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A probabilistic feature to determine type and extent of winding mechanical defects in power transformers

K. Pourhossein[a,*], G.B. Gharehpetian[b,1], E. Rahimpour[c], B.N. Araabi[d]

[a] Department of Engineering, Science and Research Branch, Islamic Azad University, Tehran, Iran
[b] Electrical Engineering Department, Amirkabir University of Technology, Tehran, Iran
[c] ABB AG, Power Products Division, Transformers, R&D Department, Bad Honnef, Germany
[d] Control and Intelligent Processing Centre of Excellence, Department of Electrical and Computer Engineering, University of Tehran, Tehran, Iran

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ABSTRACT

Frequency response analysis (FRA) is a widely-used method to detect axial displacement (AD) and radial deformation (RD) in windings of power transformers, because of its high sensitivity to small amount of mechanical defects. Interpretation of frequency response curves has been the most intricate problem of FRA method. To solve it, different numerical indices have been introduced by researchers to evaluate the frequency response of power transformers, but (1) the researchers have not discussed on genesis origin of the proposed indices and (2) most of these indices can not present a regular and linear behavior. In this paper, a probabilistic feature has been utilized to demonstrate how an efficient index originates, to diagnosis axial displacement and radial deformation in windings of power transformers. The resulted index presents a nearly linear mapping between frequency response curves and their related defect extent. To verify usefulness of this index, it has been applied to several sets of measured frequency response curves. It is illustrated that the extracted index is able to determine extent of the defects. To discriminate between axial displacement and radial deformation, local behavior of TF curves has been used.

1. Introduction

Power transformers belong to the most expensive and most important equipments in electrical power transmission and distribution systems. Failure of a power transformer is a very costly event and cause reduction of the power system reliability and interruption of power supply [1,2]. Failures and their location in transformers are reported in [3] as follows; on-load tap changers (41%), winding (19%), tank/fluid (13%), terminal (12%), accessories (12%) and core (3%). Minor mechanical defects in windings are hard to detect in power transformers but they may lead to sudden and severe faults. High short-circuit currents and improper transportation are well-known causes of these defects. There is no reliable statistics about percentage for causes of mechanical defects in power transformer windings because different factors that cause a mechanical failure are not independent from each other. For example, usual short-circuit currents can not distort windings if there is not an incipient asymmetry in windings due to improper transportation, reduction in clamping pressure, insulation aging and so on. Such deformations do not necessarily lead to an immediate failure of transformer, but its ability to withstand future mechanical and dielectric stresses may be strongly reduced [4,5]. A reliable detection of mechanical failures in power transformers, due to winding displacement and deformation, requires the implementation of a sensitive method for the detection of this type of damage without opening the unit [4]. FRA, also called TF, method that was introduced by Dick and Erven in [6], is the most sensitive and widely used method for this purpose [4]. Practical experiences, as well as scientific investigations, show that currently no other diagnostic test method can deliver such a wide range of reliable information about the mechanical status of a transformer's active part (core-coil assembly) [7]. TF method is based on the concept that changes in the windings due to deformation and displacement cause changes in the parameters of the transformer (capacitances, inductances. . .) and consequently a modification of its TF [4]. Based on a set of TF traces (mainly the amplitude shown over the frequency), an evaluation of the transformer's mechanical condition can be made. Although FRA is emerging as a powerful diagnostics technique, there is still no general guideline for interpreting resultant TFs. In test fields, the evaluation is presently done by experts in the topic through the visual inspection of TF traces. In some cases two experts' opinion may differ considerably. On

* Corresponding author. Tel.: +98 914 1060783, fax: +98 411 5544154.
E-mail addresses: k.pourhossein@yahoo.com (K. Pourhossein), grptian@aut.ac.ir (G.B. Gharehpetian).
[1] Tel.: +98 21 646 6009; fax: +98 21 640 6469.

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the other hand, some manufacturing industries use their own procedure. Organizations such as IEEE and CIGRE are attempting to develop standards, guidelines and tests for TF method on transformers [7]. The most important methods, proposed so far for the interpretation of FRA results, can be classified in three categories, as follows:

(I) *Using an Equivalent Circuit*. These equivalent circuits consider the behavior of the core and windings as a function of the frequency [4], [8–11].
(II) *Using Mathematical Models*. In these methods the TF is considered as a rational function with real coefficients [12,13].
(III) *Using Numerical Indices*. In literature, different deterministic and statistical numerical indices have been used for TF Interpretation [14], namely: correlation coefficient (CC) [15,16], spectrum deviation (SD) [16] and maximum absolute difference (DABS). Other parameters such as sum squared error (SSE), sum squared ratio error (SSRE), sum square max–min ratio Error (SSMMRE) and absolute sum of logarithmic error (ASLE) [17] were proposed by the authors in order to improve the interpretation of TF results [4].

The numerical indices preferred to use in transformer industry because they are straightforward and easy to implement in comparison to the other above-mentioned methods. The numerical indices act as mapping from the space of the transfer function to the space of the defect extent. In spite of their usefulness, they suffer from following two disadvantages:

(1) The researchers have not discussed on genesis origin of the proposed indices.
(2) Most of these indices can not present a regular and linear behavior.

In the subsequent sections, a probabilistic reasoning will be used to illustrate how a useful index can be extracted to diagnose axial displacement and radial deformation in windings of power transformers. The linearity of obtained index will be compared to other useful indices.

2. Probabilistic classification

The TF evaluation may be considered as a probabilistic classification problem in order to determine the type and extent of mechanical defects in power transformers. Any degree of defect may be treated as a class of defect. Then, a probabilistic classifier should be designed in order to classify an unknown TF curve, named TF_x, in the most probable class of k defect classes. It is assumed that the number of classes, k, is known. Each TF curve is uniquely represented by a single vector that contains amplitudes of measured points and it belongs to only one class of defect. Given TF_x and a set of k classes, i.e., d_i; $i = 1, 2, \ldots k$, the bayes theory [18] states that:

$$P(d_i|\mathrm{TF}_x) = \frac{p(\mathrm{TF}_x|d_i)P(d_i)}{p(\mathrm{TF}_x)} \quad (1)$$

where $P(d_i)$ is the priori probability of class d_i and $p(\mathrm{TF}_x)$ is the probability density function (pdf) of TF_x, expressed by the following equation:

$$p(\mathrm{TF}_x) = \sum_{i=1}^{k} p(\mathrm{TF}_x|d_i)P(d_i) \quad (2)$$

The bayes classification rule can now be written, as follows:

$$\mathrm{TF}_x \text{ is classified to } d_j \textit{ if } \quad P(d_j|\mathrm{TF}_x) > P(d_i|\mathrm{TF}_x), \quad \forall i \neq j \quad (3)$$

$p(\mathrm{TF}_x)$ is not taken into account, because it is the same for all classes and it does not affect the final decision [18]. Furthermore, if the priori probabilities are equal, (3) becomes:

$$\mathrm{TF}_x \text{ is classified to } d_j \textit{ if } \quad p(\mathrm{TF}_x|d_j) > p(\mathrm{TF}_x|d_i), \quad \forall i \neq j \quad (4)$$

where $P(d_i|\mathrm{TF}_x)$ is the posteriori probability of class d_i given the value of TF_x. $p(\mathrm{TF}_x|d_i)$, is the class conditional pdf of TF_x given d_i (sometimes called the likelihood of d_i with respect to TF_x) [19].

Instead of working directly with probabilities, it may be more convenient, from a mathematical point of view, to work with an equivalent function of them, for example, $h_i(\mathrm{TF}_x) = f(p(d_i|\mathrm{TF}_x))$, where $f(\cdot)$ is a monotonically increasing function. $h_i(\mathrm{TF}_x)$ is known as a discriminant function [18]. The decision test, i.e., (4), is now rewritten, as follows:

$$\text{classify } \mathrm{TF}_x \text{ in } d_j \text{ if } \quad h_j(\mathrm{TF}_x) > h_i(\mathrm{TF}_x) \quad \forall i \neq j \quad (5)$$

The central limit theorem states that the pdf of the sum of a number of statistically independent random variables tends to the gaussian one as the number of summands tends to infinity [20]. In practice, this is approximately true for a large enough number of summands. This is the case we confront in this investigation. The multidimensional gaussian pdf in the n-dimensional space has the following form:

$$p(\mathrm{TF}_x) = \frac{1}{(2\pi)^{n/2}|S|^{1/2}} e^{(-1/2(\mathrm{TF}_x - m)^T S^{-1}(\mathrm{TF}_x - m))} \quad (6)$$

where m is the mean vector (representative of the defect class), S is the covariance matrix defined by $S = E[(\mathrm{TF}_x - m)(\mathrm{TF}_x - m)^T]$ and $|S|$ is the determinant of S. Because of the exponential form of the involved densities, it is preferable to work with the following discriminant functions, which involve the (monotonic) logarithmic function, $\ln(\cdot)$:

$$h_i(\mathrm{TF}_x) = \ln(p(\mathrm{TF}_x|d_i)p(d_i)) = \ln p(\mathrm{TF}_x|d_i) + \ln P(d_i) \quad (7)$$

or

$$h_i(\mathrm{TF}_x) = -\frac{1}{2}(\mathrm{TF}_x - m)^T S_i^{-1}(\mathrm{TF}_x - m) + \ln P(d_i) - \left(\frac{n}{2}\right)\ln 2\pi - \left(\frac{1}{2}\right)\ln|S| \quad (8)$$

If we now assume that the covariance matrix is the same in all classes, i.e., $S_i = S$, and neglecting constant terms, then we have:

$$h_i(\mathrm{TF}_x) = -\frac{1}{2}(\mathrm{TF}_x - m)^T S^{-1}(\mathrm{TF}_x - m) \quad (9)$$

The Eq. (9) presents a well-known mathematical distance function called mahalanobis distance. The key point is that a probabilistic classifier leads to a distance function. If the covariance matrix is the identity matrix, the Mahalanobis distance reduces to the Euclidean Distance (ED) function [18]. It must be stated that the Euclidean Distance function is often used instead of mahalanobis distance, because of its simplicity, even if we know that the previously stated assumptions are not valid [19]. The Euclidean Distance or Euclidean metric is the distance between two points in Euclidean space. The Euclidean Distance between TF_x and TF_i is defined, as follows [19]:

$$\mathrm{ED}_i = ||\mathrm{TF}_x - \mathrm{TF}_i|| = \sqrt{(\mathrm{TF}_x - \mathrm{TF}_i)^T(\mathrm{TF}_x - \mathrm{TF}_i)} \quad (10)$$

where $\mathrm{TF}_i = [l_{i1}, l_{i2} \ldots l_{in}]$, $\mathrm{TF}_x = [l_{x1}, l_{x2} \ldots l_{xn}]$ and T stands for transpose of the vector. j-th belongs to j-th class of defect if:

$$\mathrm{ED}_j < \mathrm{ED}_i, \quad \forall i \neq j \quad (11)$$

It assigns an unknown TF curve to the class whose representative is closest to it with respect to the Euclidean norm.