Fuzzy Logic Based Identification of Deviations in Frequency Response of Transformer Windings

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Abstract—**Sweep frequency response analysis (SFRA) is a leading winding deformation diagnostic technique employed for power transformer windings. Statistical indicators are invariably used to judge the amount of deviations between two sets of SFRA data. This paper presents a complementary way to judge the deviations using a fuzzy logic approach. It helps a user to take cue from chosen statistical indicators for confirming the level of deviation. The technique is validated through a few case studies.**

Keywords: frequency response analysis, statistical parameters, transformer winding

I. Introduction

FREQUENCY response analysis is an established technique for diagnosing deformations in windings of transformers [1-3]. The frequency response of the winding is compared with its fingerprint and any deviation between the two can be suspected as due to some kind of deformation.

There are a few other reasons [4–6] also, which may lead to different responses. The possible phenomena are: (1) an individual phase has minor constructional disparity, (2) difference in internal lead to bushing connections, (3) differences in layouts and connections of measuring instrument leads, (4) different amounts of stored residual energies, (5) different lengths of magnetic paths in case of design based comparison between end and central phases, etc. Hence, the first check while diagnosing is to judge whether the deviation is due to reasons listed above or due to some kind of deformation. The responses should be examined carefully and an expert intervention is essential for the diagnostics.

In practice, large deviations, due to fault/s, can be identified through visual inspection. One such case for a medium power transformer is shown in Fig.1. The transformer had a short circuit between its low voltage winding and core. The design based comparison of the SFRA curves shows large/unusual deviations. In such cases, the issue is to investigate as to what kind of fault/major deformation has led to the large deviation in data. On the other hand, in majority of the cases, when the transformer is working normally, during a routine maintenance if a frequency response is captured and compared, minor deviations may be observed. Under such cases, to identify a deviation and to correlate it to a deformation is a major challenge. Some SFRA instrument manufacturers suggest ± 3 dB difference between the curves as normal/allowable, although this is not universally accepted. For such cases, researchers take help of statistical indicators to quantify the amount of the deviation between the data sets. Many statistical parameters have been proposed in past to numerically represent the amount of deviation.

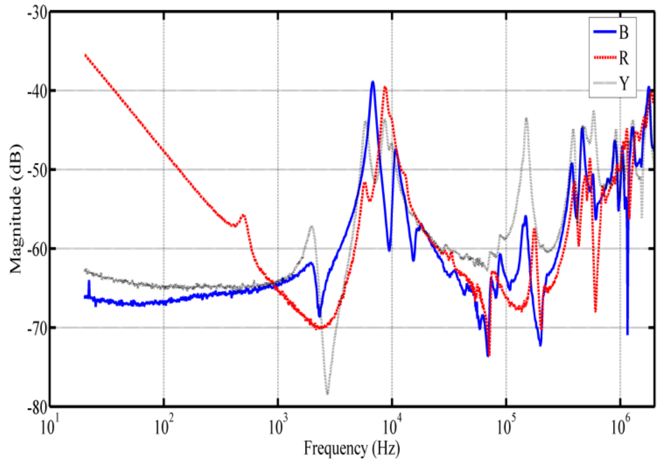

Fig. 1 Frequency responses of a transformer with a LV-core short-circuit [courtesy: GETCO]

Indicators such as correlation coefficient (CC), root means square error (RMSE), mean square error (MSE), absolute sum of logarithmic error (ASLE), absolute difference (DABS), min-max ratio (MM) etc. have been introduced in past [7–12]. Recently, two new indicators, viz., comparative standard deviation (CSD) and *t*-test have been proposed [13]. It is observed that in certain borderline cases, it is difficult to take decision based on a single parameter. All these parameters need to be used in a complementary way to come to a conclusion [7], [13]. In literature, such an approach has rarely been attempted [14] to the best of authors' knowledge. In this work, a fuzzy logic based approach has been proposed, which takes into account a value given by each of the above mentioned statistical indicators (SIs) and gives an output which would aid the diagnosis process.

The paper is organized as follows. Section II does a brief review of the major statistical indicators including the recently proposed parameters e.g. CSD and *t*-test. Section III presents the fuzzy logic based approach. Section IV gives the application of the fuzzy method to a few cases. Section V concludes the work and identifies the scope of future work.

II. A Review of SIs for SFRA studies

In literature, various SIs have been used to aid the SFRA diagnosis. They give a measure of the difference between the compared data. In this work, the considered indicators are CC, RMSE, MSE, ASLE, DABS, MM, CSD, and *t*-test. The CC parameter is one of the most employed parameters for SFRA. It gives correlation of the two compared data; a value approaching to '1' indicates a good match between the compared curves [7–12]. MSE gives the average of difference between the squares of data points [12]. RMSE is nothing but the square root of the MSE parameter. DABS parameter averages the absolute difference between the data sets [7], [10], while ASLE does the same but on a log scale [7], [9], [11], [12]. MM is a ratio of sum of minimum of each data pair to that of maximum, for a considered frequency interval [7], [10]. CSD has been recently proposed to correctly make use of the concept of standard deviation (SD); it compares SD of the two data sets [13]. The key feature of the *t*-test is that it gives binary answer, 0 or 1, for no appreciable deviation and considerable deviation, respectively. The other beneficial feature is that it does not require two compared data sizes to be same [13].

The CC and MM parameters are sensitive to sharp changes in the compared data, but are less sensitive to smoother and constant deviations. The sensitivity of ASLE and DABS to differences in amplitudes in sub-ranges of frequency could be reduced, since these are calculated by averaging. MSE is, sometimes, an ill-scaled parameter that exaggerates / underestimates the deviations as a squaring operation is involved in it [12]. RMSE and CSD, generally, give similar values. The *t*-test does not indicate the severity of the deviation as it gives a *binary* answer. The sensitivity of each SI along with its limitation is documented in [13]. The decision about the deviation, based on a single SI, may lead to erroneous judgement. A complementary approach, taking clue from each indicator, is the best way to arrive at a conclusion about the deviation between the data sets. The following section proposes a fuzzy logic based approach to harmonize the eight statistical indicators to aid SFRA diagnostics.

III. The FL based algorithm

The SIs, considered in this work, are observed to give results which are bound by their individual sensitivity. Sometimes, these SIs give conflicting indications which may lead to confusion about deviations. Fuzzy logic based systems are useful under such cases, wherein the membership of each input parameter is used to conclude a single output [15]. The proposed FL based algorithm tries to map each SI value into a triangular membership function. Eight membership functions are defined based on their normal range of values. The range of each parameter is defined as given in Table 1. These ranges are derived through a study involving many field SFRA data. The expert is free to choose his own range of data according to his/her perception about the parameter.

Table 1 Normal range of SIs

Sr. no.	SI	Range
1	CC	0.8 ↔ 1
2	MSE	0 ↔ 9
3	RMSE	0 ↔ 3
4	ASLE	0 ↔ 0.6
5	DABS	0 ↔ 2.4
6	MM	1 ↔ 1.09
7	CSD	0 ↔ 3
8	*t*-test	0 and 1

For negligible deviations, the values of CC, MSE, RMSE, ASLE, DABS, MM, and CSD should be close to 1, 0, 0, 0, 0, 1, and 0 respectively, while the value of *t*-test should be 0. As each of the SIs has different range of values, they are normalized between 0 and 1.

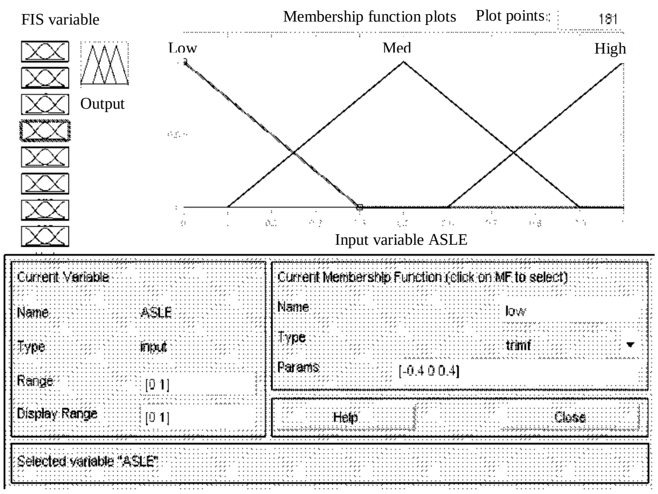

Fig. 2 Triangular membership function for each SI

The normalized value of each SI is multiplied with a weight factor. The weights assigned to various SIs can be different to reflect their significance. In the present study, all the eight weight factors are kept as 1, as equal weightage has been given to each SI. Each SI value is given a linguistic attribute as low, med and high, as shown in Fig. 2 through triangular membership function.

The SI values are then given to a fuzzy inference system (FIS). In the study 'MAMDANI' FIS is employed, which is the most popular FIS [16]. The output is mapped through triangular membership functions. The centroid method is employed for its defuzzyfication. The seven SIs can hold three linguistic logic levels while the eighth SI, i.e. the *t*-test, can hold two levels.

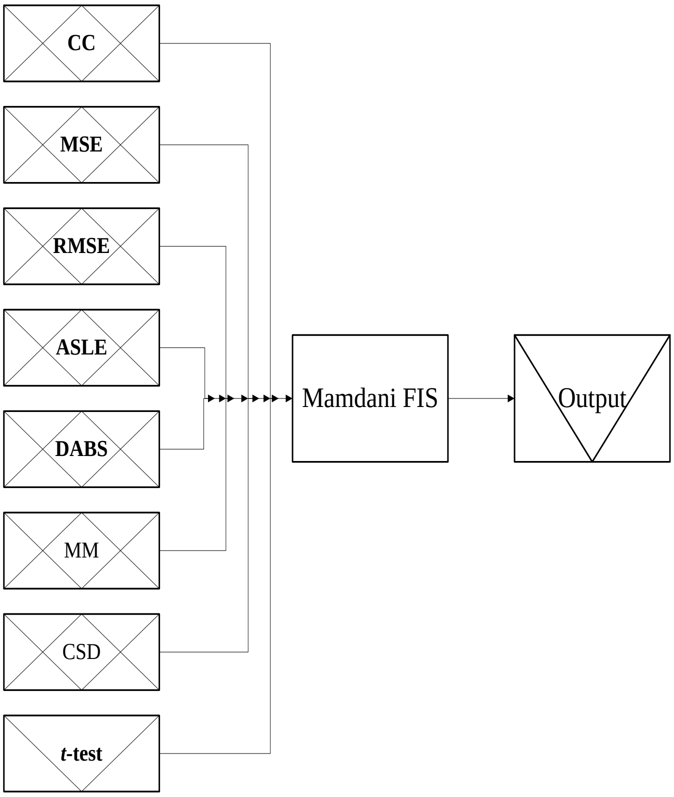

Fig. 3 The Fuzzy Inference System (FIS)

It is difficult to formulate rules for eight input variables and one output variable manually; therefore a code is written in MATLAB for the purpose. Total 4378 rules ($3^7 \times 2 = 4378$) are formed, using if…then logic. The FL system is kept flexible in a way such that any number of SIs can be accommodated, since the corresponding rules are formed through the code. The block diagram of the Fuzzy system is given in Fig. 3 while the logic of the algorithm is explained through a flow chart given in Fig. 4. The output value can hold a value between 0 and 1. The output can be categorized into three regions of the linguistic variable: low, med and high deviation level. A low value (0 ↔ 0.33) indicates a minor deviation, a med value (0.33 ↔ 0.66) represents moderate amount of deviation, while a high value (0.66 ↔ 1) indicates significant deviation. The results, thus obtained, are more trustworthy as the method considers eight established SIs; a user can include more SIs depending upon the available expertise. Merely the indication of a deviation does not give conclusion about damage or deformation; however the expert will get an authentic confirmation about the amount of deviation. Ultimately the expert has to decide if the deviation is normal or investigable. The proposed algorithm is now validated through a few case studies.

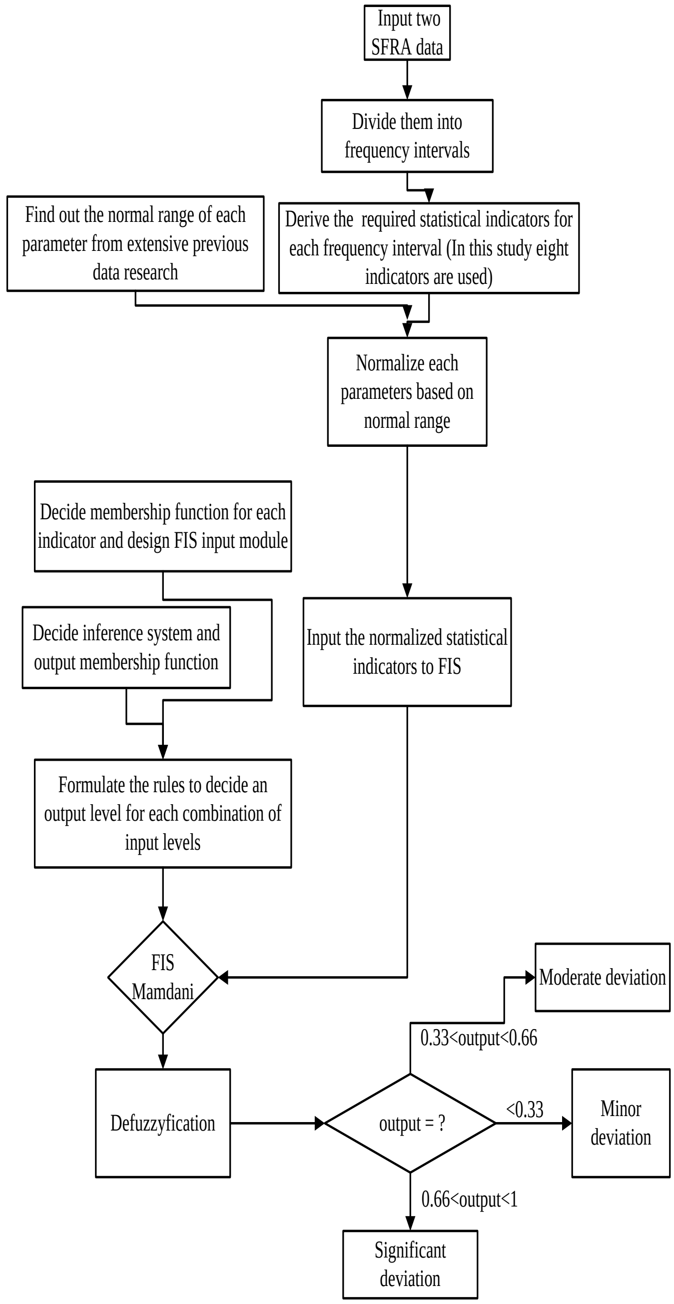

Fig. 4 The flowchart of the proposed algorithm

IV. Case Studies

Case 1

Frequency response of a 100 MVA, 220 kV / 66 kV power transformer was recorded on two different occasions, i.e. one in October 2011 and the other in May 2012. The SFRA data, for end-to-end open-circuit connection, is shown in Fig. 5 for B phase of the LV winding.

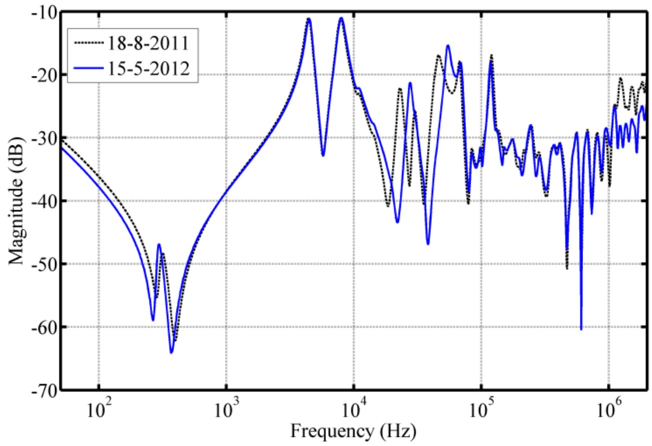

Fig. 5 SFRA data for case 1

Table 2 Statistical indicators for case 1

	SI	LF	MF	HF
1	CC	0.990	0.497	0.961
2	MSE	3.272	53.582	2.272
3	RMSE	1.180	7.338	1.511
4	ASLE	0.301	1.530	0.310
5	DABS	1.262	5.070	1.134
6	MM	1.037	1.189	1.035
7	CSD	1.640	7.274	1.481
8	t-test	1	1	0

The visual inspection shows a few deviations between the compared curves, but these deviations need to be judged as either nominal or investigable. The discussed SIs are computed for the data and are reported in Table 2. SIs have been computed for three frequency intervals, viz., low-frequency (LF) (20 Hz – 10 kHz), med-frequency (MF) (10 kHz – 100 kHz), and high-frequency (HF) (100 kHz – 1 MHz).

In the LF region, a constant deviation is observed for some portions of the compared curves; however the values of CC and MM parameters are observed to be near to their ideal values indicating very low deviation. This is obvious since the sensitivity of CC and MM to such deviations is low. Other SIs in the LF region, indicate moderate amount of deviations. In the MF region, deviations are observed at a few places and all the parameters indicate the same. In the HF region, although minimal deviation is observed, the parameter CC, which is sensitive to sharp changes, is away from its ideal value. Other parameters indicate the values which are low to moderate. The computed SIs are used in the proposed algorithm to obtain a conclusive answer regarding the deviation. The output variable is obtained as shown in Fig. 6

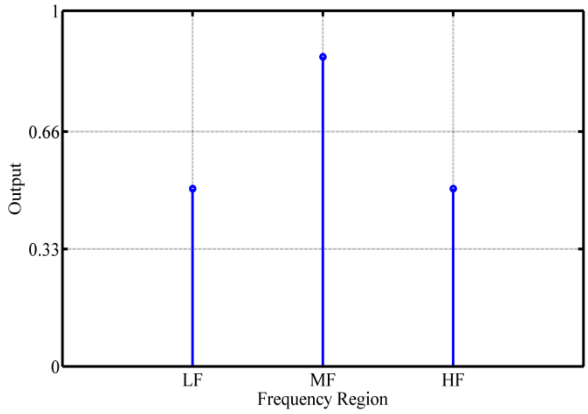

Fig. 6 The output variable of FL algorithm for case 1

In the LF and HF regions, the output variable shows a moderate deviation, while in the MF region the deviation is significant. The reason for a high MF region deviation should be investigated.

Case: 2

Frequency response of a 30 MVA, 33 kV/11 kV transformer is recorded through a Megger instrument. The SFRA curves and the corresponding SIs are reported in case-1 of [13]. The computed output variable has been shown in Fig. 7. Moderate to high amount of deviation is observed for the R-Y and Y-B phase comparisons in all the frequency ranges. Such deviations, in the LF region, may be attributed to the inherent phenomenon of different magnetic lengths of the three phases. The deviation in the HF region for the considered comparison is high and investigable. For the B-R phase comparison, the expected deviation is negligible, due to their similar design and construction, and the same is indicated in the LF and MF ranges. However, a high deviation is observed in the HF range. In fact all the phase comparisons have indicated high deviation in the HF range, which has to be investigated, since the service life of the transformer has seen two short circuit events, which may have caused modifications in series/ shunt capacitances.

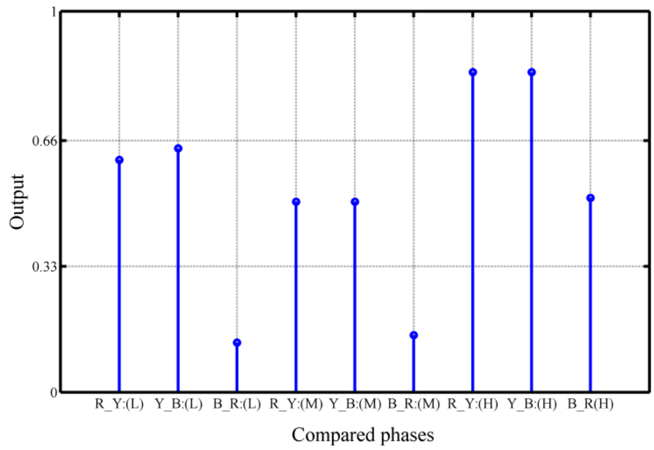

Fig. 7 The output variable of FL algorithm for case 2

Case: 3

SFRA data of 125 MVA, 230 kV/ 68 kV power transformer is used for the case. The corresponding SFRA curves and SIs are reported as case-2 in [13]. High values of the output variable in the LF and MF frequency bands for the R-Y and Y-B phase comparisons are seen in Fig. 8, which may be considered as normal as explained in case 2.

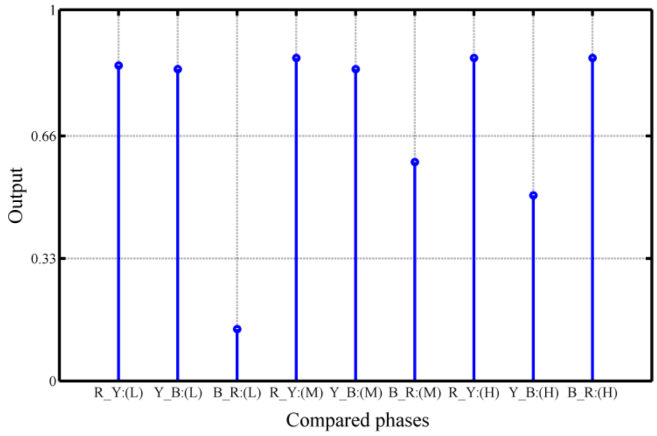

Fig. 8 The output variable of FL algorithm for case 3

In the HF region, for the B-R and R-Y phase comparisons, high deviations are observed. After opening of the transformer, buckling was observed in the R phase. The output variable found through the proposed algorithm, very well indentifies the deviation. There have been conflicting trends observed for ASLE and DABS parameter in the case as reported in [13]; however the proposed algorithm would be best employed for such cases as the output variable clearly indicates high and moderate deviations for the two discussed conflicting cases. A high sensitivity issue of the CC parameter, for the Y-B phase comparison in the HF region, as discussed in [13], is also sorted out with the proposed output variable which indicates a moderate value.

Thus, the proposed algorithm readily identifies the amount of deviation based on the eight SIs. The approach is simple and easily implementable for the SFRA diagnostics. The indication of deviation, derived through such an approach, gives confidence to the expert regarding the validity of the deviation. However, it is to be emphasized that the deviation should be confirmed by the expert, either as normal or investigable. Once it is concluded as investigable, other SFRA connections or other diagnostics approaches should be applied to determine the nature of the problem.

V. CONCLUSION

In this work, a brief review about commonly used statistical indicators for deformation diagnostics of transformer windings has been presented. Normal ranges of the statistical parameters have been tabulated. However, these ranges are not sacrosanct and there is a certain amount of fuzziness associated with them. Therefore, a fuzzy logic based approach is suggested in this paper, which can give a conclusive decision regarding deviations observed in frequency response. The generation of fuzzy logic rules is deskilled by formulating a code. There is flexibility to add more number of statistical indicators, if desired. The weightage of each indicator can be altered, if required. The output variable assists the diagnosis since the derived figure is not obtained from a single parameter but derived from eight parameters.

The proposed algorithm is then applied to three SFRA cases. It is observed that the algorithm clearly identifies the severity of deviations, if present, in the compared data sets. This gives a clear indication to the technical expert who then has to identify the cause of the problem. The presented fuzzy logic based algorithm can be verified on more transformers as a part of future work.

VI. ACKNOWLEDGEMENTS

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