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A survey on statistical indexes applied on frequency response analysis of electric machinery and a trend based approach for more reliable results

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ABSTRACT

This work presents some guidelines in order to achieve a more reliable diagnosis using the frequency response analysis (FRA) technique. Conventionally, this technique relies on comparisons between spectra obtained at different stages of the machine lifespan. A difference between the spectra may indicate the onset of a failure. However, these comparisons are very subjective to the experience of the analyst. To achieve a more objective diagnosis, statistical indexes have been introduced in the literature of FRA. This work presents a survey on these indexes and also compares them using experimental data. Another contribution of this work is the proposition of a trend based diagnostics. Thus, even if the FRA measurements are obtained at different temperatures/humidity or other external factors, the trend curve of the indexes is able to provide a more reliable diagnosis.

1. Introduction

Condition based monitoring (CBM) methods have gained a lot of attention in the recent years, due to the possibility of schedule maintenance work and avoid loss of production. Among CBM methods used for diagnosis of failures in electric machines, it can be highlighted the frequency response analysis (FRA) technique. FRA has been widely used on transformers [1] and, recently, has gained attention on rotating machines [2]. Although FRA is essentially an offline technique, Ref. [3] reports several efforts towards online operation on in-service transformers.

Basically, the FRA technique consists in the injection of a high frequency signal into the windings of the machine and the calculation of a spectrum of a given quantity (impedance, admittance, etc.) over frequency (more details about this technique, such as circuit topology and type of excitation, can be found in Ref. [4]). Then, the obtained spectrum is compared against its historical data. Differences between the spectra may indicate the onset of a failure in the machine under test. However, the inconvenience of this technique is that a specialist is required to analyze the data and provide a diagnosis of the machine condition.

Several statistical indexes have been proposed in the literature ([5–16], each of them are discussed in Section 2), where the result is a number that gives a more objective indication of the machine condition. Nevertheless, each of these indexes has its own particularities and it is advisable to use more than one to double check the results.

However, the use of these indexes only gives a numerical result on how much the two spectra being compared differ from each other. Most of the time, the measurements have some degree of imprecision, being affected by external factors such as temperature and humidity. In the case of rotating machines, there is still another factor that affects the results, which is the variation of winding inductance with the variation of rotor position [17,4]. In these cases, where external factors have influence on the measurements, a single comparison of spectra (using statistical indexes or not) may result in a wrong diagnosis. To avoid such errors, Ref. [4] has proposed to analyze a trend curve of the results. This proposition is further developed in Section 3 of this paper. With the proposed approach, even if there is imprecision in the measurements, the analysis of the trend curve gives a more clear indication of the machine condition.

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2. Statistical indexes used on FRA literature

This section presents a survey on the statistical indexes already proposed on the literature of FRA. These indexes express how similar (or how different) two sets of data $X = \{x_1, x_2, \ldots, x_n\}$ and $Y = \{y_1, y_2, \ldots, y_n\}$ are.

2.1. Correlation coefficient (CC)

In the FRA literature, the CC index is usually expressed by two different formulas, whose results may be different, depending on the average value of the measurements. The first one is given by Eq. (1) and is discussed in Kennedy et al. [5],[1] Wimmer et al. [6], Secue and Mombello [7],[2], Reykherdt and Davydov [8], Badgujar et al. [9], IEEE-Std-C57 [1] and Behjat and Mahvi [10]. The second formula is given by Eq. (2) and is discussed in Ryder [11], Kim et al. [12], Nirgude et al. [13], Tang et al. [14], Ji et al. [15] and Bagheri et al. [16].

$$CC_1 = \frac{n\sum_{i=1}^{n}[x_i \cdot y_i] - \sum_{i=1}^{n}x_i \cdot \sum_{i=1}^{n}y_i}{\sqrt{\left[n\sum_{i=1}^{n}x_i^2 - \left(\sum_{i=1}^{n}x_i\right)^2\right] \cdot \left[n\sum_{i=1}^{n}y_i^2 - \left(\sum_{i=1}^{n}y_i\right)^2\right]}} \tag{1}$$

$$CC_2 = \frac{\sum_{i=1}^{n}[x_i \cdot y_i]}{\sqrt{\sum_{i=1}^{n}x_i^2 \cdot \sum_{i=1}^{n}y_i^2}} \tag{2}$$

2.2. Mean squared error (MSE)

The MSE index is given by Eq. (3) and is discussed in Badgujar et al. [9]. This same index is also known as sum squared error (SSE) in Kim et al. [12].

$$MSE = \frac{\sum_{i=1}^{n}(x_i - y_i)^2}{n} \tag{3}$$

2.3. Root mean squared error (RMSE)

The RMSE index is given by Eq. (4) and is discussed in Badgujar et al. [9]. This same index is also known as standard deviation (SD) in Nirgude et al. [13] and Bagheri et al. [16].

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(x_i - y_i)^2}{n-1}} \tag{4}$$

2.4. Comparative standard deviation (CSD)

The CSD index is given by Eq. (5) and is discussed in Badgujar et al. [9].

$$CSD = \sqrt{\frac{\sum_{i=1}^{n}[(x_i - \mu_X) - (y_i - \mu_Y)]^2}{n-1}} \tag{5}$$

where μ_X and μ_Y are the average values of sets X and Y, respectively.

2.5. Sum squared ratio error (SSRE)

The SSRE index is given by Eq. (6) and is discussed in Kim et al. [12].

$$SSRE = \frac{\sum_{i=1}^{n}\left(\frac{y_i}{x_i} - 1\right)^2}{n} \tag{6}$$

2.6. Sum squared max–min ratio error (SSMMRE)

The SSMMRE index is given by Eq. (7) and is discussed in Kim et al. [12].

$$SSMMRE = \frac{\sum_{i=1}^{n}\left(\frac{\max(x_i,y_i)}{\min(x_i,y_i)} - 1\right)^2}{n} \tag{7}$$

2.7. Absolute sum of logarithmic error (ASLE)

The ASLE index is given by Eq. (8) and is discussed in Kim et al. [12].

$$ASLE = \frac{\sum_{i=1}^{n}|20\log_{10}y_i - 20\log_{10}x_i|}{n} \tag{8}$$

2.8. Absolute difference (DABS)

The DABS index is given by Eq. (9) and is discussed in Secue and Mombello [7].

$$DABS = \frac{\sum_{i=1}^{n}|y_i - x_i|}{n} \tag{9}$$

2.9. Minimum–maximum ratio (MM)

The MM index is given by Eq. (10) and is discussed in Secue and Mombello [7].

$$MM = \frac{\sum_{i=1}^{n}\min(y_i, x_i)}{\sum_{i=1}^{n}\max(y_i, x_i)} \tag{10}$$

2.10. Spectrum deviation (σ)

The σ index is given by Eq. (11) and is discussed in Tang et al. [14] and Ji et al. [15].

$$\sigma = \frac{1}{n}\sum_{i=1}^{n}\sqrt{\left(\frac{x_i - (x_i + y_i)/2}{(x_i + y_i)/2}\right)^2 + \left(\frac{y_i - (x_i + y_i)/2}{(x_i + y_i)/2}\right)^2} \tag{11}$$

2.11. Hypothesis tests (t-test and f-test)

Two types of hypothesis tests are found in the FRA literature: *t*-test (proposed by Badgujar et al. [9]) and *f*-test (proposed by Behjat and Mahvi [10]). In both cases, the procedure consists in finding a *p*-value, that indicates the probability of a null hypothesis being true. The null hypothesis considers that the average of measurements at a given condition is equal to the average of measurements at the baseline condition.

The first step is the calculation of the test statistics (*t* or *f*, depending on the test) and the degrees of freedom ν. Then the *p*-value can be obtained in tables of cumulative distribution functions or using a numerical software (such as Matlab, Minitab, Excel, etc.).

Considering a *t*-test (as proposed by Badgujar et al. [9]), the test statistics is given by Eq. (12) and the degrees of freedom by Eq. (13).

$$t_0 = \frac{X - Y}{\sqrt{\frac{S_X^2}{n_X} + \frac{S_Y^2}{n_Y}}} \tag{12}$$

[1] It can be analytically proved that the formula presented in [5] is the same as Eq. (1).

[2] The formula presented in [7] is the same as Eq. (2), however, considering $x_i = x_n - \mu_X$ and $y_i = y_n - \mu_Y$, it results in Eq. (1).