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Improved Power Transformer Incipient Fault Detection Using a New Gas Ratio and Decision Tree Algorithm based on Dissolved Gas Analysis

Milad Shafiei*[1], Farhad Haghjoo[1]

[1] *Department of Electrical Engineering, Abbaspour School of Engineering, Shahid Beheshti University, Tehran, Iran*

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ABSTRACT

This paper introduces a novel adaptive second-order sliding mode algorithm for finite-time control of uncertain nonlinear systems. Traditional first-order sliding modes are hindered by chattering and dependence on the upper bound of uncertainty. Although adaptive sliding modes with dynamic gains remove the need for this upper bound, they still suffer from chattering and lack finite-time stability. The proposed algorithm incorporates an additional term in the control law, ensuring a smooth control signal, eliminating chattering, and achieving finite-time stability of the closed-loop system. This method is applied to a thrust vector-based flying object for pitch angle tracking amidst aerodynamic coefficient uncertainties and environmental disturbances. The performance of the proposed thrust vector system is demonstrated through computer simulations, comparing it with two other adaptive first-order and an adaptive super-twisting sliding mode methods. Simulation results show significant improvements in control performance, including reduced chattering and enhanced stability, underscoring the practical effectiveness of the proposed method.

1. Introduction

Power transformers are among the most critical and expensive pieces of equipment for power system utilities. They are essential components of the power grid, playing vital roles in both transmission and distribution systems. Therefore, it is crucial to ensure that these transformers are properly managed, controlled, and maintained for long-term use. Early detection of transformer faults is important as it helps avoid service interruptions, abnormal operating conditions, and unwanted service losses. Fault occurrences, such as overheating failures, partial discharges (corona), or arc discharges (arcing), expose the insulating medium to abnormal electrical or thermal stresses. For example, internal arcing initially causes insulation breakdown. In such a state, the transformer must be disconnected to address the affected winding, requiring costly repairs and leading to prolonged downtime [1]. A variety of approaches have been devised for interpreting DGA, spanning both traditional and computational intelligent methods. Conventional methods such as the Key gas method introduced in [2, 3], the Doernenburg ratio [4], and

* Corresponding author
E-mail address: m.shafieiasl@mail.sbu.ac.ir
https://orcid.org/0009-0004-5589-0925
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Rogers ratio [5] rely on evaluating the concentration and ratio of dissolved gases. Furthermore, graphical methods like Duval triangle 1 [6], Duval pentagon 1 [7] have been introduced, showcasing their superior accuracy. In recent times, computational intelligence methods have gained increased attention due to significant advancements in processor speed and computer memory capacity.

Artificial Intelligence (AI) classification techniques have enhanced fault detection. In [8], a new decision-making framework based on Support Vector Machines (SVM) for transformer fault diagnosis is proposed; this framework is capable of performing effective pattern recognition on seven main operating states of transformers. In [9] , a model based on deep learning is proposed for online inspection of transformer insulations. In [10], a new fault gas interpretation approach for oil-filled power transformers is proposed. In [11], graphical analysis of dissolved gases in oil has been conducted using the Duval triangle method to better estimate internal faults in transformers with the aid of a fuzzy inference system (FIS) based on logical rules. In [12], fault classification in power transformers based on DGA is conducted using various machine learning techniques. Each machine learning algorithm possesses its own set of advantages and disadvantages, and the selection of the appropriate classifier among the available options is crucial to achieve the desired performance. In [13], a DT has been constructed for detecting transformer faults using different gas ratios and varying gas concentrations. Despite the improved accuracy of early fault detection methods for power transformers, many of these approaches present challenges for users, requiring a high level of expertise in machine learning and the use of powerful tools. However, simpler ratio-based methods were more user-friendly for engineers but lacked adequate accuracy. Therefore, presenting a method that combines the simplicity of ratio-based approaches with high accuracy will be crucial.

The objective of this paper is to introduce a new gas ratio (NGR) method based on the DT algorithm for detecting incipient faults in transformers using DGA. This method incorporates ten gas ratios to create a new ratio-based approach. The advantage of this method is quick and easy detection, along with proper accuracy. In section 2, DGA is described along with the interpretation methods of this test. Section 3 describes the basic concepts and settings of the DT. In section 4, it is said how the DT was used to build the *NGR* method. The section 5 is the statement of the results of the method, and in section 6, the conclusions of the discussions have been made.

2. Dissolved gas analysis

DGA testing is crucial as it furnishes transformer specialists with vital insights into the emergence of critical conditions. In fact, conducting this test allows for the assessment of the oil-immersed transformer's condition and facilitates the detection of potential defects before the gas levels released from the transformer oil reach critical thresholds. Different methods exist for analyzing dissolved gases in transformer oil; Some of these methods merely determine faults based on gas values, while others identify faults based on gas ratios, and still others graphically detect faults.

Rogers Ratios Method [5] is summarized in Table 1. It uses three gas ratios indicating five different types of faults, depending on the values of the ratios in column 1 through column 3 of Table 1. The limitation of the Rogers Ratios Method is that it cannot identify faults in a relatively large number of DGA results (typically 35%), because they do not correspond to any of the cases in rows of Table 1, even when values are high and there is obviously a fault [2].

Doernenburg ratio method [4] is a historic method less used today. It has the same limitation as the Rogers ratio method. The values for these gases are first compared to special concentrations based on Table 2 and flow chart method is shown in Figure 1 [2].

The most important graphical methods used in the industry today are the Duval triangle 1 and the Duval pentagon 1. Fault regions in these methods are located within the triangle and pentagon, respectively. By placing samples within these regions, the type of fault can be determined. These methods are illustrated in Figures 2 and 3, respectively. Graphical methods are newer approaches and generally offer better accuracy in fault detection. Moreover, fault detection in these methods is more user-friendly for the operators.

3. Decision Tree

A DT is a supervised learning approach used in machine learning. In this approach, a classification or regression DT is employed as a predictive model to analyze a set of data. Supervised learning is a machine learning approach for problems where each data point contains features and a specified label. When quantitative outputs are predicted, or when continuous values can be taken by the target variable, a regression tree is called. Conversely, when qualitative outputs are predicted, or when a discrete set of values can be taken by the target variable, a classification tree is called. In this study, classification DTs were used.

A tree represents a hierarchical structure with a set of nodes, branches, and leaves. In this structure, leaves represent class labels. Each node contains the terms and conditions of the DT. Branches in this structure indicate the “**YES**” or “**NO**” status of a condition applied to a node.

DTs are among the most popular and useful machine learning algorithms due to their intelligibility, simplicity, and interpretability. A single DT is easy to understand for anyone with a basic knowledge of mathematics. In this study, a single DT was used to detect transformer faults, and its accuracy and efficiency were analyzed.

For the development of a DT, certain parameters are needed. In this case four important parameters need to be determined:

1- DT features

In the initial stage, the necessary features to construct the tree should be generated. To achieve this, the primary features of the dataset, comprising the concentration of five gases dissolved in the transformer oil are utilized and new features, encompassing ten gas ratios are created. These gas ratios differ from those outlined in the IEEE C57.104 standard. The newly introduced features are illustrated in Figure 4.

2- Maximum depth of the DT

The second parameter is Max-depth. Maximum depth of DT specifies the depth of the roots of a DT. In other words, the number of lower layers of the root node is determined by it.

3- Impurity criterion of the DT

The third parameter is the impurity measure. The impurity function measures the extent of purity for a region containing data points from possibly different classes. There are several ways to measure impurity. In this study, two methods were used: the Gini Index and Entropy. These criteria are defined according to equations (1) and (2) [14].

Gini index: $$\sum_{k \neq k'} p_{mk} \times p_{mk'} = \sum_{k=1}^{K} p_{mk}\,(1 - p_{mk}) \qquad (1)$$

Entropy: $$-\sum_{k=1}^{K} p_{mk} \times \log p_{mk} \qquad (2)$$

Here, p_{mk} represents the proportion of samples belonging to node m (N_m) and class k, y_i is the class of sample, and it is defined as follows [14]:

$$p_{mk} = \frac{1}{N_m} \sum I\,(y_i = k) \qquad (3)$$

Table. 1. Rogers ratio method [2].

C2H2/C2H4	CH4/H2	C2H4/C2H6	Suggested fault diagnosis
< 0.1	0.1 to 1.0	< 1.0	Normal
< 0.1	< 0.1	< 1.0	Low-energy density arcing
0.1 to 3.0	0.1 to 1.0	> 3.0	Arcing / High-energy discharge
< 0.1	0.1 to 1.0	1.0 to 3.0	Low temperature discharge
< 0.1	> 1.0	1.0 to 3.0	Thermal < 700 °C
< 0.1	> 1.0	> 3.0	Thermal > 700 °C

Table. 2. Limit concentrations of dissolved gases [4].

Key gas	Concentration (L1)
H2	100
CH4	120
CO	350
C2H2	1
C2H4	50
C2H6	65

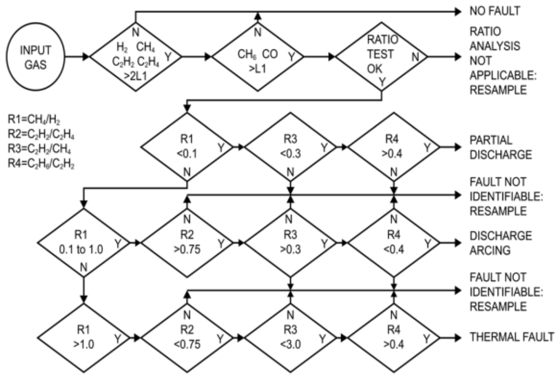

Fig. 1. Doernenburg ratio flow chart [2].

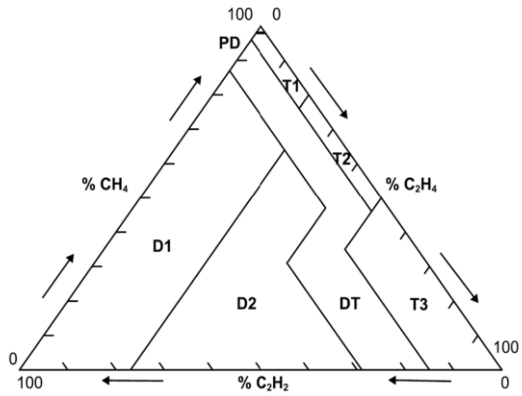

Fig. 2. Duval Triangle 1 [2].

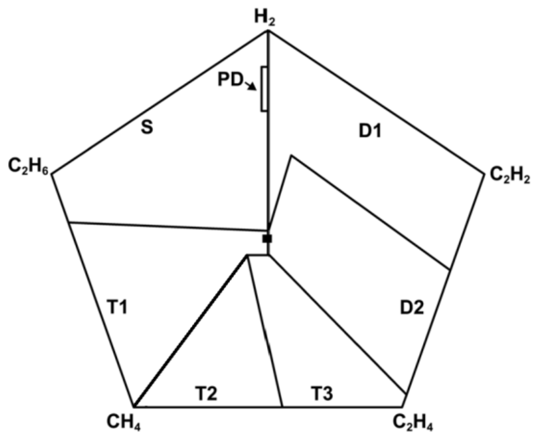

Fig. 3. Duval Pentagon 1 [2].

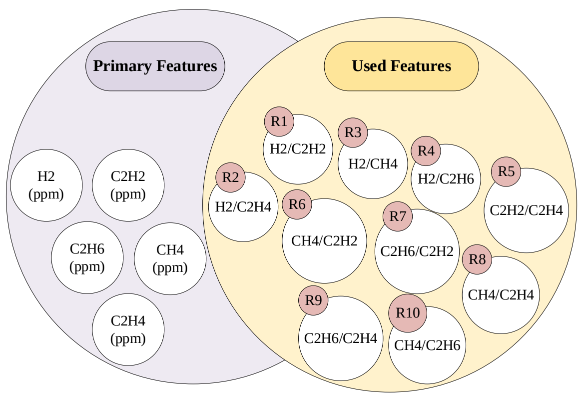

Fig. 4. Possible and used DT features.

4- Minimum samples required to split branches

This setting determines the minimum number of samples required to split an internal node. For example, if the Min-samples-split is set to 10, the nodes will be split until the samples of a class do not reach 10 samples, provided that they do not exceed the specified Max-depth.

4. Employment the DT in developing the new gas ratio method

In this paper, leveraging the beneficial effects of artificial intelligence algorithms, a new method based on gas ratios has been introduced, utilizing a suitable DT and gas ratios as features of this DT. The methodology of this paper is visually represented in the flowchart provided in Figure 5.

To construct a DT for fault detection, a dataset comprising 589 samples has been utilized, as outlined in Table 3. These samples were obtained from the Egyptian Electricity Holding Company (EEHC) [15]. The dataset encompasses concentrations of five gases in parts per million (ppm): hydrogen, ethane, methane, ethylene, and acetylene.

The gases mentioned are dissolved in the oil sample, and their values are measured in ppm. The notations used in Table 3 include (T is Temperature):

PD: Partial discharge
D1: Low energy discharge
D2: High energy discharge
T1: Low temperature overheating ($T < 300$ºC)
T2: Medium temperature overheating ($300^o < T < 700$ºC)
T3: High temperature overheating ($T > 700$ºC)

According to the settings introduced for the DT in Section 3, this section examines the impact of different settings on the performance of the DT. For this analysis, two important statistical indicators are used.

Table. 3. Count of samples for each fault type [15].

Fault Type	PD	D1	D2	T1	T2	T3
Count	74	91	149	111	60	104

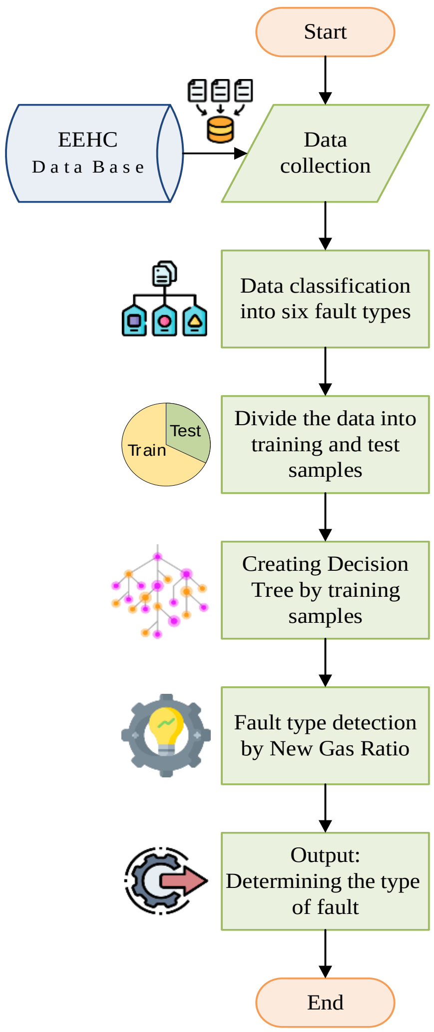

Fig. 5. Proposed method flow chart.

The Accuracy metric for selecting the best model and the Recall metric for comparing the model's performance with other methods. These two statistical indicators are defined according to equations (4) to (7).

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{4}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{5}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{6}$$

$$\text{F1-score} = \frac{2 \times Precision \times Recall}{Precision + Recal} \tag{7}$$

In these relationships, TP, TN, FP, and FN represent true positive, true negative, false positive, and false negative, respectively.

5. Results and discussion

To construct the DT, the dataset samples are initially divided into training and testing samples. In this process, 80% of the samples are allocated as training data, while the remaining 20% are designated as test data. This DT is then built using the training samples. In order to select the best tree model for detecting transformer faults, the effect of changing three main tree settings, including maximum depth (Max-Depth), impurity criterion, and minimum samples required to split a node (Min-Sample-

Split) on accuracy score index has been investigated. Table 4 shows the impact of changing two settings, Max-Depth, and Min-Sample-Split on *Accuracy Score* for training samples of DTs with Gini impurity criterion. Table 5 presents the same changes for test samples. According to Table 4, decreasing Min-Sample-Split and increasing Max-Depth lead to an increase in the algorithm's accuracy, attributed to the enlargement of the DT and an increase in its node count for better detection of the maximum discernible samples. However, as shown in Table 5, reducing Min-Sample-Split and increasing Max-Depth do not always result in an increase in model accuracy. This is because the model becomes overfit from a certain point onwards, leading to a significant gap between the model's accuracy on training and test samples. For instance, with Min-Sample-Split=2 and Max-Depth=9, the difference in model accuracy between training and test samples reached 15.67%.

Tables 6 and 7 respectively illustrate the impact of changing two settings, Max-Depth, and Min-Sample-Split, for training and test samples of DTs with Entropy impurity criterion on *Accuracy Score*. The highest accuracy for test samples under this criterion is 86.44%, while with the Gini criterion, the maximum test sample accuracy was 84.75%. Furthermore, it's crucial to note the significance of the difference in model accuracy between training and test samples. According to Tables 4 and 5, when the maximum test sample accuracy is achieved, the difference in accuracy between test and training samples reaches 8.24%. In contrast, this difference is only 2.52% for DTs with the Entropy criterion, indicating better performance of the selected model. Therefore, the final DT selected has an Entropy impurity criterion, with Min-Sample-Split=6 and Max-Depth=6.

Table. 4. Adjusting Max-Depth and Min-Sample-Split for training samples of DTs with Gini impurity criterion.

		Min-Sample-Split								
		2	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Max-Depth	**3**	79.4	79.4	79.4	79.4	79.4	79.4	79.4	79.4	79.4
	4	85.35	85.36	85.35	85.35	85.35	85.14	85.14	84.93	84.93
	5	89.38	88.96	88.86	88.96	88.96	88.54	88.54	88.32	88.32
	6	90.87	90.45	90.02	90.02	90.02	89.38	89.38	89.17	89.17
	7	92.99	92.36	91.72	91.72	91.51	90.87	90.87	90.66	90.66
	8	95.12	94.27	93.42	93.42	92.78	92.14	91.72	91.51	91.51
	9	97.03	95.97	95.12	94.69	94.05	93.42	92.99	92.57	92.57

Table. 5. Adjusting Max-Depth and Min-Sample-Split for test samples of DTs with Gini impurity criterion.

		Min-Sample-Split								
		2	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Max-Depth	**3**	77.12	77.12	77.12	77.12	77.12	77.12	77.12	77.12	77.12
	4	78.81	78.81	78.81	78.81	78.81	78.81	78.81	79.66	79.66
	5	82.2	82.2	82.2	82.2	82.2	82.2	82.2	83.9	83.9
	6	83.9	84.75	84.75	84.75	84.75	82.2	82.2	83.05	83.05
	7	84.75	83.05	82.2	82.2	83.9	83.9	83.9	83.9	83.9
	8	82.9	84.75	83.05	83.05	83.9	81.36	83.05	83.05	83.05
	9	81.36	83.05	83.05	82.2	83.05	82.2	82.2	82.2	82.2

Table. 6. Adjusting Max-Depth and Min-Sample-Split for training samples of DTs with Entropy impurity criterion.

		Min-Sample-Split								
		2	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Max-Depth	**3**	81.53	81.53	81.53	81.53	81.53	81.53	81.53	81.53	81.53
	4	84.29	84.29	84.08	84.08	84.08	84.08	84.08	84.08	84.08
	5	87.26	87.05	86.84	86.84	86.84	86.84	86.84	86.84	86.84
	6	89.6	89.38	88.96	88.96	88.96	88.75	87.69	87.69	87.69
	7	92.99	92.57	91.93	91.93	91.3	91.08	90.02	89.6	89.6
	8	96.39	95.75	94.9	94.06	93.63	93.21	92.14	91.72	91.51
	9	97.24	96.6	95.33	94.48	94.06	93.21	92.14	91.72	91.51

Table. 7. Adjusting Max-Depth and Min-Sample-Split for test samples of DTs with Entropy impurity criterion.

		Min-Sample-Split								
		2	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Max-Depth	**3**	80.51	80.51	80.5	80.51	80.51	80.51	80.51	80.51	80.51
	4	79.66	79.66	79.66	79.66	79.66	79.66	79.66	79.66	79.66
	5	81.36	81.36	81.36	81.36	81.36	81.36	81.36	81.36	81.36
	6	86.44	86.44	86.44	86.44	86.44	83.9	84.75	84.75	84.75
	7	83.05	84.75	83.05	83.05	84.75	83.05	83.05	83.9	84.75
	8	83.9	82.2	80.5	82.2	83.9	82.2	82.2	83.05	83.9
	9	80.5	81.36	82.2	82.2	83.9	82.2	82.2	83.05	83.9

Accuracy score calculated as below:

$$\text{Accuracy Score} = \frac{\sum_{i=1}^{n} N_i \times \text{Accuracy}_i}{\sum_{i=1}^{n} N_i} \qquad (8)$$

Where, i is the class number, n is the count of classes, and N_i is the number samples in class i.

Figure 6 illustrates the confusion matrix related to selected DT. The provided confusion matrix visually represents the performance of a classification model in predicting six different faults. The matrix layout is a 6x6 grid where rows represent the true labels and columns represent the predicted labels. Each cell at the intersection of a row and column shows the number of instances where the true label (row) was predicted as the corresponding label (column). This confusion matrix provides a comprehensive view of how well the classification model is performing across the six different classes. The diagonal elements (highlighted cells) represent the number of correct predictions for each class, while the off-diagonal elements show the misclassifications. Based on this confusion matrix, some statistical indexes calculated as Table 8.

The procedure chart is shown in Figure 7. This flowchart is obtained using different gas ratios. As mentioned in the previous sections, fault detection is done easily by this method. All conditions of this DT are "<" (**smaller than**) and gas ratios are compared in this way. If the condition is true, the branches are extended from the right side, and if it is not, the branches are extended from the left side of that node and finally reach the type of fault.

In Table 9, a performance comparison between the proposed method and prevalent fault detection methods is presented based on the Recall statistical index. The results indicate that the *NGR* method demonstrates the highest performance in all fault classes except D1. Specifically, for the PD fault class, the *NGR* method achieves approximately 54% greater accuracy than the Duval Pentagon 1 and 28% greater than DT_F (Decision Tree to Fault type detection) method described in [16]. Additionally, when considering all test data, the proposed method surpasses DT_F, Duval Pentagon 1, Duval Triangle 1, and IEC 60599 ratio by 8.1%, 24.2%, 25.6%, and 44.5% respectively.

The proposed method in this article surpasses limitations found in traditional techniques like the Doernenburg ratio and Rogers ratio methods. These established methods, while valuable, suffer from restricted fault class identification. Instead of differentiating between various discharge fault types, they lump all discharge activity under a single, broad category labeled "D" (Discharge). This lack of granularity can lead to misdiagnosis and hinder targeted maintenance actions. The proposed method, however, offers a more nuanced approach, distinguishing between different discharge fault types, allowing for more precise fault identification and facilitating focused repair strategies.

Utilizing ten gas ratios in procedure resulted in achieving a high level of fault detection accuracy, surpassing the performance of DT_F [16] model. The primary motivation behind employing a DT algorithm for constructing the new proportional model lies in the precise and explicit formation of numerical conditions for constructing the decision nodes of *NGR* approach.

One drawback of this method compared to the Doernenburg Ratio or Rogers Ratio methods is its inability to identify the normal status of samples. To address this limitation, the DT specifically designed for normal/faulty (DT_{NF}) sample status identification in [16] can be employed. In practice, DT_{NF} can be utilized initially; if its output indicates a fault, the method proposed in this paper can be applied to determine the fault type. However, it is important to note that the primary objective of this paper is to present a fault detection method, and sample health status diagnosis is not the main focus.

6. Conclusion

The proposed *NGR* method based on a DT algorithm significantly enhances the accuracy and simplicity of fault detection in power transformers using DGA. By integrating ten gas ratios, this method provides a robust tool for identifying various types of transformer faults, achieving a maximum test sample accuracy of 86.44% with the Entropy impurity criterion. Specifically, the method demonstrated superior performance in detecting PD faults with an accuracy of 93.3% and T3 faults with an accuracy of 90.9%. Although the method cannot identify normal operational states, it can be combined with existing techniques for comprehensive fault diagnosis. The final DT model selected with a Min-Sample-Split of 6 and Max-Depth of 6 showed a recall of 76.5% for low energy discharge (D1) faults, 85.7% for high energy discharge (D2) faults, 94.4% for low-temperature overheating (T1) faults, and 80.0% for medium-temperature overheating (T2) faults. This study demonstrates the potential of the *NGR* method to improve transformer maintenance practices, reducing downtime and repair costs, thereby contributing to the overall reliability and efficiency of power systems.

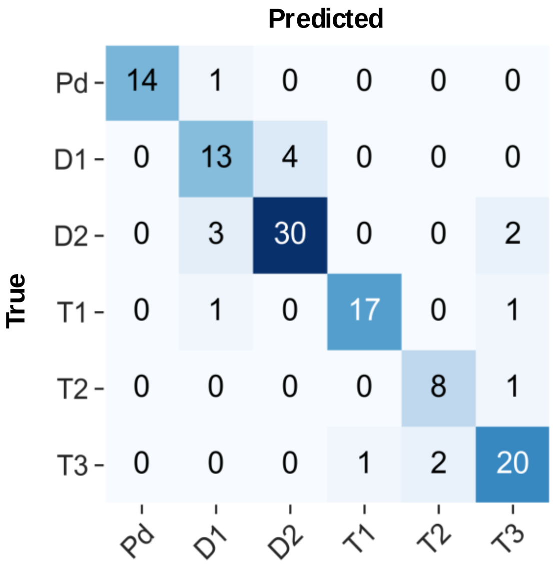

Fig. 6. Confusion matrix for the selected DT Model.

Table 8. Performance evaluation of NGR model.

Fault	Precision	Recall	F1-Score	Accuracy
PD	1.000	0.933	0.965	0.990
D1	0.722	0.765	0.743	0.919
D2	0.882	0.857	0.869	0.919
T1	0.944	0.944	0.944	0.971
T2	0.800	0.800	0.800	0.971
T3	0.833	0.909	0.870	0.936

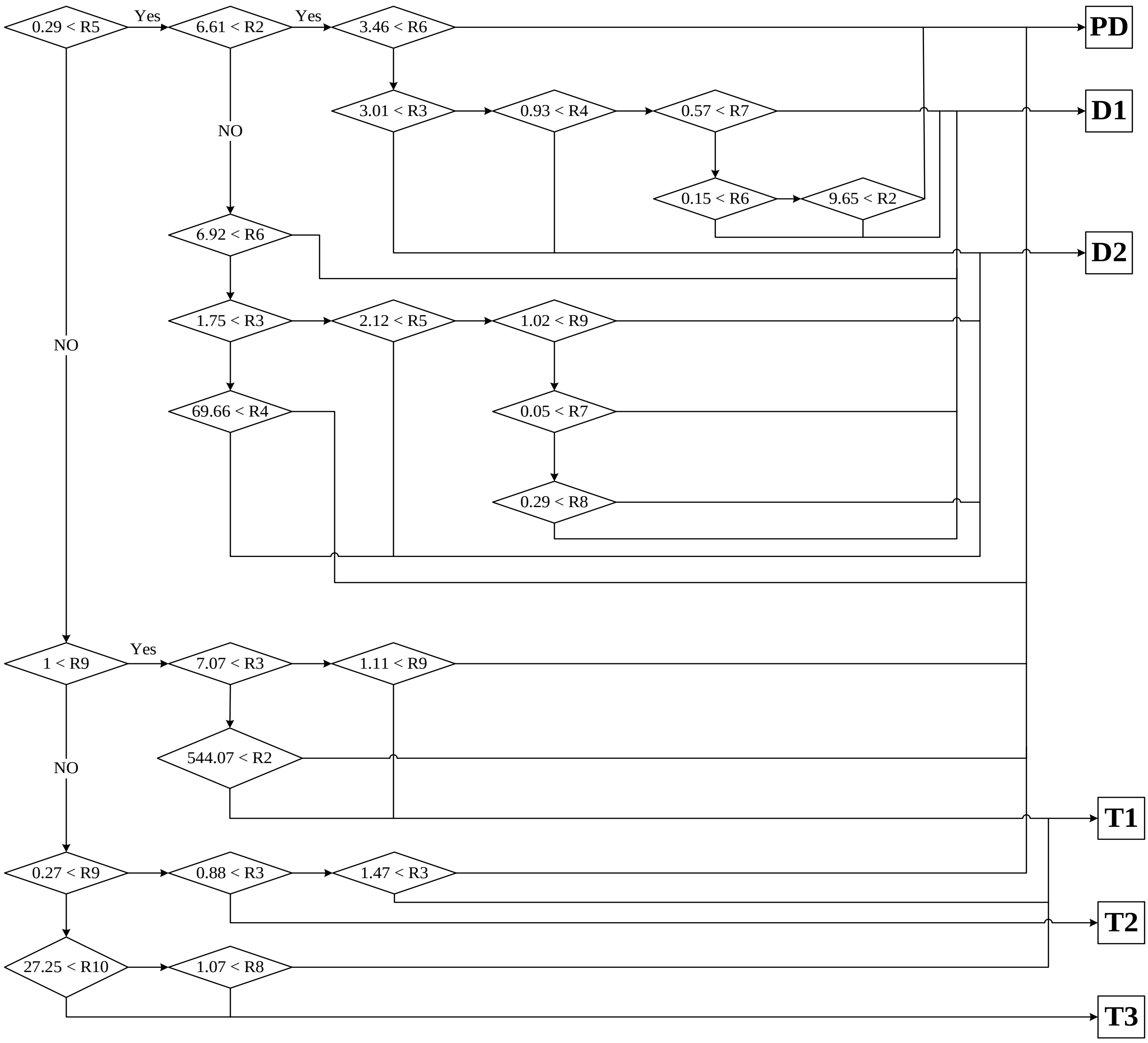

Fig. 7. NGR method to detect incipient faults in oil immersed transformers.

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