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Performance of Mathematical Indices in Transformer Condition Monitoring Using k-NN Based Frequency Response Analysis

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ABSTRACT: Despite the development of the use of frequency response analysis (FRA) in condition monitoring of power transformers, how to interpret the results of FRA measurements has not yet been standardized. Therefore, proposing new methods to interpret the results of FRA measurements in research works. is followed by a great interest by researchers. This paper proposes a k-nearest neighbor (k-NN) based method for condition monitoring of the transformers, using the results of FRA measurements. First, the necessary measurements are performed on healthy and faulty transformers (under different fault conditions), and the required database is created. Later, by extracting the peak (resonance) and trough (anti-resonance) points of the measured transfer functions from the transformer, several mathematical features for training and validation of k-NN are extracted. Finally, by applying the data obtained from actual transformers, the performance of k-NN in different states is evaluated and compared. The results show that the proposed method is able to determine the condition of the transformer (whether it is healthy or defective) with high accuracy, and if it is defective, identify the type of defect. In addition, in order to prove the ability of k-NN, a comparison is made with the results of the artificial neural network (ANN).

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1- INTRODUCTION

Power transformers are one of the most important and expensive equipment in the electricity transmission network. Hence, this equipment is studied from different aspects such as inrush current, transient states, harmonics, and condition monitoring [1]. One of the new methods for monitoring the status of transformers is the FRA (frequency response analysis) method. The use of FRA in transformer condition monitoring has become widespread; therefore, today in monitoring the status of special transformers such as traction transformers and autotransformers are also used [2-4]. The FRA method, also known as the transfer function (TF) method, is a comparative method [5-6]. After designing and manufacturing the transformer and delivering to the customer, the transformer healthy state TF is measured. The result of this measurement is stored as a reference TF with the customer or manufacturer. During the annual visits or when a fault occurs in the transformer, the same measurement is performed again with the same terminal connection and the same environmental conditions. It is also advisable to measure the FRA when performing periodic maintenance or annual visits (to monitor the transformer status). If variations are observed in the measured TFs in comparison with the healthy one, this procedure helps the operator to detect a probable fault and disconnect the transformer terminals.

By comparing the results of the reference measurements and the results of the new measurements, the condition of the transformer can be evaluated. In other words, to evaluate the condition of the transformer, two sets of data must be compared, which is done with the help of the mathematical indicators. Although valid standards in the field of FRA have been developed [7-8], these standards further discuss measurement requirements and test circuits, and do not provide a way to interpret the results of FRA measurements. Therefore, in recent years many studies have been conducted to interpret the results of FRA measurements to obtain information about the status of the transformer [9-16]. Past researches [2-6], [9-19] have shown that the FRA can be used to detect five faults: axial displacement (AD), radial deformation (RD), disc space variation (DSV), short circuit (SC) and deformation of core sheets (DCS). Diagnosis of these defects in transformers is done in the following four steps:

- Detection of fault occurrence
- Identify the type of fault
- Determine the severity of the fault
- Detection of fault location

Obviously, the first two stages are more important and determine the condition of the transformer in terms of being healthy or defective [16]. Therefore, the main focus of this article is on diagnosing the occurrence and type of fault.

It can be said that transformer condition monitoring is a classification problem [4-5], [18-19]. Thus, the proposed

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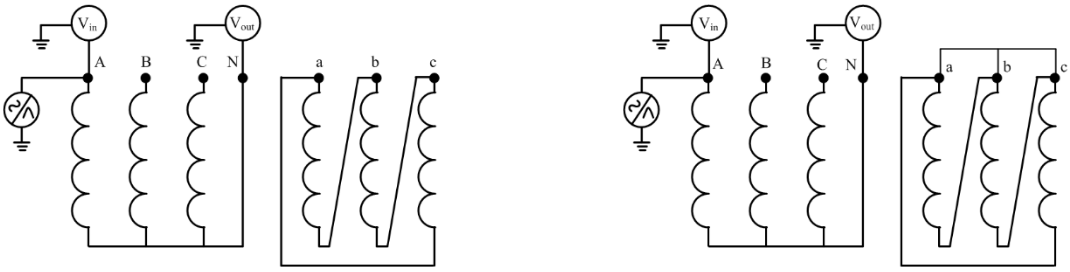


Fig. 1. Measurement circuits of TFs

method for condition monitoring should work in a way that by applying the features extracted from the measurement results in the first step, it can be determined whether the transformer is healthy or defective, and if it is defective, determine its type. For this purpose, a lot of research works have been done in this field and their main focus has been on the use of intelligent classifiers. One of the best intelligent classifiers used in transformer fault diagnosis is the k-nearest neighbor (k-NN) method. Analysis of oil-dissolved gases to diagnose transformer defects using k-NN method has been done in [20-21]. In [22], detection of transformer insulation failures has been performed using a method based on k-NN and cross-correlation techniques. However, the FRA method has not been employed in these studies. Although, in [23] using the k-NN and FRA-based techniques, the transformer faults have been detected. However, only the two AD and RD defects have been examined. Therefore, there are also shortcomings in this regard, which can be expressed as follows:

➢ Very few studies [24-25] have diagnosed DCS fault using FRA. In these studies, only the effect of DCS fault on the frequency response of the transformer has been studied and the diagnosis of the fault type has not been considered. Meanwhile, in many studies [4-6], [9-19], two or three faults have been examined. Although, all five faults have been considered in [16], the proposed method is not intelligent and it cannot determine the condition of the transformer with certainty. In addition, its conclusion emphasizes that intelligent classifiers should be used in future research studies.

➢ The results of research works [5-6], [26] show that the five mentioned defects further affect the peak and trough points of the TFs; therefore, it seems that focusing on amplitude and frequency variations at these points can lead to desirable results. While in most research works, statistical indicators have been used for this purpose [13-16].

➢ In most research studies [5-6], [13-19], it has been assumed that the transformer is defective and later, the classification of defects has been performed. While the transformer operating engineer must first ensure that the transformer is defective, and later diagnose the type and severity of the fault. That is, the healthy condition should also be considered as one of the classes in the classification process.

In the current research, the following steps have been taken to solve the mentioned shortcomings:

1- Introducing 8 mathematical indicators used in valid references [26-28], based on peak and trough points

2- Creating a database of measurement results under healthy and defective conditions of transformers

3- Calculating mathematical indicators by applying them to the measured TFs and extracting the necessary features

4- Applying the features to the k-NN classifier for its training and validation

5- Checking the reliability of the features with the help of the data obtained from actual transformers

6- Proposing the most reliable feature for classifying the conditions of transformers in the industry

Organizing the rest of the article is as follows: in section 2, data acquisition details are given. The proposed method is presented in Section 3. Section 4 presents the classification results. Section 5 includes the conclusion.

2- DATA ACQUISITION

First, a database of the healthy and faulty condition of the transformers (at different fault intensities), must be created in order to evaluate the performance of the k-NN. For this purpose, three sets of transformers have been tested in this study. In the measurements performed in this research, the circuit of Fig. 1 has been used [8]. It is important to note that in Fig. 1, instead of the output voltage (V_{out}), the output current can be measured, in which case the TF will be of the admittance type.

2-1- The First Set of Transformers

The first set of transformers are the model transformers. A model transformer is a transformer that its structure is exactly the same as an actual transformer, but its voltage and power level may not be real. Therefore, it is only used for laboratory studies. In addition, different connections are available from its windings and it is possible to intentionally apply various defects on the transformer in order to obtain a more complete database. This group of transformers with almost similar structures have been tested and one of the studied defects (AD, RD, DSV, SC and DCS) has been applied to each of them.

2-2- The Second Set of Transformers

The second set are transformers that have a defect during operation, and their type of defect is unidentified at the beginning, and after opening its accessories, the type of fault is determined. It should be noted that the TF has been measured before opening the active part of the transformer.

Table 1. Description of tested transformers

Case study		Rated values	Winding structure	Transformer condition
Set 1	1	10/0.4 kV, 1.3 MVA	HV: 31 double disc, 6 turns in each disc LV: 4 layers, 99 turns in each layer	Displacement of LV winding relative to HV winding in 8 steps and creation of 1 cm displacement (equal to 1.2% of winding axial length) in each step
	2	10/0.4 kV, 1.2 MVA	HV: 30 double disc, 11 turns in each disc LV: 1 layer, 23 turns in each layer	Deformation of the 6th to 54th discs by 7% of the winding radius in 4 degrees (from 1, 2, 3 and 4 sides of the winding)
	3	10/0.4 kV, 1.2 MVA	Similar to Case 2	Change the space between healthy discs from 5 mm to 7.5, 10, 15, 20 and 25 mm and make changes in 3 locations including 2, 4 and 16 discs
	4	10 kV, 1.2 MVA	HV: 60 disc, 9 turns in each disc Without LV winding	SC between consecutive discs
	5	10 kV, 1 MVA	HV: 10 disc, 11 turns in each disc Without LV winding	Deformation of the core on one side at the rate of 10% ofcore radius
Set 2	6	20/0.4 kV, 0.4 MVA	HV: 40 disc, 17 turns in each disc LV: 2 layer, 9 turns in each layer	defective transformer (fault type: AD)
	7	20/0.4 kV, 1 MVA	HV: 50 disc, 11 turns in each disc LV: 2 layer, 11 turns in each layer	defective transformer (fault type: RD)
	8	63/20 kV, 30 MVA	HV: 80 disc, 15 turns in each disc LV: 5 layer, 64 turns in each layer	defective transformer (fault type: DSV)
	9	20/0.4 kV, 0.5 MVA	HV: 45 disc, 13 turns in each disc LV: 2 layer, 10 turns in each layer	defective transformer (fault type: DSV)
	10	20/0.4 kV, 0.5 MVA	Similar to Case 9	defective transformer (fault type: SC)
	11	20/0.4 kV, 1 MVA	Similar to Case 7	defective transformer (fault type: DCS)
Set 3	12	63/20 kV, 30 MVA	Similar to Case 8	healthy transformer
	13	20/0.4 kV, 0.5 MVA	Similar to Case 9	healthy transformer

2-3- The Third Set of Transformers

This set of transformers is intact and two measurements have been performed on them at different time intervals. The first measurement was performed in the factory and after the completion of the assembly process, at the time of delivery to the customer. Later, after installation at the operation site and before energizing the transformer, another measurement was performed. The purpose of this measurement is to show whether the k-NN based monitoring system can also predict the healthy condition of the transformer.

Table 1 provides complete information on all the three sets of transformers. Fig. 2 shows a number of test objects that have been tested in the laboratory. Fig. 3 also shows a sample measurement result from some of the transformers. It is evident that the DCS fault only affects the low frequency range, which is consistent with the results obtained in [24].

The peak and trough points of the measured TFs are clearly shown in Fig. 3. These points are actually the resonance and anti-resonance points of the TFs. Therefore, in some authorities, they are known by different names. It is evident that there are several resonance and anti-resonance points in each FRA trace. By changing the status of the transformer, the amplitude and frequency of the TFs change at these points. Therefore, by extracting the necessary features from the amplitude and frequency variations in these points, the condition of the transformer can be evaluated, which is performed in the next section.

3- THE PROPOSED METHOD

In this paper, the k-NN classifier is used to monitor the condition of the transformer. The theory of this method has been studied in detail in [29-30]. Therefore, it is briefly discussed in this section.

The k-NN is a simple and standard tool for solving classification problems. This algorithm is defined in two phases and the available data should be divided into two categories of training and test datas. The training phase includes the storage of the feature vectors and class labels of the training data. That is, the class for each training data is devoted. In the classification phase, the test data as well as the k value

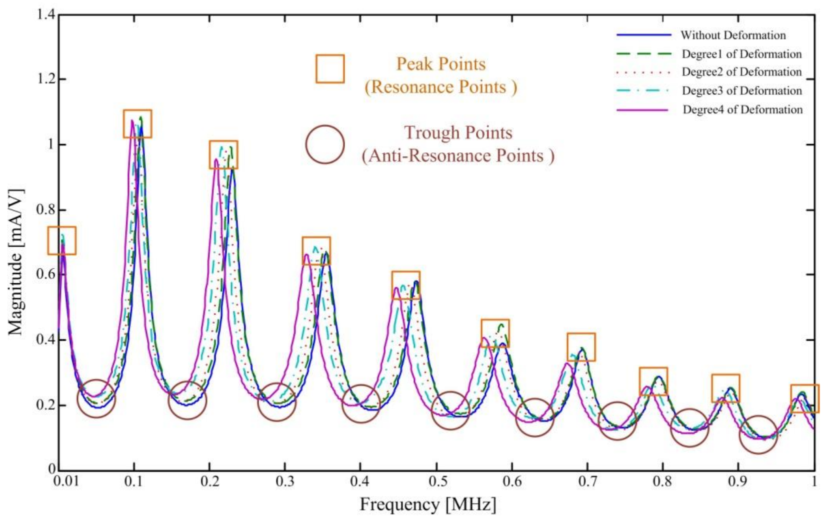
a) Case 3

b) Case 6

c) Case 7

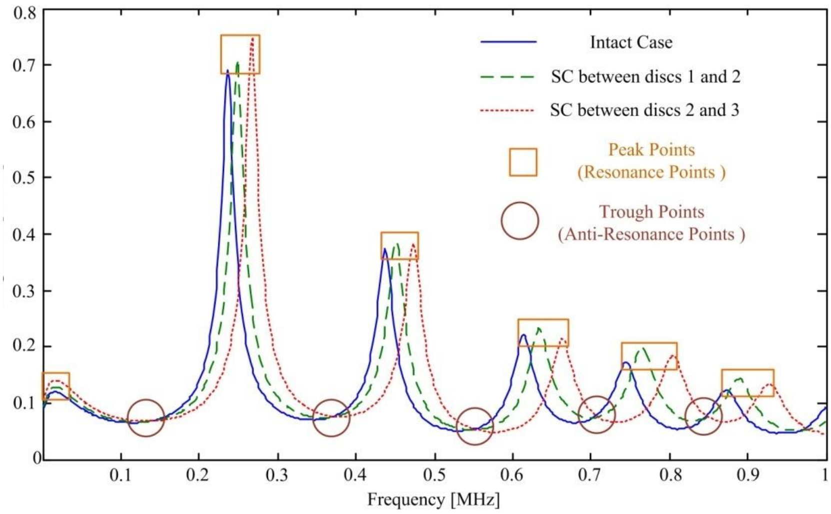
d) Case 11

Fig. 2. A view of the test objects in the laboratory

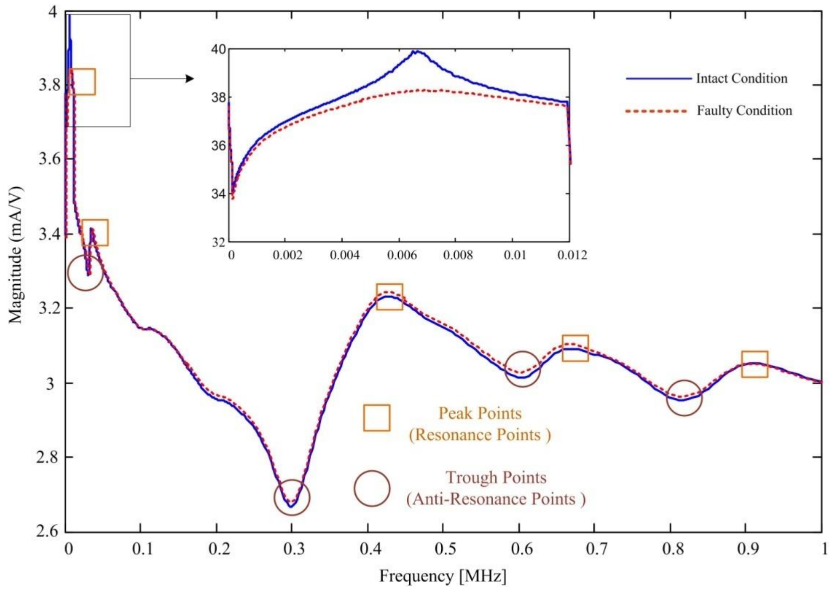


a) Case 2

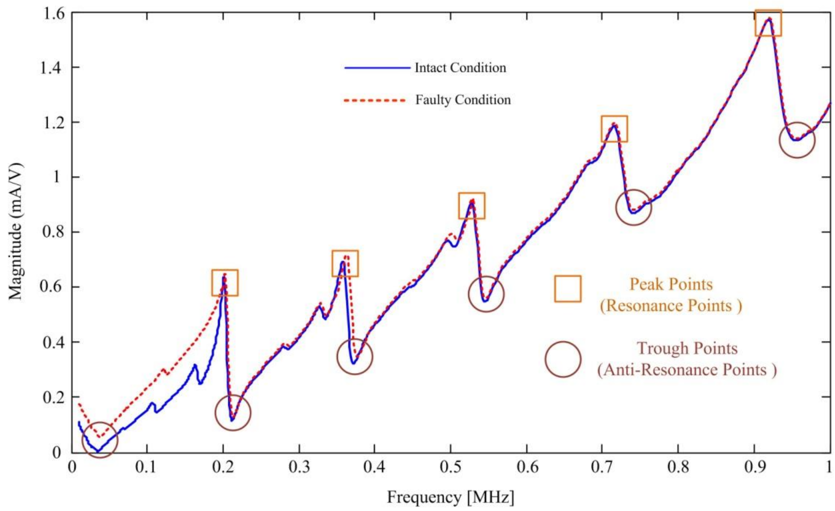
Fig. 3. Some of measured TFs of transformers



b) Case 4

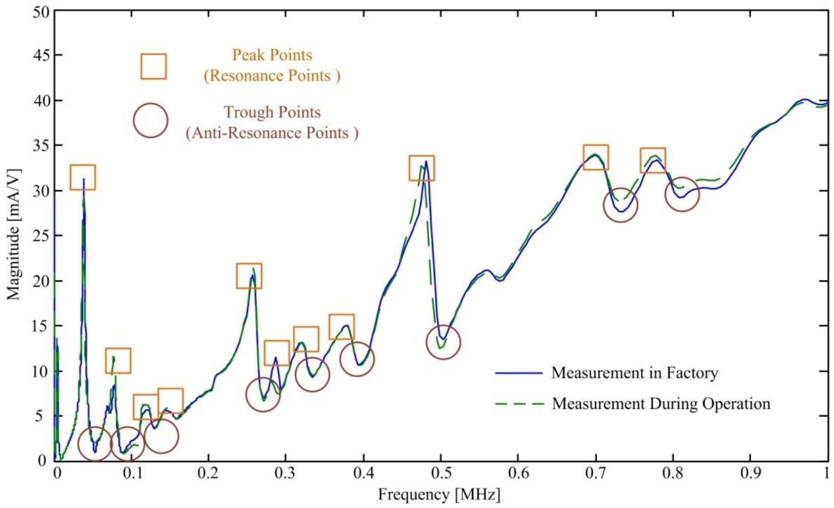


c) Case 5



d) Case 11

Fig. 3. Some of measured TFs of transformers



e) Case 13

Fig. 3. Some of measured TFs of transformers

(which is defined by the user), are given to the algorithm. The algorithm determines the distance of the test data from all training data, and if k=1 returns the nearest neighbor to the new data as the winning class. But if k is greater than 1, find the k neighbors for the new data, and whichever class has the most neighbors, the new data will belong to them. Therefore, k must be an odd number for the test data to only belong to a unique class. Determining the appropriate value of k depends on the data. Although larger values of k reduce the effect of noise on the classification, the boundary between classes becomes ambiguous and classification becomes difficult. The value of k is usually determined by trial and error. In this article, its value is considered 3. Fig. 4 shows the k-NN classifier flowchart.

The criterion for calculating the distance between data is the Euclidean Distance (ED), which is defined as follows:

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

Where, z and y are training and test vectors, respectively, and n is the number of data.

In order to apply the data to k-NN, the necessary features must be extracted from the measurements results. In this paper, feature extraction is based on the use of information comparing the new TF with the reference TF. One of the best possible methods to compare the TFs with the reference TF is to use mathematical indices based on resonance and anti-resonance points in the measured TFs. These indicators are defined in Table 2.

Where, the subscripts X and Y refer to the reference and the new TFs, respectively. $A(i)$ and $f(i)$ are the amplitude and frequency of the i-th resonance or anti-resonance point, respectively. If we consider the number of resonance and anti-resonance points as n, i will equal i=1,…, n. w_{ai} and w_{fi} are the weight coefficients of amplitude and frequency for resonance points, calculatng them is determined in [27].

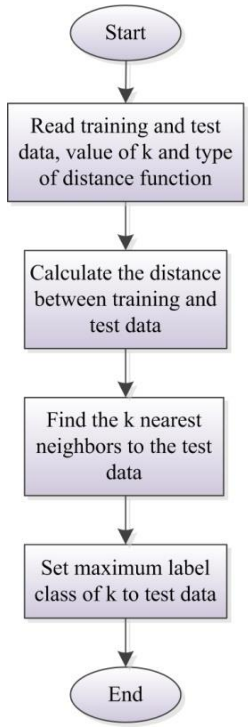


Fig. 4. Flowchart of k-NN classifier

After calculation of the above features for the training and test data sets, the training features are first applied to the k-NN and the class label of each data is specified. Later, by applying test data, the class of each new data is specified. The proposed method in this paper can be described as follows:

1- Measurement of reference TF and new TF of transformers

2- Calculation of resonance points and anti-resonance of measured TFs

Table 2. Indicators used to extract the features

Abbreviation	Definition	Equation number	Equation
DA	Deviation of Areas	(2)	$DA_i = \lvert A_Y(i) - A_X(i) \rvert$
DF	Deviation of Frequencies	(3)	$DF_i = \lvert f_Y(i) - f_X(i) \rvert$
IAD	Index of Amplitude Deviation	(4)	$IAD_i = \left\lvert \frac{A_Y(i) - A_X(i)}{A_X(i)} \right\rvert$
IFD	Index of Frequency Deviation	(5)	$IFD_i = \left\lvert \frac{f_Y(i) - f_X(i)}{f_X(i)} \right\rvert$
F_a	Amplitude Function	(6)	$F_{ai} = \frac{A_Y(i)}{A_X(i)}$
F_f	Frequency Function	(7)	$F_{fi} = \frac{f_Y(i)}{f_X(i)}$
W_a	Weighted Amplitude Function	(8)	$W_{ai} = \frac{A_Y(i)}{A_X(i)} \times w_{ai}$
W_f	Weighted Frequency Function	(9)	$W_{fi} = \frac{f_Y(i)}{f_X(i)} \times w_{fi}$

Table 3: Number of training and test data and their class labels

Transformer condition	Training data		Test data		Class label
	Case study	Number of data	Case study	Number of data	
Healthy	Case 13	1	Case 12	1	1
AD	Case 1	8	Case 6	1	2
RD	Case 2	4	Case 7	1	3
DSV	Case 3	15	Cases8, 9	2	4
SC	Case 4	8	Case 10	1	5
DCS	Case 5	1	Case 11	1	6

3- Feature extraction with the help of relations (2) to (9)

4- Applying the training data along with the class of each data to k-NN

5- Calculating the distance between the test data and the training data using (1)

6- Selecting the first k member of the ordered set (from small to large), from the distance matrix and returning the class of new data

Based on the measurements made in Section 2, Table 3 lists the number of training and test data along with their class labels. In the next section, this data is applied to k-NN and the performance of various features is evaluated.

4- RESULTS AND DISCUSSION

First, to train classifiers, their structure (input/output data) should be determined. For this purpose, the features introduced in equations (2) to (9) are used. Therefore, the input matrix for DA indicator (for example) can be defined as follows:

$$\text{input} = \begin{bmatrix} DA_{1,\mathrm{h}} & DA_{1,AD_a} & DA_{1,RD_b} \\ \vdots & \vdots & \vdots \\ DA_{\mathrm{n},\mathrm{h}} & DA_{\mathrm{n},AD_a} & DA_{\mathrm{n},RD_b} \\ DA_{1,DSV_c} & DA_{1,DCS_d} & DA_{1,SC_e} \\ \vdots & \vdots & \vdots \\ DA_{\mathrm{n},DSV_c} & DA_{\mathrm{n},DCS_d} & DA_{\mathrm{n},SC_e} \end{bmatrix} \tag{10}$$

Where, n represents the number of trough and peak points in TFs (the number of rows in the matrix), h is the number of healthy transformers, a, b, show the severity of AD and RD, respectively, c illustrates the severity of DSV, d demonstrates the location of SC for three locations, and e represents the severity of DCS. Based on the information given in Table 1, it can be said that the values of a, b, c, d, e, h are equal to 8, 4, 15, 8, 1, and 1, respectively. Therefore, the number of matrix

Table 4. Classification error resulting from the application of validation and test data to classifiers (in percentage)

Index	Classifier			
	k-NN		ANN	
	Validation	Test	Validation	Test
DA	8.1	28.6	25.3	57.1
DF	8.1	28.6	25.3	57.1
IAD	5.4	14.3	21.6	42.9
IFD	5.4	14.3	21.6	42.9
F_a	13.5	42.9	27	57.1
F_f	13.5	42.9	27	57.1
W_a	10.8	42.9	25.3	57.1
W_f	10.8	42.9	25.3	57.1

Table 5: Performance of IAD and IFD features in response to test data

Transformer condition	Case study	Detection by		
		IAD	IFD	IAD-IFD
Healthy	12	Healthy	Healthy	Healthy
AD	6	AD	AD	AD
RD	7	AD	RD	RD
DSV	8	DSV	DSV	DSV
DSV	9	DSV	DSV	DSV
SC	10	SC	RD	SC
DCS	11	DCS	DCS	DCS

columns in the training data will be 37. For other indicators, the input matrix can be defined similarly to Equation (10). Output of k-NN in each indicator can have six different classes (according to six conditions). Therefore, the output vector in the training data will be a 1×37 vector.

By applying the features extracted from the TFs to k-NN, its performance is evaluated. In addition, in order to prove the capability of k-NN, a comparison is made with the results of the artificial neural network (ANN). Since the perceptron neural network with back-propagation algorithm is one of the best methods to solve classification problems [31], this method is used to classify transformer conditions in this section. The network used in this research is a three-layer perceptron network consisting of an input layer, a hidden layer and an output layer. The back-propagation has been used to train the network. The hidden layer activation function is a hyperbolic tangent (known in the neural network toolbox in MATLAB software as *tansig*), and the output layer activation function is a linear function (known in the neural network toolbox in MATLAB software as *purelin*).

In addition to test data, some training data is also used for validation to prevent over-fitting. For this purpose, K-Fold Cross Validation method is used [32]. In this method, the classification is performed K times and each time a fraction of 1/K of data is used for validation, and the rest for classifier training. The mean of the errors is then returned as the calculation error. In this paper, the value of K is 5.

Table 4 shows the classification error resulting from the applying of validation and test data to k-NN and ANN for all indicators.

In ANN, s shown in Table 4, for any index the test data error is not less than 40%. In addition, the validation error is always above 20%. Therefore, the use of ANN is not recommended in solving the classification problem raised in this article. In k-NN, the rate of classification error for indicators F_a, F_f, W_a, and W_f in test data is more than 40%. In addition, the classification error in these indicators is also high in the validation data. In DA and DF indices, although the classification error is less than 10 % in the validation data, nonetheless, in the test data this error is more than 20% and out of the 7 examined cases, 2 cases are incorrectly detected. The IAD and IFD indices have the lowest classification error for validation and test data compared to other features. Therefore, they can be used as appropriate features in transformer condition monitoring. Table 5 details the condition monitoring of actual transformers using these two features. It can be seen that the k-NN in the IAD feature could not correctly detect the RD defect. While, in the IFD feature, the SC defect is not correctly diagnosed. Therefore, it seems that by combining these two indicators, all cases can be correctly identified. For this purpose, with a combination of these features and simultaneous use of both IAD and IFD, new feature was used for k-NN training and validation. As can be seen in the last column of Table 5, the IAD-IFD combination feature monitors the transformer condition correctly in all cases. Therefore, it can be used as a reliable method in industry.

5- CONCLUSION

In this paper, due to the increasing use of FRA in transformer condition monitoring, one of the most widely used intelligent classifiers (k-NN) was used to classify the healthy and defective conditions of the transformer. For the k-NN training and testing, mathematical indicators based on the peak and trough points of the transformer TFs were used. Data for feature extractions were obtained by performing the necessary measurements on healthy and defective transformers (in different fault conditions). By applying the features to the k-NNs, their performance was evaluated. The obtained results show that the two IFD and IAD features are more accurate than others. Combining these two features, a new feature called IFD-IAD was introduced that was able to monitor the condition of the transformer with 100% accuracy. Although, transformer condition monitoring has been investigated using a k-NN based FRA in this research, nonetheless, further studies on multiple cases are needed to approve the functionality of the proposed method in other cases.

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