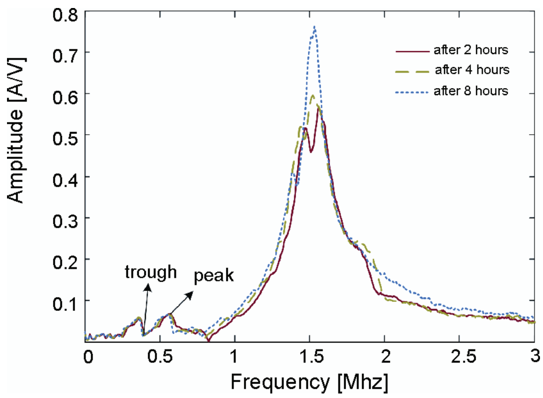


Fig. 3. The measured TFs for three different time intervals (58, 60, and 64 hours) during end hours of process

To reach this goal, there are various comparative algorithms which are introduced in the literatures [3-5, 12-14]. One of the reliable methods for comparison of TFs versus the reference TF is developed by application of the mathematical indices such as index of frequency ratio (IFR), index of amplitude ratio (IAR) and the other one is correlation coefficient (CC). In this paper, both of them are used. Afterward, using algorithms based on IFR, IAR and CC methods, appropriate indices are extracted with the required accuracy. The features extracted with IFR, IAR and CC methods are then used as inputs to ANN in order to predict the required time for drying process. These methods will be described briefly here.

4.1. IFR and IAR Indices

In transformer drying process, the significant changes on TF characteristics are in peak and trough points (this is shown in Figures 2, 3). Thus, the frequency and amplitude variations in these points can be used as reliable indices to train the ANN. The variation of the i-th frequency, in peak and trough points; also referred to i-th index of frequency ratio (IFR) is defined as follows:

$$IFR_{ti} = \frac{f_{o,ti}}{f_{k,ti}}, \tag{1}$$

$$IFR_{pi} = \frac{f_{o,pi}}{f_{k,pi}}, \tag{2}$$

where $f_{k,\,ti}$ and $f_{o,\,ti}$ represent i-th frequency in trough points and $f_{k,\,pi}$ and $f_{o,\,pi}$ are i-th frequency in peak points (k indicates reference TF and o is indication of other conditions).

Similarly, the variation of amplitude in the peak and trough points, are represented through the index of amplitude ratio as follows:

$$IAR_{ti} = \frac{A_{o,ti}}{A_{k,ti}}, \tag{3}$$

$$IAR_{pi} = \frac{A_{o,pi}}{A_{k,pi}}, \tag{4}$$

where $A_{k,ti}$ and $A_{o,ti}$ represent the amplitude of TF at i-th trough point, and $A_{k,pi}$ and $A_{o,pi}$ are the amplitude of TF at i-th peak point, respectively.

4.2. CC Index

The correlation coefficient is a measure for the similarity of two curve progressions. For two TFs —TF_1 and TF_2— this factor can be determined as follows:

$$CC = \frac{\sum_{i=1}^{N}\left[TF_1^*(f_i)\cdot TF_2^*(f_i)\right]}{\sqrt{\sum_{i=1}^{N}\left[TF_1^*(f_i)\right]^2\cdot\left[TF_2^*(f_i)\right]^2}}. \tag{5}$$

At which:

$$TF_1^*(f_i) = |TF_1(f_i)| - \frac{1}{N}\sum_{i=1}^{N}|TF_1(f_i)|, \tag{6}$$

$$TF_2^*(f_i) = |TF_2(f_i)| - \frac{1}{N}\sum_{i=1}^{N}|TF_2(f_i)|. \tag{7}$$

The measured TFs (Figure 2 and Figure 3) imply that the changes in TFs do not spread equally over the entire frequency range but are often bounded in several frequency areas. On the other hand, CC to compare the TFs devotes a numeric value that is not suitable for training the neural networks. Hence, studying the TFs in smaller frequency ranges could be helpful in training of ANN. In this regard, the three ranges are called: 1) low frequency (LF): 0-1 MHz; 2) medium frequency: MF: 1-2 MHz; and high frequency (HF): 2-3 MHz and the calculated CC for these ranges are CC_{LF}, CC_{MF}, and CC_{HF}, respectively, for LF, MH, and HF.

5. Time estimation using ANN

In general, an ANN process is formed from three steps: in the first step measurements should be carried out to acquire TFs needed. The second step is related to feature extraction, in which the most proper features found for prediction. In the third step, using features extracted in the previous step, the prediction will be done. Extracted features in previous items are used for training ANN. Then, using trained ANN decision will be made on new data.

5.1. Feature extraction

In order to estimation of the required time to dry of power transformers, features extraction is based on using the information of TFs. The measured TF at the end of drying process is considered as a reference TF and the other TFs (in different time intervals) are compared against the reference one. Therefore, the defined indices in Equations (1)-(4) can be applied as an input to ANN. On the other hand, the CC between two measured TFs in the three frequency ranges is changed due to drying process. So, these coefficients (Eq. 5) are used as another efficient index for training of ANN.

5.2. Training procedure

To train ANN first of all, its structure (input/output data) should be determined. In order to improve the prediction performance, two different conditions of extracted features have been tried.

In first state, the defined indices in Equations (1)-(4) have been used for training of ANN. Therefore, input matrix in this case (feature 1) can be defined as Equation (8).

$$input_{feature1} = \begin{bmatrix} IFR_{t1,ti_1} & \cdots & IFR_{t1,ti_s} \\ \vdots & \cdots & \vdots \\ IFR_{tj,ti_1} & \cdots & IFR_{tj,ti_s} \\ IFR_{p1,ti_1} & \cdots & IFR_{p1,ti_s} \\ \vdots & \cdots & \vdots \\ IFR_{pk,ti_1} & \cdots & IFR_{pk,ti_s} \\ IAR_{t1,ti_1} & \cdots & IAR_{t1,ti_s} \\ \vdots & \cdots & \vdots \\ IAR_{tj,ti_1} & \cdots & IAR_{tj,ti_s} \\ IAR_{p1,ti_1} & \cdots & IAR_{p1,ti_s} \\ \vdots & \cdots & \vdots \\ IAR_{pk,ti_1} & \cdots & IAR_{pk,ti_s} \end{bmatrix} \tag{8}$$

where in (8): *ti*: is abbreviation of time interval, *s*: shows the number of time intervals that TF is measured, and *j, k*: represent the number of trough and peak points in measured TFs, respectively.

In second state, the defined index in equations (5) is used for training of ANN. Equation (9) shows the input matrix in this case (feature 2):

$$input_{feature2} = \begin{bmatrix} CC_{LF,ti_1} & \cdots & CC_{LF,ti_s} \\ CC_{MF,ti_1} & \cdots & CC_{MF,ti_s} \\ CC_{HF,ti_1} & \cdots & CC_{HF,ti_s} \end{bmatrix}, \tag{9}$$

where CC is correlation coefficient, and s shows the number of time intervals that TF is measured.

Meanwhile, the output of ANN is single dimension vector that shows the required time to dry. After finding features 1, 2, results of these calculations are applied to ANN as an input.

It should be noted that in order to obtain a suitable measure for comparison, the features extracted (Eqs. 8, 9) should be normalized using the following equation:

$$X = \frac{x - \mu}{sd}, \tag{10}$$

where x stands for each of the matrix rows (in Eqs. 8, 9), μ and sd denote the mean value and standard deviation of x, and X is the normalized vector of x.

5.3. Results and discussion

Accidentally 70% of measured data are used for network training and 30% are used for its validations. After training, data related to validation is applied to it. The results obtained from validation of network are shown in Figures 4 and 5.

The obtained results are satisfying. In proposed method both features (1, 2) have come up with appropriate results, although the accuracy of feature 1 is higher than feature 2. It can be explained that the figures of measured TFs are generally similar, except in location of frequencies and amplitudes in peak and trough points. Consequently, the statistical indices such as CC are the same for many TFs and therefore they are not suitable as the inputs of neural network. As a result, it is difficult for ANN to estimate the drying time in feature 2.

It can be summarized that: an ANN based method with feature 1 produces the best results in estimation of drying time. Thus, it can be used for evaluating the drying quality in power transformers as a reliable method.

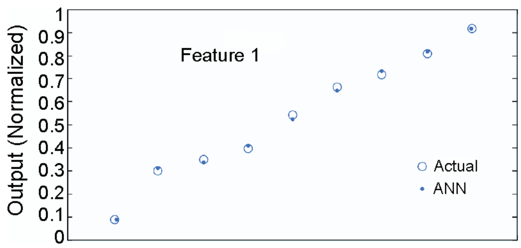


Fig. 4. Performance of ANN in response to validation data (feature 1)

Fig. 5. Performance of ANN in response to validation data (feature 2)

6. Conclusion

Estimation of the required time for drying of power transformers is an important subject for transformer manufacturers. However, it is not possible find a reliable method for this purpose, in the literatures. In this paper, a new method for estimation of above mentioned time is proposed by application of ANN technique. The proposed method is able to accurately estimate the drying time. For training and testing purposes of the ANN, the measured data related to 50 MVA 132 KV/33 KV power transformer is employed. After extracting the features of the measured TFs by IFR and IAR indices (feature 1) and CC method (feature 2), they are applied to ANN algorithm. The validation process reveals that the proposed method, based on ANN using feature 1, has a high accuracy. This method is valid to predict required time of drying process for all same design power transformers in production lines.

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