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Discrimination among Winding Mechanical Defects in Transformer Using Noise Detection and Data Mining Boosting Method

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ABSTRACT

This paper proposes, an efficient method to detect and discriminate mechanical defects of transformer winding based on extracting the winding frequency responses using outlier data detection and ensemble algorithms, which together constitutes an efficient hybrid method. First, the frequency response of the high voltage winding of a real transformer model (1.6 MVA) was extracted in different condition and arranged as primary data. Then, due to the high standard deviation of the characteristics and the weight of the outlier samples above the threshold of 1.1, the Local Outlier Factor (LOF) method was used to clean the samples. Finally, data mining algorithms have been used to detect and distinguish mechanical defects. Based on the results, the decision tree bagging ensemble method reported the best accuracy compared to other techniques and improved the accuracy of the decision tree with total accuracy of 92.68% by LOF. These results also showed that all methods improved accuracy by LOF. It can, therefore, be claimed that the proposed method is capable of discriminating transformer winding mechanical defects accurately.

Article Info

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Decision tree, Ensemble algorithms, Frequency response, Local Outlier Factor.

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I. INTRODUCTION

Transformers play a major role in electric power generation, transmission, distribution and utilization, from both technical and economic perspectives. Transformer performance at different levels has a vital and effective role in maintaining the stability and improving the reliability of the power system. Therefore, it is paramount to use of efficient protection systems to clear faults as fast and safe as possible. One way to predict failure or defects is to use data mining methods. Data mining can be defined as the process of discovering meaningful relationships and patterns by examining large volumes of data [1]. This concept has recently been the subject of many scientific papers, conferences and dissertations. Data mining is a combination of machine learning techniques, pattern recognition and statistical methods.

According to [2, 3], the most common techniques in fault prediction are regression methods and neural network. The paper [4] evaluates data mining techniques in predictive maintenance (PdM) to predict the insulation fault using the analysis of data on the gas dissolved in oil of power transformers. In this evaluation, the accuracy and efficiency of the RBF artificial neural network is compared with Gaussian kernel methods in the support vector machines (SVMs) model, the C4.5 decision tree and the nearest neighbor K.

Ref. [5], proposes a new approach with wavelet transform

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method and modeling with LS-SVM method to predict the amounts of dissolved gases in oil-immersed transformers. The particle optimization algorithm was used to optimally select the parameters in the wavelet transform. The results were compared with several neural network models, regression and support vector machines, and the error of the proposed model was evaluated less with a large difference. The importance of feature selection and removal of excess space is examined to detect the pattern in the Ref. [6], They used the RF random forest technique to select effective features. In Ref. [7], ANN neural network method was applied to the data to distinguish among mechanical defects of windings and other electrical faults. This paper is dependent on the training data and if the location of the windings was changed, the model error would be reduced.

In [8], a fault prediction model is proposed by first determining the parameters and signals in MATLAB software and changing them to a suitable value to detect mechanical defects in the data preparation step, the internal and external fault types of the device and the input current of the transformer are simulated. These signals are then converted into the properties of the training model by wavelet transform and, during the training, the decision tree classifier and artificial neural network are used to do modeling.

Various intelligent methods have also been used in the articles for detecting and classifying types of faults, including decision tree (DT) methods [9], artificial neural network (ANN) [10], SVMs [11], Fuzzy algorithm [12].also methods used to extract feature vector have included intelligent transformations such as wavelet transform [13], S transform [14-15], Time-time conversion [16], mathematical indicator [17], numerical indices [18] which have good learning capability and generalizability.

This paper used ensemble machine learning techniques to identify and distinguish transformer fault with two types of axial deformation (AD) and radial deformation (RD) faults. Algorithms in a comparative mode include the C4.5 decision tree base methods, the support vector machines ,the bagging ensemble methods, the random forest, and the new boosting gradient method which has received less attention in recently published articles about transformer fault prediction , were also tested in this research.

II. STUDY OF TRANSFORMER WINDING MECHANICAL DEFECTS

Many transformer insulation faults are a direct result of reduced insulation strength due to mechanical faults in transformers winding. Two types of common mechanical faults are AD and RD which are investigated in this paper.

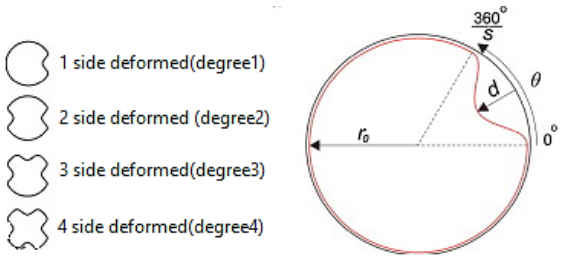


Fig. 1. Different degrees of radial deformation

As shown in Figure 1, the recessed shape of the winding has a sinusoidal curve with a certain depth and width. This condition increases the capacitance between the coils and decreases the capacitance between the high-voltage winding and the ground. r(θ) can be modeled as Equ.(1).

$$r(\theta) = \begin{cases} r_0 + \frac{d}{2}(\cos(s\theta - 1) & for\ 0 < \theta < \frac{2\pi}{s} \\ r_0 & otherwise \end{cases} \quad (1)$$

where, d represents the depth of the deformation and, s represents the width of the deformation. Furthermore, θ is the angle of deformation extent level and r_0 is the radius of the winding in the healthy state. Figure 2 shows an example of this fault on the transformer winding.



Fig. 2. Radial deformation on the transformer winding

In the detailed model, the parallel capacitor represents the electric field between the disks with each other or with the ground. In the defective state, the parallel capacitor C_i is calculated by Equ.(2) [19].

$$C_i = \sum_{\theta=0}^{2\pi} \left[\frac{2\pi\varepsilon_0\varepsilon_r}{Ln\left(\frac{r_0}{r(\theta)}\right)} \right] . \Delta\theta \quad (2)$$

The results of the experimental and numerical research confirm the relationship between the change of the detailed model parameters and the mechanical deformation of the winding. To model the axial displacement defect of the winding, it is assumed that the high-voltage winding is displaced by an impact in the direction of its axis. Figure 3 shows an example of this type of fault.

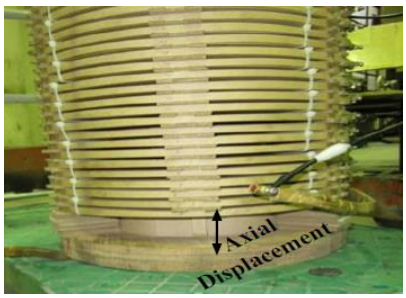


Fig. 3. Axial displacement fault on the transformer winding

According to the studies, it is clear that the axial displacement changes the components of the inductance matrix (M) that describes the mutual inductances between the components of the winding.

III. RESEARCH METHOD

The method presented in this paper is composed of three parts. After obtaining the technical specifications of a real transformer from the manufacturer and simulating this transformer with CST software , the frequency response of the transformer winding was firstly calculated in different modes of mechanical defects. Then, according to the high standard deviation of the characteristics and the weight of the outlier samples exceeding the threshold of 1.1, the LOF method was used to remove the samples and finally, the machine learning methods were used to classify and to detect the type of Fault. Figure 4 shows the classification method.

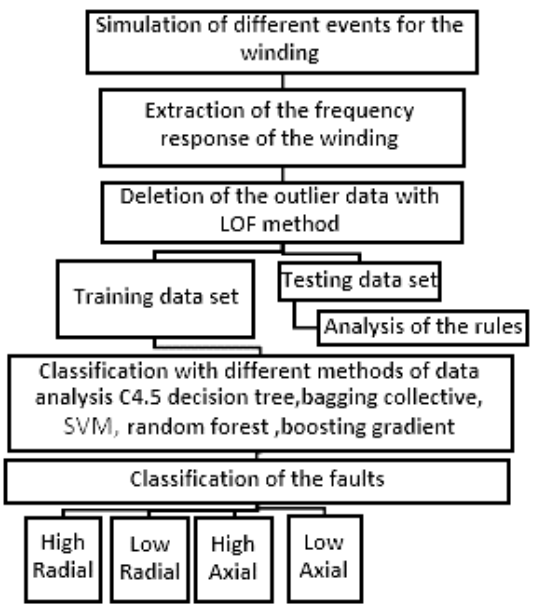


Fig. 4. Classification method diagram of transformer mechanical faults

A. *Frequency response of the transformer winding*

The winding of each transformer has a unique frequency response, known as the fingerprint of that winding. the slightest mechanical and electrical change in the winding causes a change in the frequency response of them. In the dataset of this investigation, the resulting data from frequency response of the winding and their correlation index were used in various events.

B. *LOF method to samples purging*

Outlier data is an observation that is farther away from other data and is different from the expected value [20]. In this method, three steps are performed to calculate data discrepancy. In the first step, a point is calculated for each K point to the nearest neighbor. Then, the maximum value of the distance between two points $(dis(p,o))$ and K to its nearest neighbors $(k-distance(o))$ is considered to calculate the accessible distance of one point relative to other points (reach-dist) Equ.(3).

$$reach-distA(p,o)=\max\{k-dist.(o),dis(p,o)\} \quad (3)$$

In the next step, the local density of each point is equal to the inverse of the mean K of the nearest neighbors Equ.(4). Finally, the rank of the outlier data is calculated which is equal to the average local density rate of each data sample relative to its neighbors, Equ. (5).

$$LRd_k(\mathrm{p})=1/\frac{\sum reach-dist_k(\mathrm{p},\mathrm{o})}{K} \quad (4)$$

$$(LoF_k\ (p))=\frac{\sum\frac{LRd_k(\mathrm{o})}{LRd_k(\mathrm{p})}}{K} \quad (5)$$

C. *Classification of faults*

In the fault type classification step, several basic decision tree classifications were used, including support vector machines and collective methods of bagging, random forest and boosting gradient.

The main idea of bagging algorithms is to use several learning methods and to combine their predicted result as a group of classifiers to increase the overall accuracy of learning. Each member of this group of learners is called a base classifier. The use of collective algorithms reduces error. One of the collective methods is the bagging method. Random tree forest produces many decisions. To classify a new type, it places the input vector at the end of each random forest tree. Each tree provides a classifier, and it is said that this tree gives that class a "vote." The forest chooses the category with the most votes (among all the trees in the forest). The boosting gradient method uses "weak" decision trees like a random forest. The big difference between these two methods is that in the boosting gradient method, the trees are trained one after the other. Each subset tree is primarily trained with data that was erroneously predicted by the previous tree. This makes the model less focused on issues that are easy to predict.

IV. TRANSFORMER UNDER STUDY AND SIMULATION

The specifications of a transformer of 20/0.4 kV and 1.6

MVA with Dyn11 connection were obtained from the manufacturer to perform the study and simulations. The characteristics of the geometric dimensions of the transformer are given in Table I. The high-voltage winding of this transformer consists of 20 disks, of which the first four and last disks of 20 loops and 16 intermediate disks have 21 loops. The LV winding also consists of two 13-loop layers.

Table I.
Dimension Specification of the Transformer Winding

Description	(mm)	Description	(mm)
Internal radius LV	93	Cross section LV	11.8*3.35
External radius LV	106	Cross section HV	8.5*2.12
The channel between two layers LV	4	Thickness of insulating paper	0.5
The channel between two layers LV, HV	12.5	Coil height LV	536
Internal radius HV	118.5	Height HV	494
Internal radius HV	176.5	Core radius	90

The high frequency module of the powerful CST software was used to describe the real behavior of the transformer and to extract the frequency response as accurately as possible. For this purpose, the complete specifications of a sample transformer Table I, were entered in the model. The three-dimensional model of the transformer is shown in Figure (5) and the three-dimensional models of several different events for the high voltage coil are displayed in Figure (6). The meshing was done with high accuracy and in an optimized way with three-dimensional elements. considering a compromise between time and simulation accuracy, the number of elements reached 10,600 so that the minimum element size was defined as 3 mm and the maximum as 13 mm. The simulation was performed by defining the appropriate ingredients and boundary conditions as well as the frequency band of 1 to 900 MHz.

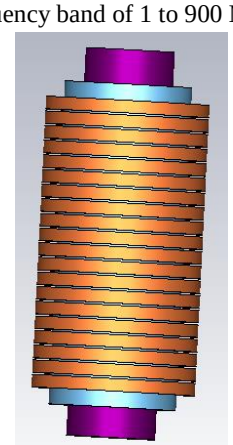


Fig. 5. Three-dimensional model of the phase A of the transformer in the healthy condition

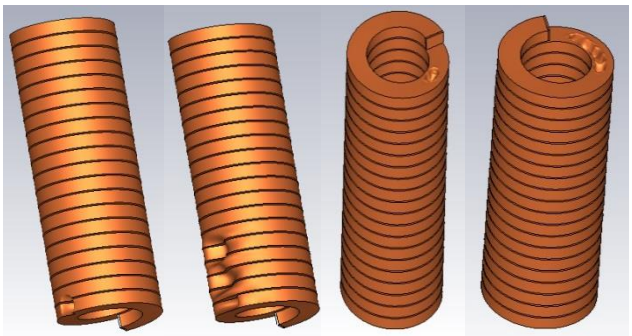


Fig. 6. HV winding in the condition of low and high radial fault, and low and high axis fault

V. EVALUATION OF THE SIMULATION RESULTS

A. Results of radial and axial deformation

Figure 7 shows the healthy frequency voltage response and a sample of low and high axial deformation, and Figure 8 displays the voltage frequency response in the healthy mode and a sample of low and high radial deformation. A total of 348 received signal samples is defined with four independent frequency characteristics, healthy state correlation index, high fault state correlation index, and low fault correlation index. The standard deviation reports a high-frequency characteristic that indicates outlier data. To calculate the correlation indices, the CST results are exported to MS-Excel Format. Then, in the data Analysis tab of MS-Excel software, the correlation option is selected and a new window opens, in this window by selecting the input/output range of data the correlation coefficients will be calculated.

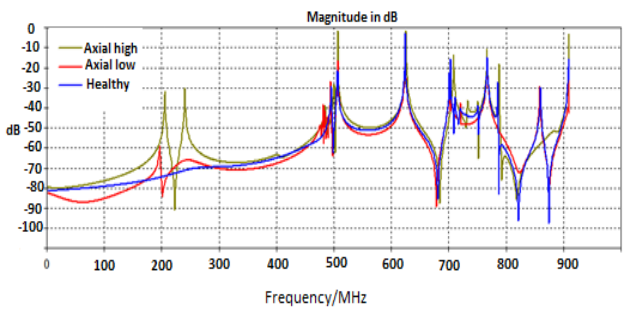


Fig. 7. Frequency response magnitude of axial deformation

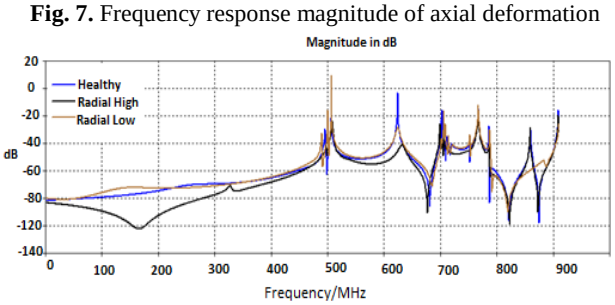


Fig. 8. Frequency response magnitude of radial deformation

No missing data can be seen in the columns. According to Table II, the average correlation index in the healthy mode of

the device with a value of 95.57 is between the two values of the correlation index in the high mode (94.71) and that in the low mode (93.8). The mean and a minimum correlation indices in the low fault mode (axial and radial) than in the high fault mode (axial and radial).

TABLE II.
The Statistical Information Of The Dataset

Index name	Type	Miss data	Statistical information			
			Min	Max	Ave.	Dev.
Frequency (kHz)	Real	0	1930.1	906707.8	152503	223362.5
Corr. with healthy	Real	0	4.336	100	95.57	11.8
Corr. with high defect	Real	0	4.715	100	94.71	13.11
Corr.with low defect	Real	0	4.336	100	93.8	14.656

Given that some data are discarded based on the variances and graphs specified in the input data topic, deleting this data can help improve the model. Therefore, the technique of removing the detection and deleting the LOF outlier data was applied to the data at this step. The method with values of k = 10 (the value of the nearest neighbor) reported the results of Table III in which the rank of the outlier data shows the outlying data that should be removed.

TABLE III.
Outlier Data Detection Algorithm Setting

Outlier variable: real number	Setting	Method
Outlier data rank :1.349-1.043 Mean :1.07 Standard deviation :0.042	K Small :10 K Large:20 Distance: Euclidean Combined measurement	LOF

This algorithm introduces an outlier data rate of approximately higher than 1 and 1.1 [21]. The data weighing less than 1.1 were considered normal and the rest were deleted. After applying this algorithm, out of 348 samples, 18 outlier data samples were deleted and 330 samples remained.

B. Results of events classification unit

The confusion matrix Table IV, shows how the classification algorithm works according to the input dataset by different types of classification problem categories. The concepts of True Positive, False Positive, True Negative and False Negative are as follows.

TABLE IV.
Confusion Matrix

		Predicted Value	
Actual values		Negative(-)	Positive(+)
	Negative(-)	TN	FP
	Positive(+)	FN	TP

TP: The actual value is positive (error) and the classifier has correctly identified as positive.
FP: The actual value is negative (no error) and the classifier has incorrectly identified as positive.
TN: The actual value is negative (no error) and the classifier has correctly identified as negative.
FN: The actual value is positive (error) and the classifier has incorrectly identified as negative.

We have two evaluation criterions are the precision criterion ,Equs.(6),(7).

$$Recall = \frac{Ntp}{Ntp + Nfn} \tag{6}$$

$$Accuracy = \frac{Ntp}{Ntp + Nfp} \tag{7}$$

According to the results of Table V, the ensemble methods that use several decision tree classifiers have more accurate results than the tree base model and, the tree accuracy is developed in both of the gradient method and the bagging method. In general, tree methods reported higher accuracy in detecting the type of transformer fault. In the fault type classification step, several basic decision tree classifications, support vector machines, and ensemble methods of bagging, random forest and boosting gradient. To train the models, the data were divided into two categories of training (75%) and test data (25%) by validation method in the software environment. In the training phase, the classifiers are applied to the training data and the prediction function predicts the test data for each model, category and type of fault. To evaluate the models, the prediction results are compared with the actual values and the accuracy of the model is evaluated based on the parameters of total accuracy and accuracy of each type of fault. The parameter for each classifier are set.

For the decision tree of the information gain index, the maximum depth were considered 10, the minimum leaf size were considered 3 and minimum number of separation records were considered 4. In the support vector machine with linear kernel and boosting gradient with 20 trees, the learning rate was considered 0.08 and the random forest were considered with 20 tree models. In Table V, the results of the methods were simulated once without removing outlier data and once with the LOF method of removing the outlier data, and it was compared and analyzed based on the evaluation parameters.The accuracy of all models has been increased when the outlier samples were discaded. In tree methods, the model was improved by, on average of 9% by removing outlier samples. The results of the fault type classifications show that the bagging C4.5+ LOF with 92.68% total accuracy is the best and the least faulty model in detecting each fault sample. In the class of being healthy with no fault, 100% accuracy with the bagging method, and on average, in each type of class, high accuracy was reported to detect the

type of fault with the proposed Bagging + LOF technique. The support vector machine method performed poorly in fault type classification. Even with the removal of the outlier data, an an average accuracy of 43.55% was achieved in this method. The matrix presented in Table VI, specifies the number of correctly predicted samples and the fault ,only 1 error was noticed in the low axial class, 2 errors in the high axial, and 3 errors in the low radial.

TABLE V.
Accuracy of the Classifiers

Model	Accuracy (ACC)	Recall healthy	Recall axial high	Recall axial low	Recall radial high	Recall radial low
C4.5	86.21%	100%	66.67%	85.71%	94.12%	77.78%
C4.5+LOF	89.15%	100%	82%	83%	78%	89%
SVM	40.07%	58%	0%	15%	18%	27%
SVM+LOF	43.55%	58%	50%	25%	33%	36%
Bagging C4.5	83.91%	100%	66.67%	92.86%	76.47%	77.78%
Bagging C4.5+LOF	92.68%	100%	87.50%	83.33%	100%	84.62%
Random forest	86.21%	100%	66.67%	85.71%	94.12%	77.78%
Random forest+LOF	89.22%	100%	93.75%	83.33%	70.20%	76.92%
GTB	88.50%	100%	82%	75%	87%	79%
GTB+LOF	89.45%	100%	82.30%	83%	78%	89%

TABLE VI.
The Matrix Of the Decision Tree Bagging Confusion

	healthy	axial low	axial high	radial low	radial high
healthy	31	0	0	0	0
axial low	0	11	0	3	0
axial high	0	0	14	0	0
radial low	0	1	0	10	0
radial high	0	0	2	0	10

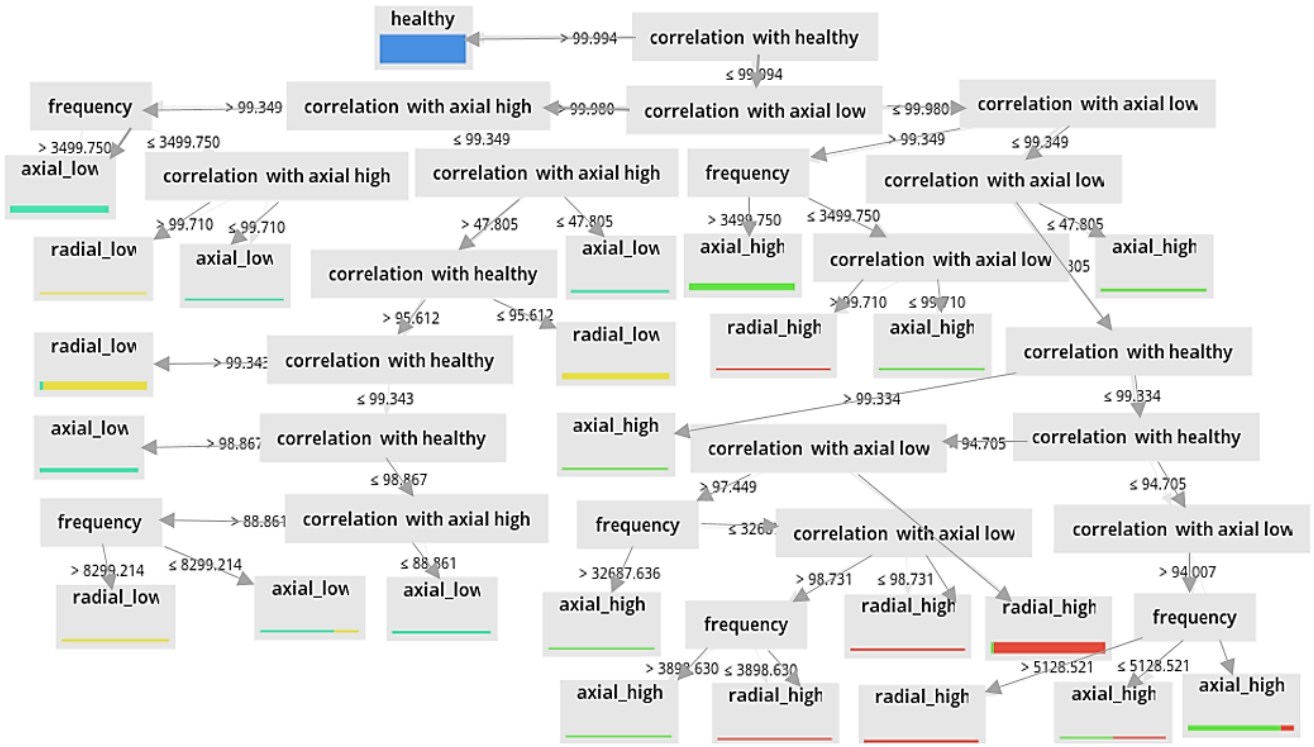


Fig. 9. The decision tree model

Figure (9) reports the decision tree model with high accuracy. Most of the reported rules are with higher certainty and probability of occurrence. If the correlation index in the healthy state is more than 99.99, the device is 100% in the healthy condition. The condition of the device is very likely in axial mode(low displacement of the axis).If the correlation index is less than 99.99 in the healthy mode , much more than 99.98 in the low-displacement mode of the coil axis, and more than 99.34 in the high-displacement mode of the winding and the received frequency is more than 34499.7,the condition of the device is very likely in the axial low mode (low axis displacement).

VI. CONCLUSION

In this study, to discriminate the types of transformer mechanical faults, the transformer behavior with frequency response and correlation indices in five models of device condition (healthy, high axial, low axial, high radial and low radial) was collected with 348 samples in two axial and radial deformation conditions. In the analysis section of the results, it was observed that the properties had outlier values. Therefore, in the preprocessing step by LOF method and threshold of 1.1, 18, outlier data samples were removed.

Decision tree, machine learning techniques, neural network, support vector machines, and ensemble methods of bagging, boosting gradient and random forest were used to classify the type of faults. The frequency responses of the transformer were modeled once without LOF and then by LOF, and the results showed increased accuracy and reduced error when the outlier data removing in all techniques, especially in the tree methods.

The technique of support vector machines with linear kernel reported poor results up to 49% and low accuracy in all types of fault classes. Basic and combined tree methods had a good average accuracy for classifying the type of transformer fault, The best accuracy was more than 92.68% exhibited by decision tree bagging. bagging ensemble methods and boosting gradients improved the results of the base decision tree and proved the need to use ensemble methods to improve the models. Compared to other articles, the presented study focused on generating hidden rules regarding the type of transformer fault and frequency responses with ensemble methods and to constructing a model of classification of fault with ensemble methods that have not been used in other published articles.

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