Performance Comparison of Ensemble Classifiers Algorithms Used in Transformer Fault Detection

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Abstract - **Power transformers are essential elements in the production and distribution of electricity, and keeping them in optimum operating condition is a constant concern for specialists in the field. The condition of power transformers is mainly determined by the condition of the mixed insulation system, i.e. solid cellulose paper insulation and liquid insulating oil insulation. The identification method, described in this paper in order to determine the fault condition for power transformers is based on the fact that the assessment of their condition is mainly determined by the condition of the mixed insulation system, namely the solid insulation made of cellulose paper and the liquid insulation made of insulating oil. This is why the Three Ratio Technique (TRT) is used with good results for the early detection of power transformer faults. This method is considered as simple, but at the same time efficient in interpreting the results of dissolved gas analysis. It uses three new gas ratios to differentiate between thermal and electrical faults. In this paper, the ratios defined by the TRT method are used to train a machine learning classifier based on Ensemble Classifiers using Bagged Trees (random forest), Boosted Trees, and RUSBoosted Trees algorithms. The validation of the power transformer fault identification software application for the proposed method is carried out in the experimental section.**

Cuvinte cheie: *transformator de putere, analiza gazelor dizolvate, tehnica cu trei rapoarte, pădure aleatoare.*

Keywords: *power transformer, dissolved gas analysis, three ratio technique, random forest.*

I. INTRODUCTION

High-power transformers have proven to be elementary equipment of the power system. The importance of their functioning in optimal parameters makes it mandatory to ensure an active maintenance program. It is known that the state of degradation of the mixed insulation system (paper-oil) is a decisive indicator in keeping/taking the transformer out of service [1, 2].

The methods for diagnosing the fault condition of power transformers have been the subject of many studies in the specialized literature. The most common methods are based on Dissolved Gas Analysis (DGA), this method has proven to be highly effective and at the same time economically convenient [3].

A multitude of DGA techniques have been developed to interpret incipient transformer faults, such as Doernenburg ratio [4], Rogers ratio [5], IEC ratio [6], Duval triangle/pentagon Duval/pentagon triangle [7], Gouda triangle [8] and three ratio technique (TRT) [9].

Fault states or anomalies occurring in the mixed insulation system is signaled by the formation of gases dissolved in oil. Depending on the gas concentrations (hydrogen H2, methane CH4, ethane C2H6, ethylene C2H4, acetylene C2H2, carbon monoxide CO, carbon dioxide CO2, nitrogen N2 and oxygen O2), with the help of DGA, the faults can be identified and localized at their early stages [10].

The methods listed above have advantages as well as weaknesses. To increase diagnostic accuracy it is recommended to use complementary methods or to improve them by developing an analysis program based on one or more methods.

The prediction and monitoring of the condition of electrical equipment has evolved in the sense that a complete characterization of the paper-oil insulation condition can be done by DGA tests, tests that give much information about the phenomena occurring in this equipment. Monitoring key parameters for detecting the transformer condition can be done online or off-line by realizing DGA from oil. It is unanimously accepted that both electrical and thermal faults can be determined from this analysis [11-13].

Regarding the development of transformer fault analysis/detection software, we mention the use of fuzzy logic based systems [14], neural networks [15] and classifiers based on machine learning algorithms [16].

In the case of the application in this paper, the aim is to use a machine learning type classifier which, after appropriate training, is able to estimate with an accuracy of more than 95% the type of fault of a transformer for which the dissolved gas concentrations are known. Based on their values, using the TRT type method with the ratios defined in it, are used as attributes of each training sequence of the classifier that will provide as output the type of defect. Based on the TRT method for DGA analysis, this paper presents a transformer fault condition classifier based on random forest algorithms [17-19].

The paper is structured as follows: Section II presents the TRT-type method and Section III presents the implementation of a random forest classifier. Test results for identifying power transformer faults using the TRT-type method and random forest classification algorithms are presented in Section IV, while the final section presents some conclusions and proposals for future work.

II. THREE RATIO TECHNIQUE

Osama E. Gouda, developed the TRT (DGA technique used in transformer oil) in order to increase the precision/accuracy of transformer fault diagnosis compared to classical methods such as Duval triangle 1, Doernenburg ratio, IEC ratio and Rogers ratio.

In accordance with the theory of thermodynamics, which is based on the equilibrium pressures of hydrocarbon gas formations at different temperatures, in oil-immersed transformers, each hydrocarbon gas varies with respect to the others in relation to the decomposition temperature. So we can conclude that there is an increasing proportion of hydrocarbon gases with respect to temperature fluctuation.

The maximum rate of formation of a gas is reached at a certain temperature, and each individual gas can reach its maximum rate at a different temperature.

Fig. 1 shows the formation of fault gas as a function of temperature and type of fault [13]. These are the same in all mineral oil electro-technical equipment (e.g. current or voltage transformers, free-breathing or sealed power transformers, bushings, etc.).

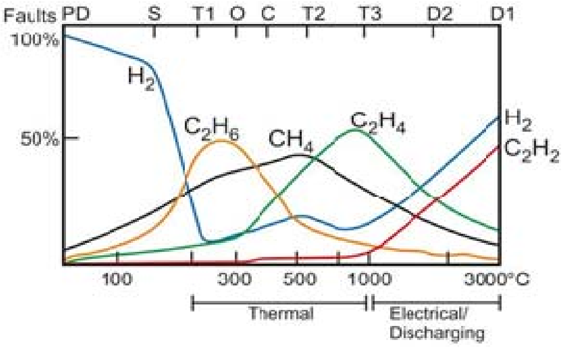

Fig. 1. Defect gas formation as a function of temperature.

The TRT is a simple and effective method of interpreting dissolved gas analysis results. It uses three new gas ratios to differentiate between thermal and electrical faults. The three new ratios are the result of reorganizing the five key gas concentrations into gas pairs that can clearly classify faults for each ratio. These ratios are [9]:

$$R1 = \frac{C_2H_6 + C_2H_4}{H_2 + C_2H_2} \tag{1}$$

$$R2 = \frac{C_2H_2 + CH_4}{C_2H_4} \tag{2}$$

$$R3 = \frac{C_2H_2}{C_2H_4} \tag{3}$$

The faults identified with the three ratios can be exemplified as follows:

- R1 distinguishes between thermal, DP and arcing faults;

- R2 distinguishes between D1 and D2 faults, between thermal faults from very low to high levels of thermal energy. This ratio can also assess the severity of thermal, electrical and partial discharge faults.

- R3 distinguishes between thermal and electrical faults, but cannot differentiate between DP, D1 and D2 faults. This ratio is also used in the Rogers, Doernenburg and IEC methods and it only confirms the fault condition identified with R1.

As with the other gas ratio methods, this technique is used when the concentration of at least one gaseous hydrocarbon exceeds the normal limits given in Table I.

TABLE I.
REFERENCE VALUES FOR KEY GAS CONCENTRATIONS

Dissolved gases	H_2	CH_4	C_2H_2	C_2H_4	C_2H_6	CO	CO_2
Reference concentrations [ppm]	100	120	1	50	65	350	2500

The TRT method is a simple and effective method of interpreting dissolved gas analysis results. By analysing these ratios, the method can effectively classify the type and severity of faults such as thermal, partial discharge and arc faults.

The evaluation of the ratios between the concentrations of three main gases: H_2, CH_4 and C_2H_4, and the comparison of these ratios with reference values lead to the identification of the different types of faults that can occur inside the transformer. For example, H_2 indicates the presence of partial electrical discharges or arcing, CH_4 results from overheating of oil or insulating materials, and C_2H_4 is associated with high energy partial electrical discharges.

By using the three combinations of gas ratios, a clearer classification of fault types and severity is achieved (Table II) [9].

TABLE II.
DIAGNOSTIC CODING OF TRT INTERPRETATION

The range of reports			Code
R1	*R2*	*R3*	
$R1 < 0.05$	$R2 < 1$	$R3 < 0.05$	0
$0.05 \leq R1 \leq 0.9$	$1 \leq R2 \leq 3.5$	$0.05 \leq R3 \leq 0.5$	1
$R1 > 0.9$	$R1 > 3.5$	$R3 > 0.5$	2

TABLE III.
FAULT DIAGNOSIS WITH TRT METHOD

R1	R2	R3	Fault type	Fault code
1or 2	0	0 or 1	High temperature thermal fault T > 700°C	T3
1or 2	1	0 or 1	Medium temperature thermal fault 300°C < T < 700°C	T2
1or 2	2	0 or 1	Low temperature thermal fault 150°C < T < 300°C	T1
1	—	0	Low temperature thermal fault T < 150°C	T0
0	1 or 2	0 or 1	Low partial discharge	PD1
0	1 or 2	2	High partial discharge	PD2
0 or 1	0 or 1	2	High energy discharge	D2
1 or 2	2	2	Low energy discharge	D1
2	0 or 1	2	Combination of electrical and thermal faults	DT

The advantages of the TRT method include:

- has a high accuracy compared to other methods that use ratios and also to the Duval Triangle1;
- has the ability to distinguish more reliably the faults according to their severity;
- leads to a significant reduction in cases (without decision) specific to methods that use ratios due to obtaining values of ratios outside the specified range and thus the inability to identify the fault.

Limitations of the technique:

- in some situations, the interpretation of the results can be difficult, especially in the case of old transformers or transformers with a complex fault history;
- the technique cannot detect all types of faults, such as natural ageing of oil or insulating materials;
- gas concentrations may be influenced by other factors such as temperature, pressure or humidity.

While the TRT method is a valuable tool, it is important to consider the following:

- The age of the transformer oil can affect the gas composition and therefore the accuracy of the results.
- Factors such as load cycling, temperature variations and moisture content can also affect gas content and diagnostic conclusions.
- Complementary analysis - the TRT method should be used in conjunction with other diagnostic tools and expert judgement for a complete assessment.

DGA using the TRT is a valuable method of monitoring the condition of power transformers However, for correct interpretation of the results, a complex analysis is recommended, taking into account both the absolute values of the gas concentrations and their evolution over time. In addition, the interpretation of results should be confirmed by other diagnostic techniques.

III. Implementation of Random Forest Algorithms in Matlab for Transformer Fault Detection

A classifier, after appropriate training, estimates the relationship between the class attribute and the other feature attributes. It extracts the model from the training data and tries to minimise the mean squared error.

The limitations of the model (consideration of the linear model versus a highly non-linear real model) result in a relatively large bias. Due to the limited amount of training data, we obtain a variance above the practically acceptable limits. In this sense, Random Forest uses multiple decision trees and performs a combination of their predictions to improve accuracy and avoid over-fitting. In the case of the application in this paper, the aim is to use a machine learning type classifier which, after appropriate training, is able to estimate with an accuracy of more than 95% the type of fault of a transformer for which the dissolved gas concentrations are known.

Based on their values, using the TRT type method described in the previous section, the ratios R1, R2 and R3 are obtained, which are the inputs of each training sequence of the classifier that will give as output the type of defect. Fig. 2 shows the block diagram of the software application for power transformer fault identification using the TRT method and the ensemble Bagged Trees classifier.

For this application, we used ensemble classifiers via the Classification Learner application from Matlab Statistics and Machine Learning toolbox. After training on a set of 200 samples, Table IV shows the training performance for the following categories of ensemble classifiers: Boosted Trees, Bagged Trees, Subspace Discriminant, Subspace KNN, and RUSBoost Trees.

It can be observed that the best performance is obtained using the Bagged Trees classifier, which is based on the Random Forest algorithm. It should be noted that this type of algorithm generally gives the best results for the range of classifiers presented [17-19].

Fig. 3 shows the confusion matrix resulting from ensemble bagged tree classifier training for the corresponding dataset. It can be seen that there is a relatively high percentage of confusion between D2 and PD2 faults. This is explained by the way they are defined, so that a large percentage of the membership intervals of the three dissolved gas ratios overlap. Confusion matrix is a visual representation of a classification model's performance and compares predicted class labels to the actual true labels.

This is also reflected in Figs 4 and 5, as the receiver operating characteristic (ROC) value for the PD2 error is less than 1, whereas the ROC value for the D2 error is less than 1. ROC curves are primarily used for evaluating the performance of binary classifiers. These classifiers predict one of two possible outcomes (positive/negative).

Another common performance ranking parameter of the algorithms used is the Area Under Curve (AUC) number. Also, AUC is a performance metric that quantifies the overall ability of a binary classifier. It represents the probability that a randomly chosen positive instance will be ranked higher than a randomly chosen negative instance by the classifier. This parameter is an overall qualitative measure of the classifiers.

TABLE IV.
Ensemble Classifier Performance For Power Transformer Fault Identification

Ensemble classifier type	Accuracy [%]
Bagged Trees	95.7
Boosted Trees	95.4
RUSBoosted Trees	95.1
Subspace KNN	73.5
Subspace Discriminant	72.7

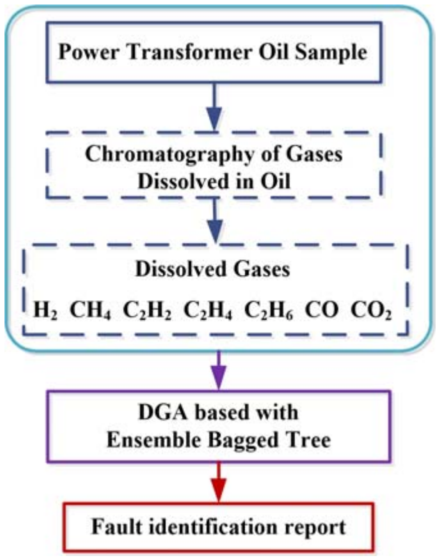

Fig. 2. Block diagram of the software application for power transformer fault identification using the TRT method and the Ensemble Bagged Trees classifier.

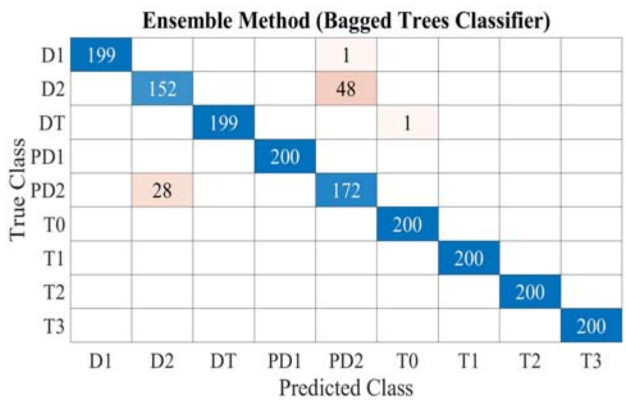

Fig. 3. Confusion matrix used to train the Bagged Trees ensemble classifier for transformer fault detection.

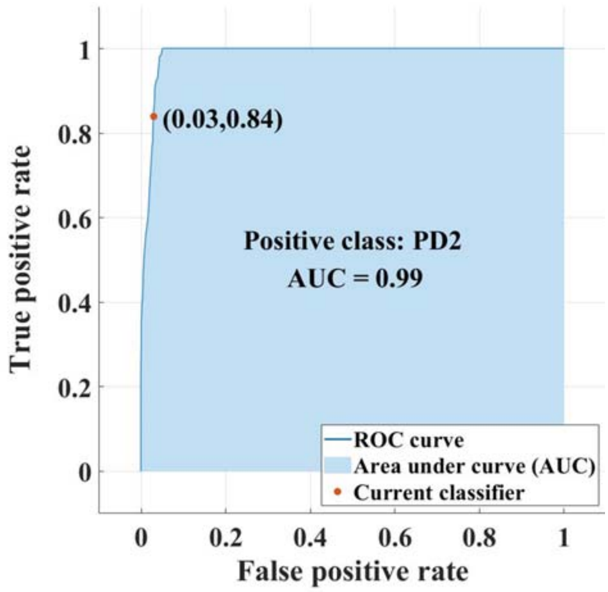

Fig. 4. ROC curve corresponding to the Bagged Trees ensemble classifier training for the PD2 error.

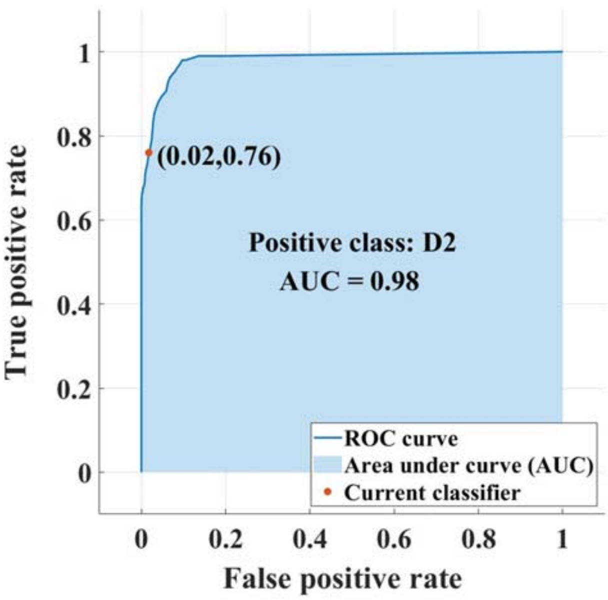

Fig. 5. ROC curve corresponding to the Bagged Trees ensemble classifier training for error D2.

Fig. 6 shows a prediction of the separation of the 9 defect classes corresponding to attributes R2 and R3, resulting from training the Bagged Trees ensemble classifier.

The study of the predictions in terms of defect class separation using the Bagged Trees ensemble classifier is shown in Fig. 7. Thus, depending on the values of the 3 ratios (R1, R2 and R3) corresponding to the training samples, a graphical image of the predicted position of the 9 defect types is obtained. In the following, in order to highlight the ranking accomplished in Table IV from the point of view of the accuracy of the classification algorithms used, we present the results obtained after training for the Boosted Trees and RUSBoosted Trees algorithms.

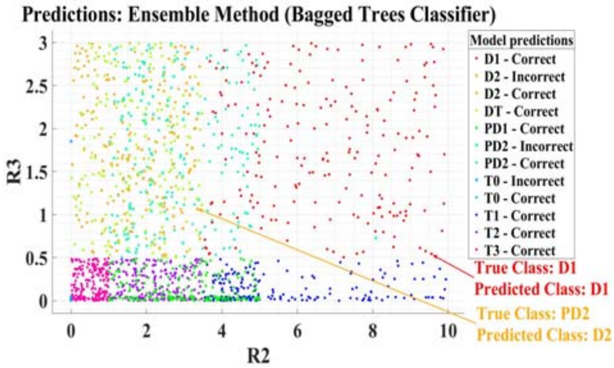

Fig. 6. Separation of defect classes using the Bagged Trees ensemble classifier and attributes R2 and R3.

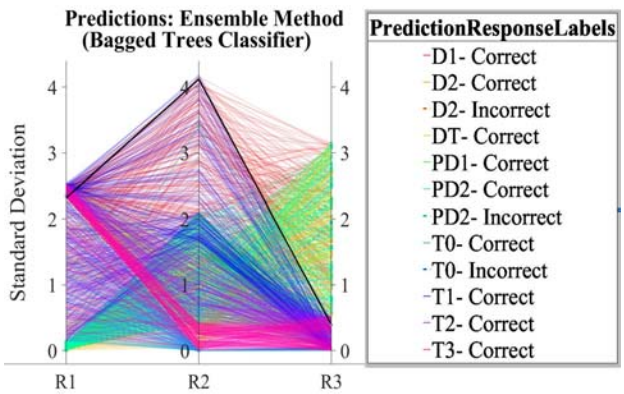

Fig. 7. Study of predictions by separation into 9 defect classes using the Bagged Trees ensemble classifier.

Thus, the resulting training confusion matrix for the Boosted Trees algorithm is presented in Fig. 8. ROC curves corresponding to this algorithm in terms of classification errors for defect classes PD2 and D2 are presented in Fig. 9 and Fig. 10. Fig. 11 shows a prediction of the separation of the 9 defect classes corresponding to attributes R2 and R3, resulting from training the Boosted Trees ensemble classifier. The resulting training confusion matrix for the RUSBoosted Trees algorithm is presented in Fig. 12. The ROC curves corresponding to this algorithm with respect to the classification errors for the PD2 and D2 defect classes are presented in Fig. 13 and Fig. 14.

Fig. 15 shows a prediction of the separation of the 9 defect classes corresponding to attributes R2 and R3, resulting from training the RUSBoosted Trees ensemble classifier. For the PD2 and D2 defect classes, it can be observed that the AUC decreases by 0.1 for the Boosted Trees algorithm and 0.2 for the RUSBoosted Trees algorithm compared to the Bagged Trees algorithm.

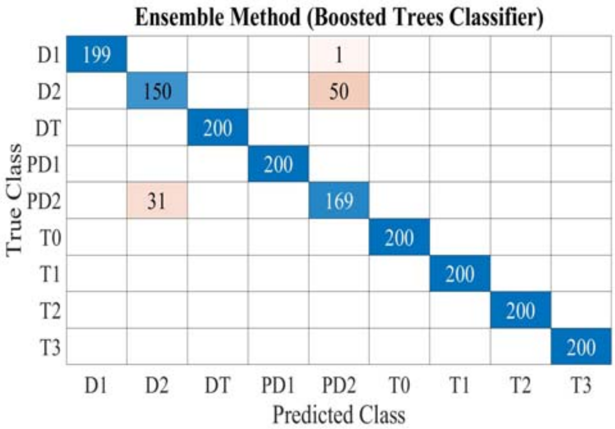

Fig. 8. Confusion matrix used to train the Boosted Trees ensemble classifier for transformer fault detection.

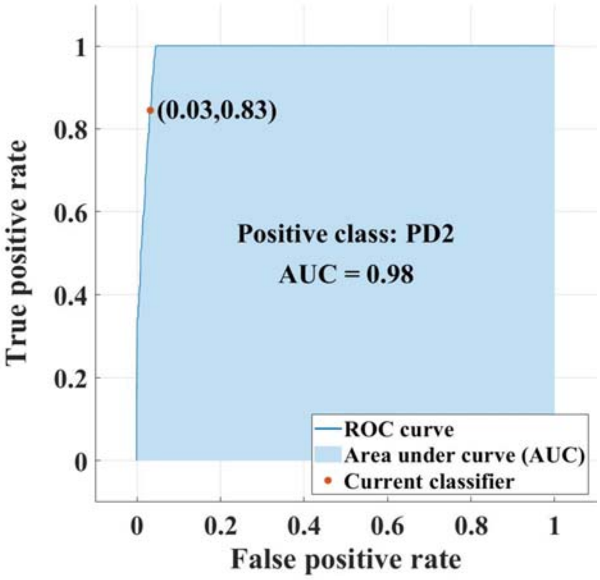

Fig. 9. ROC curve corresponding to the Boosted Trees ensemble classifier training for the PD2 error.

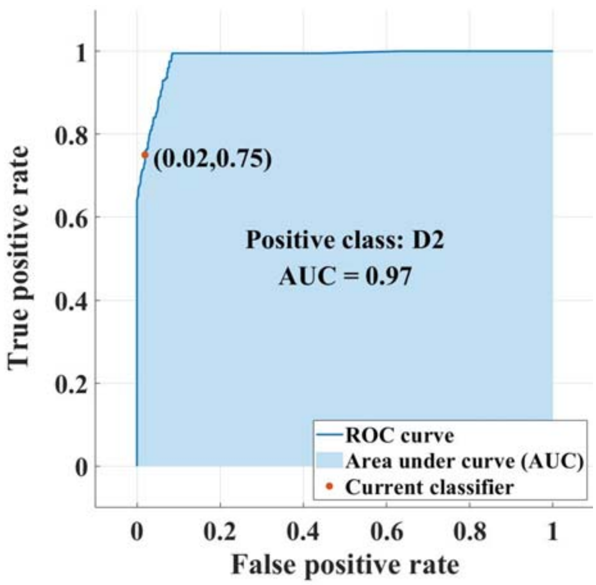

Fig. 10. ROC curve corresponding to the Boosted Trees ensemble classifier training for the D2 error.

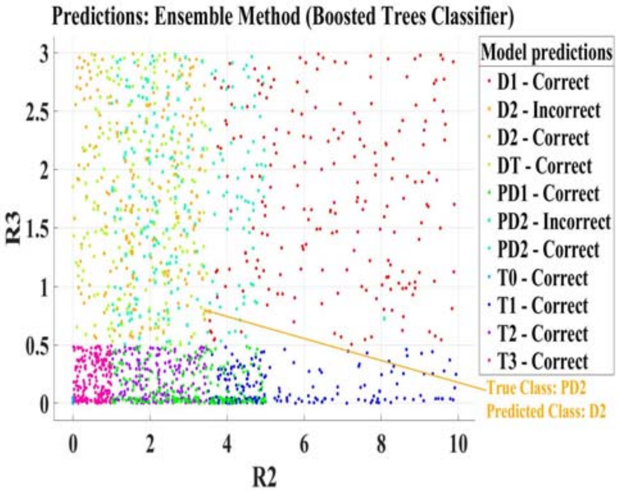

Fig. 11. Separation of defect classes using the Boosted Trees ensemble classifier and attributes R2 and R3.

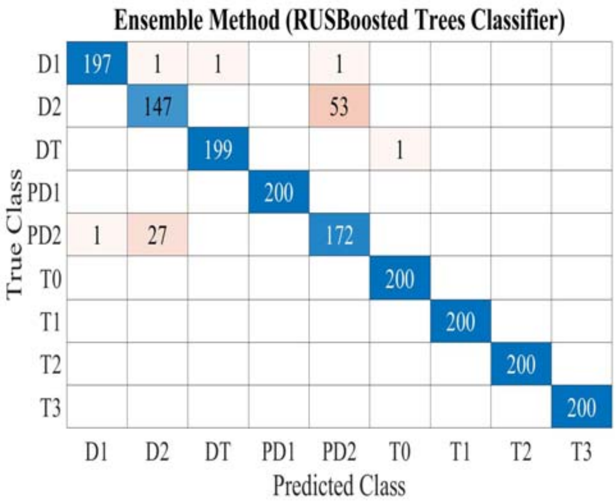

Fig. 12. Confusion matrix used to train the RUSBoosted Trees ensemble classifier for transformer fault detection.

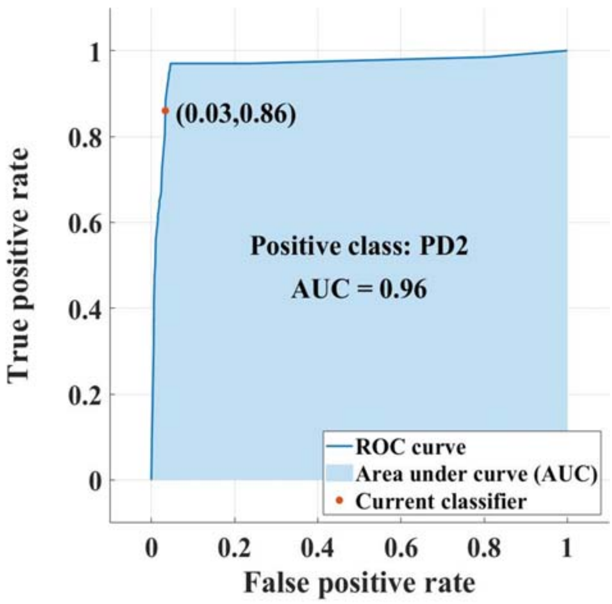

Fig. 13. ROC curve corresponding to the RUSBoosted Trees ensemble classifier training for the PD2 error.

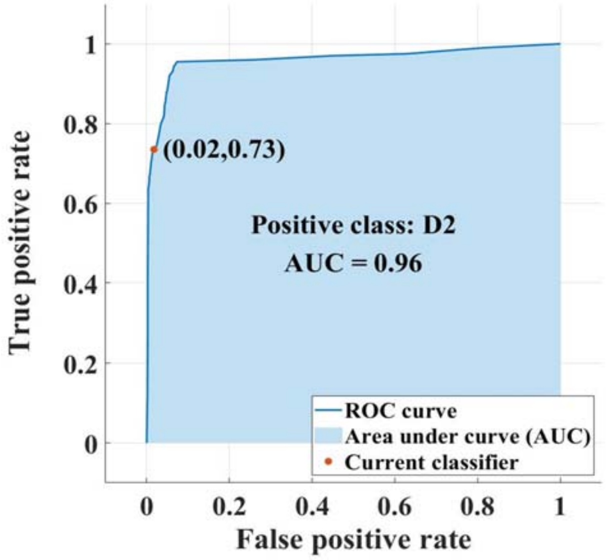

Fig. 14. ROC curve corresponding to the RUSBoosted Trees ensemble classifier training for the D2 error.

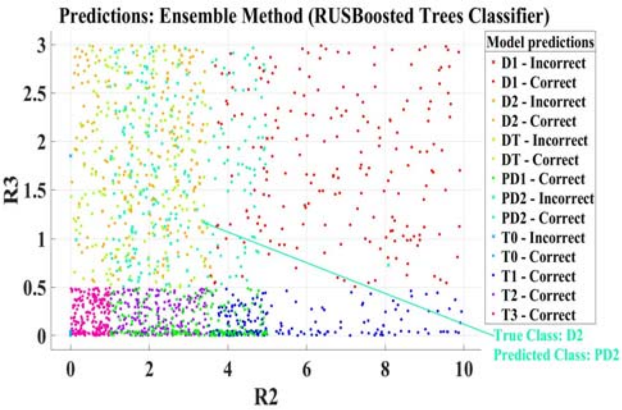

Fig. 15. Separation of defect classes using the RUSBoosted Trees ensemble classifier and attributes R2 and R3.

IV. Results of the Test for Fault Detection in Transformers Using Ensemble Bagged Tree Classifiers

The testing of the power transformer fault detection application presented in this paper was carried out on two 63 MVA 110/6.3 kV (Transformer-1) and 80 MVA 121/10.5 kV (Transformer-2) transformers undergoing prophylactic inspections. Their gas concentration values are given in Table V.

TABLE V.
Dissolved Gas Concentrations to Test the Proposed Transformer Fault Identification Method

Chromatographic analysis of gases dissolved in oil	Transformer-1 gas values [ppm]	Transformer-2 gas values [ppm]
Hydrogen H_2	19.46	455
Methane CH_4	69.92	755
Ethan C_2H_6	204.42	173
Ethylene C_2H_4	15.234	422
Acetylene C_2H_2	1.07	2
Carbon monoxide CO	154.94	1427
Carbon dioxide CO_2	1663.21	4234
Total dissolved combustible gases	465.044	3234

A. *Software Application Testing for Power Transformer Fault Detection - Type 1 Power Transformer*

In the first case, the following set of gas concentration values is used H_2 = 19.46 ppm, CH_4 = 69.92 ppm, C_2H_2 = 1.07 ppm, C_2H_4 = 15.234 ppm, and C_2H_6 = 204.42 ppm. These are used to obtain the following values of the 3 ratios defined in equations (1)-(3), which represent the inputs for the software application of the proposed random forest classifier: R1 = 10.699, R2 = 4.661, and R3 = 0.071.

After analysing the application using the Bagged Trees ensemble classifier, the fault T1 (see Fig.8) was identified, which is a thermal fault indicating temperatures between 150°C and 300°C. This fault indicates overheating due to flux concentration, most likely overheating of the LV or HV outputs due to faulty connections between the flexible joint connecting the LV or HV coil end to the copper terminal of the bushing on the LV or HV side, or poor soldering of the LV or HV coil end to the output flexible joint. The extent of the observed phenomenon is not dangerous for transformer availability.

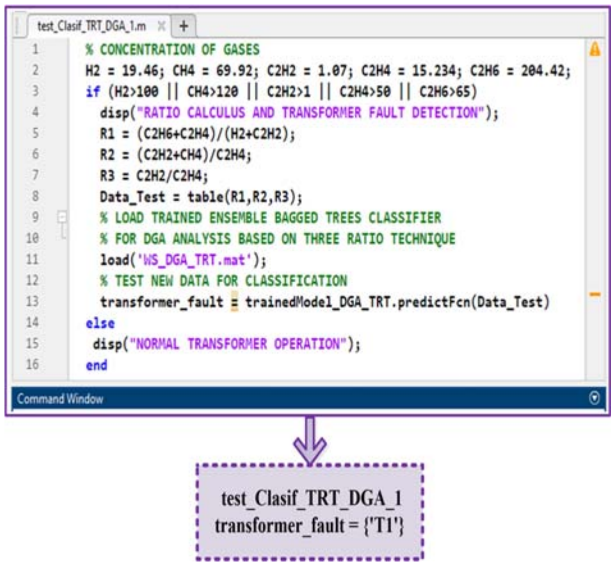

Fig. 16. Testing the Bagged Trees ensemble classifier - first test of the power transformer.

It is well known that cellulose insulation is affected by thermal degradation phenomena, so whenever a thermal defect is detected, it is imperative to determine the degree of polymerisation of the cellulose insulation by measuring the concentrations of furan compounds dissolved in oil.

As a result, the following recommendations have been made:

- Check the LV and HV winding outputs and retighten the flexible joint on the LV and HV terminals;
- Measure the concentrations of furan compounds dissolved in the oil and analyse the furan compounds to determine the state of degradation of the solid insulation and the cause of this state. The use of furan compound concentrations has the effect of increasing the accuracy of transformer faults identified by DGA [7];
- Repeat parameter measurements of the entire insulation system and complete oil analysis.

B. Software Application Testing for Power Transformer Fault Detection - Type 2 Power Transformer

In the second case, the following set of gas concentrations is used: H_2 = 455 ppm, CH_4 = 755 ppm, C_2H_2 = 2 ppm, C_2H_4 = 422 ppm, and C_2H_6 = 173 ppm. These are used to obtain the following values of the 3 ratios defined in equations (1)-(3), which represent the inputs for the software application of the proposed random forest classifier: R1 = 1.302, R2 = 1.793, and R3 = 0.004.

After analysing the application using the Bagged Trees ensemble classifier, the T2 defect was identified (see Fig.9), which is a thermal defect with temperatures between 300°C and 700°C.

According to the dissolved gas concentration values presented in Table V, the following aspects were identified:

- According to [13], the ethylene concentration decreases in case of a defect in the conductors (200 ppm < C_2H_4 < 2900 ppm). This means that the fault may be caused by overheating of the conductors due to eddy currents or poor connections between the output flexes in the winding and the terminals of the insulated bushings;
- CO = 1427 ppm > 1000 ppm and CO_2/CO = 2.96 < 3 in the presence of significant amounts of the other fault gases. Therefore, IEC 60599:2022 [11] indicates/specifies the involvement of paper in a defect with possible charring of the paper;
- Acetylene value in the oil above the required limit (2 > 1). This requires careful attention and weekly or even daily monitoring to determine if additional acetylene is being generated;
- The TDCG value of 3234 ppm classifies the transformer as Condition 3 - Extreme Caution according to IEEE Std.C.57-104:2019 [12], i.e. a high degree of cellulose and/or oil insulation degradation;
- Content of furan compounds was not determined.

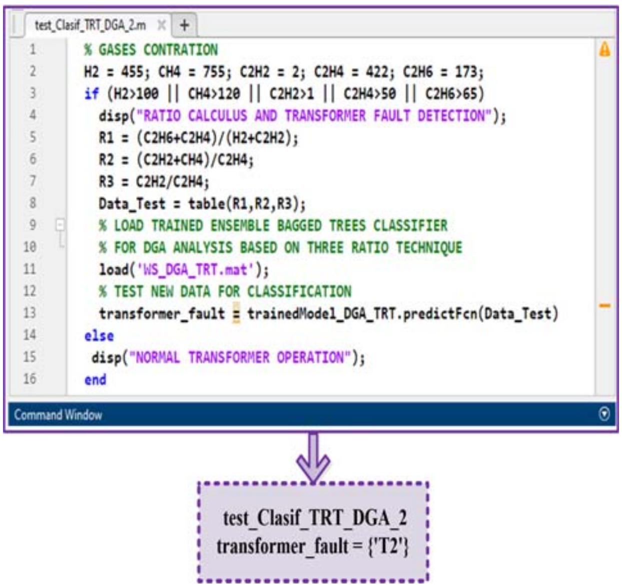

Fig. 17. Bagged Trees ensemble classifier test - power transformer second test.

As a result, the following recommendations have been made:

- Check the connections between the coil output flexible joints and the terminals of the insulated bushings and retighten the flexible joints on the LV and HV terminals;
- Measure the concentrations of furan compounds dissolved in the oil and analyse the furan compounds to determine the state of degradation of the solid insulation and the cause of this state;
- Repeat the DGA often enough to calculate the amount of gas produced per day for each gas;
- Complete oil analysis and repeat insulation system measurements.

V. Conclusions

This paper presents a method for identifying the fault condition of power transformers. It is based on the fact that the assessment of the condition of power transformers is mainly determined by the condition of the mixed insulation system, i.e. solid cellulose paper insulation and liquid insulating oil insulation. The TRT method is therefore used with good results for the early detection of power transformer faults.

The classification algorithm used was a machine learning algorithm based on ensemble and random forest algorithms from Matlab Statistics and Machine Learning toolbox. The validation of the power transformer fault detection application is carried out in the experimental section. For future work, the aim is to use combined classification algorithms with weight optimisation algorithms to increase accuracy.

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Contribution of authors:

First author –25%

First coauthor – 25%

Second coauthor – 25%

Third co-author– 25%

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