Fault diagnosis of power transformer using random forest based combined classifier

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Article Info

Article history:

Received Aug 27, 2023
Revised Sep 7, 2024
Accepted Sep 28, 2024

Keywords:

Dissolved gas analysis
Duval triangle method
IEEE C57.104-2019
Random forest
Transformer

ABSTRACT

In the power system, transformers are crucial electrical equipment that require an insulator or dielectric material, such as paper immersed in insulating oil, to prevent electrical contact between components. The dissolved gas analysis (DGA) test is important for diagnosing and determining the maintenance recommendations for transformers. The duval triangle method (DTM) is commonly used to identify faults in transformers. The data used in this article are from DGA test of power transformers in East Java and Bali transmission main unit (UIT JBM). The DGA data were analyzed based on the IEEE C57.104-2019 standards, and by using the developed random forest (RF) classifier-based DTM for easier software implementation and better accuracy. The results of fault identification in 6 transformers case study showed a low-thermal fault (T1)<300 °C in transformer 1, where methane gas increased, stray gassing (S) in transformer 5 due to escalating hydrogen gas production, overheating (O)≤250 °C indicated in transformers 2 and 6 due to rising ethane gas production. Transformers 3 and 4 were found in normal condition. This fault identification is done to enhance the accuracy of maintenance recommendation action based on DGA.

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1. INTRODUCTION

The transformer is a vital and expensive component in the power system network, used to transform electric power through magnetic coupling. Repairing a transformer takes a considerable amount of time, and replacing it is uneconomical, leading to significant costs for electrical utilities [1], [2]. To prevent transformer failure, insulation is essential to decrease the risk of faults. Transformer insulating oil, is a common form of internal insulation in power transformers, applied to immerse the transformer's winding. This serves not only to prevent the leakage of short-circuit currents from the transformer's voltage section to other components but also acts as a cooling system for the transformer [3]. The health condition of the transformer can be identified through the condition of the insulating oil [4], [5]. Therefore, it is important to diagnose the transformer through oil sampling and analysis.

The most commonly used method over the years for the early identification of transformer failure is dissolved gas analysis (DGA). This method involves identifying breakdowns through the formation of dissolved gases in the oil insulator, which are indicative of transformer failure effects [6], [7]. DGA is utilized for the detection and diagnosis of failure in transformers, especially oil-immersed types. As explained in reference [8], this assessment must be performed promptly to mitigate potential negative impacts on the transformer. The concentration of gases produced and dissolved depends on the type of fault occurring in the transformer. Generally, faults are classified into two types: electrical faults (PD, D1, and D2) and thermal faults (T1, T2, and T3). Faults in the transformer lead to the formation of gases dissolved in the dielectric fluid. These gases can be categorized into three groups: firstly, the hydrogen and hydrocarbon group, containing hydrogen (H_2), methane (CH_4), ethane (C_2H_6), ethylene (C_2H_4), and acetylene (C_2H_2); secondly, carbon oxides, containing CO and CO_2; and thirdly, non-fault gases, containing O_2 and N_2 [9], [10].

IEEE C57.104-2019 provides a standard or guideline for DGA tests on oil-immersed transformers, supporting failure identification and maintenance recommendations. Several studies have been conducted using the IEEE C57.104-2019 standard along with the duval triangle as a fault identification method. Boonseng *et al*. [11] utilizes IEEE C57.104-2019 as a guideline for inspecting a 24 MVA distribution transformer. In research by Mawelela *et al*. [12], the duval triangle method (DTM), with graphical and MATLAB bases, is used to identify faults in data from ten transformers. Machine learning, particularly the random forest (RF) classifier technique introduced by Breiman, which involves creating several distinct decision trees, each functioning as an independent classifier [13], [14], can be implemented in this research. RF exhibits the lowest error rate compared to other methods [15]. Levin *et al*. [16] developed fuzzy logic implementation on Doenenburg ratio method. While the successful software implementation is obtained, the Doenenburg ratio method is not known for its high accuracy. Research by Ekojono *et al*. [17] indicates that the RF method achieves a performance accuracy of 99.6%, compared to 90% for the neural network method and 82.3% for the naïve Bayes method. Based on these findings, the RF was chosen for this research to diagnose transformer failures more accurately. To determine transformer failures, the DTM is used [11], [12]. Ekojono *et al*. [17] describes the creation of RF models for detecting faults in power transformers, demonstrating notable accuracy compared to alternative machine learning algorithms.

Several studies have utilized the DTM in conjunction with the IEEE C57.104-2019 standard for fault diagnosis [11], [12], [18]. Additionally, the potential of machine learning techniques, such as the RF classifier, has been explored to enhance diagnostic accuracy [17]. This research seeks to address the limitations of previous studies by introducing a combination of the DTM with a RF classifier. The proposed methods is implemented to assess the condition of the transformer from East Java and Bali transmission main units (UIT JBM).

2. METHOD

The flowchart depicted in Figure 1 outlines the procedure of this study. Firstly, collecting DGA data from transformers. The delta value and rate of increase for each gas type are then computed. The DGA data are subsequently analyzed and compared with the parameters outlined in IEEE C57.104-2019.

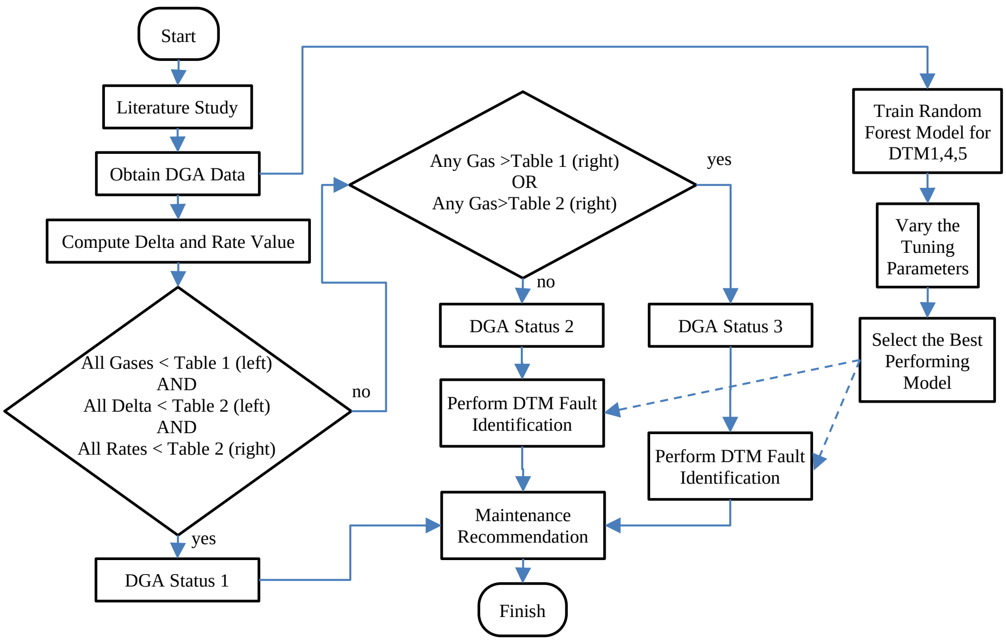


Figure 1. Research flowchart

If all gas levels are below the limits specified in Tables 1(a) and (b), all delta values and all rates are below those in Tables 2(a) and (b), the transformer is classified as DGA status 1, indicating a healthy condition. If not, the analysis proceeds to the next step: if any gas level exceeds the limits in Table 1(b) or any rate surpasses those in Table 2(b), the transformer is classified as DGA status 3, which signals an urgent issue. If neither of these conditions is met, the transformer is assigned a DGA status 2. Transformers classified with DGA status 1 will receive maintenance recommendations appropriate for their healthy status. For transformers with DGA status 2, fault identification using the DTM is conducted, followed by maintenance recommendations for less urgent issues upon fault detection. Similarly, transformers with DGA status 3 undergo fault identification using the DTM, after which maintenance recommendations are given based on the urgency of the identified faults.

Table 1(a). Gas concentration (ppm) limit on 90th percentile of transformer population [19]

Dissolved gas	Transformer age (year)			
	Unknown	1–9	10–30	>30
H2	80	75		100
CH4	90	45	90	110
C2H6	90	30	90	150
C2H4	50	20	50	90
C2H2	1	1		
CO	900	900		
CO2	9000	5000	10000	

Table 1(b). Gas concentration (ppm) limit on 95th percentile of transformer population [19]

Dissolved gas	Transformer age (year)			
	Unknown	1–9	10–30	>30
H2	200	200		
CH4	150	100	90	110
C2H6	175	70	90	150
C2H4	100	40	50	90
C2H2	2	2		4
CO	1100	1100		
CO2	12500	7000	14000	

Table 2(a). Delta value limitation [20]

Gas	Limitation
H2	40
CH4	30
C2H6	25
C2H4	20
C2H2	>0
CO	250
CO2	2500

Table 2(b). Rate of gas increase limitation [20]

Dissolved gas	4-9 months	10-24 months
H2	50	20
CH4	15	10
C2H6	15	9
C2H4	10	7
C2H2	>0	
CO	200	100
CO2	1750	1000

2.1. IEEE C57.104-2019

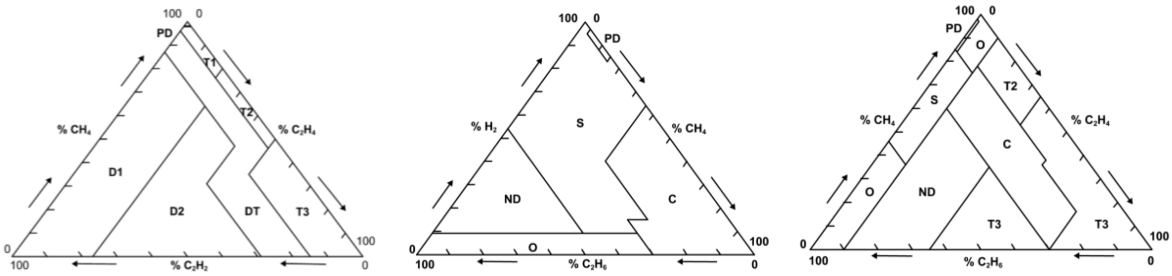
IEEE C57.104-2019 serves as a standard or reference for detecting anomalies in power transformer. The process involves computing and contrasting the obtained number with the typical ones listed in the IEEE C57.104-2019 parameter tables. This guideline delineates the transformer operational state such as status 1 signifies normal. Status 2 implies potential faults of comparatively lower urgency, while status 3 denotes an actual fault in the transformer and fault identification action is necessary. Recommendation action are outlined for each transformer state, including routine DGA testing for status 1 and performing fault identification for status 2 and 3 [19]. Table 1 presents both 90th and 95th percentile limit for various gases, namely hydrogen (H_2), methane (CH_4), ethane (C_2H_6), ethylene (C_2H_4), acetylene (C_2H_2), carbon monoxide (CO), and carbon dioxide (CO_2).

Table 2(a) shows gas concentration limit of the differences between two consecutive DGA values. This table helps determine if there is an unusual gas rise in the transformer. In such cases, it is recommended to take a confirmatory sample. Table 2(b) shows the rate of increase limit calculated using multi-point linear regression, which eliminates variations introduced by the laboratory DGA analysis method. These tables are useful in detecting the possibility of active gassing based on a series of DGA results.

2.2. Fault Identification using duval pentagon method

Fault identification in power transformers is essential for the reliable operation of the electricity grid [21]. Transformers in DGA status 2 and DGA status 3 conditions must undergo fault identification. In this research, a graphical fault identification method is employed, known as the DTM. There are five types of DTM, namely duval triangle 1, 2, 3, 4, and 5. However, for analyzing transformer failures from insulation oil, only duval triangle 1, 4, and 5 are used. Each method utilizes the percentages of three hydrocarbon gases derived from five basic hydrocarbon gases to diagnose faults on the triangle plot [22].

The DTM uses three hydrocarbon gases for mapping fault identification. In DTM 1, as depicted in Figure 2(a), methane (CH_4) is used for diagnosing low-energy/temperature faults, ethylene (C_2H_4) for identifying high-temperature faults, and acetylene (C_2H_2) for detecting faults with extremely high temperatures or high energy, such as arcing faults [10], [23]. The triangles shown in Figure 2, is used to plot the percentages of these three gases. duval triangle 4, as depicted in Figure 2(b), employs methane (CH_4), ethane (C_2H_6), and hydrogen (H_2). If the duval triangle 1 analysis indicates PD, T1, or T2 faults, additional information can be obtained by combining it with the calculations from duval triangle 4 [20]. Similarly, duval triangle 5, as depicted in Figure 2(c), utilizes methane (CH_4), ethane (C_2H_6), and ethylene (C_2H_4). If the duval triangle 1 method indicates a T2 or T3 fault, deeper insights can be achieved by supplementing it with calculations from duval triangle 5 [20].



(a) (b) (c)

Figure 2. Graphical representation of: (a) duval triangle 1, (b) duval triangle 2, and (c) duval triangle 3 [20]

Description:
PD: partial discharge
T1: low-thermal fault (below 300 °C)
T2: medium-thermal fault (300 °C - 700 °C)
T3: high-thermal fault (above 700 °C)
D1: low-energy electrical discharge
D2: high-energy electrical discharge
DT: indetermine fault (mixtures of electrical/ thermal fault)
S: stray gassing at temperature <200 °C
C: possible paper carbonization
O: overheating <250 °C without carbonization of paper
ND: not defined

The percentages of each gas need to be determined. Calculation example for duval triangle 1 is shown in (1)-(3):

$$\%CH_4=CH_4/(CH_4+C_2H_4+C_2H_2)\times 100\% \quad (1)$$

$$\%C_2H_4=C_2H_4/(CH_4+C_2H_4+C_2H_2)\times 100\% \quad (2)$$

$$\%C_2H_2=C_2H_2/(CH_4+C_2H_4+C_2H_2)\times 100\% \quad (3)$$

2.3. Random forest classifier implementations

The application of the DTM in fault identification can be done in several approaches, with a prevalent technique involving manual calculations. Machine learning provides a different way to predict faults in transformers using DTM. As part of its machine learning component, the RF classifier creates a series of decision trees using a bootstrap sample of the training data [17], [24]. The RF algorithm is a well-known and effective ensemble supervised classification method [25]. This method generates multiple distinct decision trees, each acting as an independent classifier. The final decision is made by combining the votes from all these decision trees. Figure 3 illustrates the scheme of RF implementation in the fault identification of power transformers.

This scheme for RF processing starts with the insertion of 5 hydrocarbon gas concentrations, which are then processed with the RF classifier to diagnose faults based on DTM. To achieve high precision in fault determination using the RF network, selecting the right tuning parameters is mandatory [27]. The RF algorithm is composed of an ensemble of decision trees, each built from a bootstrap sample drawn from the training set. Using independent and identically distributed random vectors, this approach involves multiple tree-structured classifiers. The selected parameters and their related values are shown in Table 3.

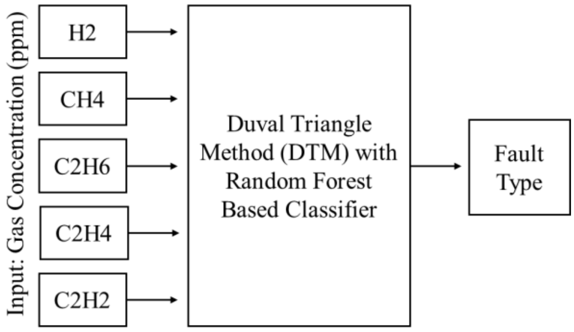


Figure 3. RF implementation scheme [26]

Table 3. Variations of tuning parameters and observed values for RF model

Parameters	Value
Number of trees	10, 50, 100, 500, 1000, and 2000
Sample leaf size	10, 20, and 30
Criterion	Gini and entropy

Determining faults using the DTM requires a dataset to train and test the RF algorithm. The results of testing are evaluated to determine the optimal approach for estimating DGA accuracy. The dataset contains information on the actual fault types of transformers identified with the DTM and is provided for duval triangles 1, 4, and 5, as shown in Table 4.

Table 4. Number of data sample

Fault type	Data number		
	Duval triangle 1	Duval triangle 2	Duval triangle 3
PD	26	26	26
T1	30	-	-
T2	48	-	91
T3	108	-	444
D1	520	-	-
D2	400	-	-
DT	270	-	-
S	-	610	126
C	-	403	268
O	-	215	168
ND	-	301	325
Total	1402	1555	1448

3. RESULTS AND DISCUSSION

3.1. Random Forest based duval triangle

First, RF models for duval triangle 1, 4, and 5 are developed. The development process begins by deciding the leaf sample size, the criterion type, and the number of trees that will be compared to other options to achieve the best classification accuracy [28]. A large number of trees in the forest can yield better performance [13]. Cross-validation is conducted by comparing two parameters taken from the tuning parameters in Table 3, which then produces a level of accuracy for each model. The results of a cross-validation graph are used to select the best number of trees, leaf sample size, and criterion for duval triangle 1, 4, and 5 RF models.

Figures 4 to 6 present graphical representation of the classification accuracy for three different leaf sizes: 10, 20, and 30, implemented with various criteria. The graphs demonstrate that the best accuracy results are achieved with a leaf size of 10 for all the DTM used. Based on the level of accuracy produced by the three parameters being compared - namely, the number of trees, leaf sample size, and criterion type - it is possible to conclude the following: for duval triangle 1, using entropy as the criterion type with a leaf sample size of 10 and a total of 500 trees achieves an accuracy level of 0.969. For duval triangle 4, using entropy as the criterion type with a leaf sample size of 10 and a total of 50 trees achieves an accuracy level of 0.996. And for duval triangle 5, using entropy as the criterion type with a leaf sample size of 10 and a total of 100 trees achieves an accuracy level of 0.977.

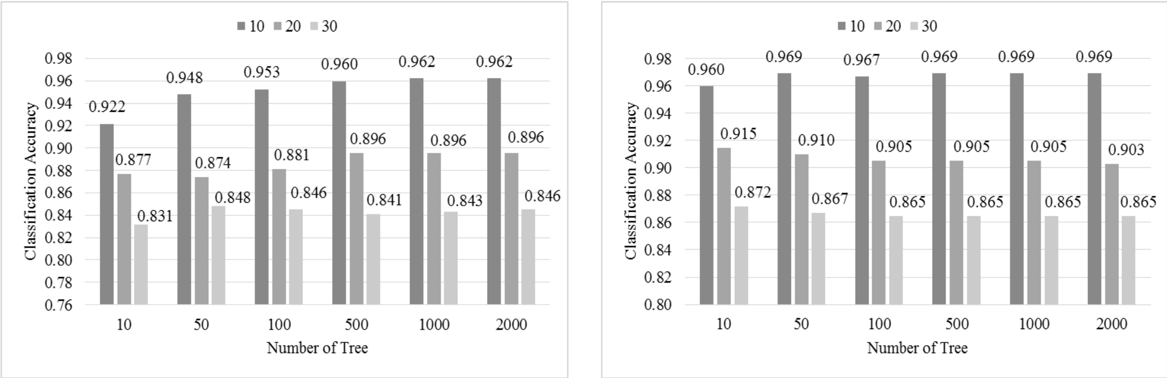


Figure 4. Classification accuracy between gini criterion (left) and entropy criterion (right) for duval triangle 1

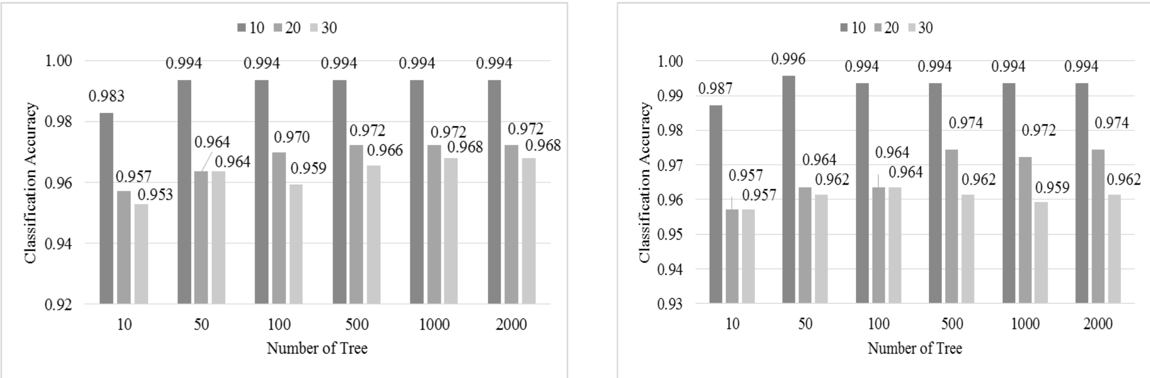


Figure 5. Classification accuracy between gini criterion (left) and entropy criterion (right) for duval triangle 4

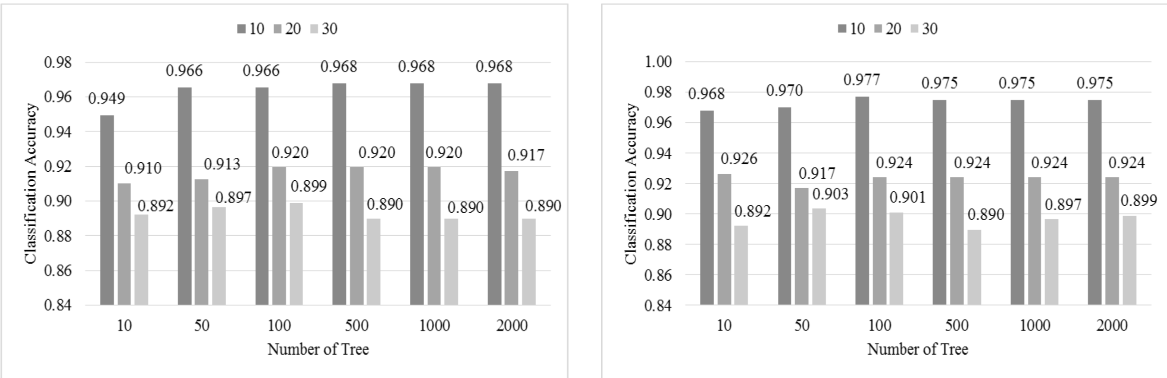


Figure 6. Classification accuracy between gini criterion (left) and entropy criterion (right) for duval triangle 5

3.2. Transformer dissolved gas analysis data

The data from DGA tests are essential for supporting the interpretation of transformer conditions and diagnosing faults that have occurred. The collected DGA data include information about the age of the transformer, the latest gas concentrations, the delta value of each gas, and the rate of gas increase for each gas, as shown in Table 5. Dissolved gases analyzed in this research include H_2, CO, C_2H_4, C_2H_2, CO_2, C_2H_6, and CH_4. The data in Table 5 was used to determine the condition of the transformers based on IEEE C57.104-2019.

Table 5. DGA data of 6 transformer case study

Case study	Age (year)	Parameters	H_2	CO	C_2H_4	C_2H_2	CO_2	C_2H_6	CH_4
T1	5	Gas concentration	21.00	226.00	2.00	0.00	2783.00	53.00	39.00
		Deltas	-9.58	201.57	2.00	0.00	1364.19	30.29	39.00
		Rate of increase	-60.13	23.78	0.40	0.00	570.42	8.70	-1.31
T2	6	Gas concentration	0.00	145.00	0.00	0.00	881.00	89.00	35.00
		Deltas	4.48	126.79	0.00	0.00	2.14.00	57.05	35.00
		Rate of increase	0.37	18.95	-0.12	0.00	189.58	8.58	4.92
T3	6	Gas concentration	0.00	104.00	2.00	0.00	386.00	27.00	14.00
		Deltas	-3.34	92.44	2.00	0.00	-298.94	15.15	11.11
		Rate of increase	-0.35	10.00	0.47	0.00	-193.25	-26.55	-16.29
T4	7	Gas concentration	0.00	64.00	0.00	0.00	782.00	20.00	10.00
		Deltas	-46.16	8.79.00	-416.14	0.00	323.31	-183.82	-214.46
		Rate of increase	-19.15	-17.67	-190.83	-0.10	-311.07	-88.81	-84.53
T5	6	Gas concentration	85.00	217.00	2.00	0.00	1326.00	55.00	43.00
		Deltas	78.86	194.70	2.00	0.00	-555.39	44.96	43.00
		Rate of increase	18.65	16.69	0.47	0.00	172.46	8.49	6.99
T6	8	Gas concentration	0.00	179.00	4.00	0.00	2818.00	318.00	133.00
		Deltas	-3.04	158.41	2.91	0.00	715.61	201.97	121.17
		Rate of increase	0.32	28.52	1.05	0.00	618.05	61.94	23.06

3.3. IEEE C57.104-2019 interpretation

The results of the interpretation of six case study transformers based on IEEE standards are status 1 to status 3, shown in Table 6. These outcomes were derived by examining the most recent gas concentrations, deltas, and rates of gas increase for each dissolved gas within the transformers. The data were then compared with the parameter table provided by IEEE C57.104-2019. According to the results, four transformers require fault identification due to their condition being classified as either DGA status 2 or DGA status 3. These transformers are transformer 1, transformer 2, transformer 5, and transformer 6.

Table 6. Interpretation result of fault identification

Transformer case study	DGA condition	RF-based DTM interpretation
Transformer 1	DGA status 2	T1–N/D
Transformer 2	DGA status 3	T1–O
Transformer 3	DGA status 1	N/A
Transformer 4	DGA status 1	N/A
Transformer 5	DGA status 2	T1-S
Transformer 6	DGA status 3	T1-O

3.4. Fault identification

To perform fault identification, the DTM with the RF algorithm is applied. The RF method is developed as an application using PySimpleGUI as a module and Python as the programming language to develop the user interface, as shown in Figure 7. This program was built to support fault identification using the combined DTM with the RF classifier. Results are provided after all gas levels are inserted and the "ANALYZE" button is clicked. The result column provides a conclusion of the fault diagnosis using DTM.

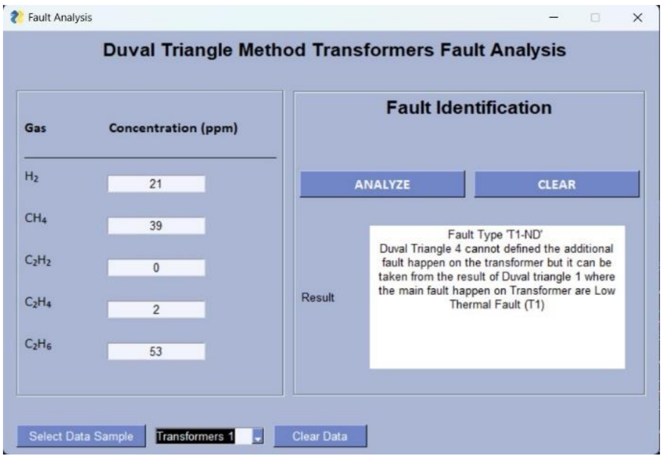


Figure 7. Interface of transformer fault analysis program

Table 6 shows the results of fault identification using combined DTM with the RF classifier on six transformers. Transformers 3 and 4 did not identify any faults because these transformers were both in the condition of dga status 1. According to IEEE C57.104-2019 standard calculations, transformers 1 and 5 both received dga status 2. Transformer 1's status was due to C_2H_6 gas concentration values of 53.00 ppm and delta gas concentrations of C_2H_6 and CH_4 exceeding the parameter limits. For transformer 5, it was due to H_2 and C_2H_6 gas concentrations of 85 ppm and 55 ppm, respectively, which exceeded the gas concentration normal limit. The identification of faults in these cases involved additional investigation to assess the possibility of faults occurring in the transformers. The fault diagnosis results for transformer 1 indicated a low-thermal fault (T1)<300 °C in duval triangle 1 and not defined (ND) detected in duval triangle 4, thus referring the fault diagnosis for this transformer to duval triangle 1. For transformer 5, a T1<300 °C was detected in duval triangle 1 and stray gassing (S) in duval triangle 4, leading the fault diagnosis for this transformer to refer to duval triangle 4. Maintenance recommendations were acquired by addressing the matter as increasing the frequency of DGA tests, and minimizing the heat production of the transformer.

Transformers 2 and 6 both received a DGA status 3. This status was assigned due to the high concentration levels of C_2H_6 gas, measured at 89.00 ppm and 318 ppm, respectively. The identification of faults in these cases is crucial to determine potential issues in the transformers. The results of the fault diagnosis for transformers 2 and 6 indicated a T1<300 °C in duval triangle 1 and O<250 °C in duval triangle 4. Therefore, the fault diagnosis for these transformers refers to duval triangle 4, leading to maintenance recommendations that should be treated as urgent issues. These recommendations include reducing heat production in the transformer, increasing the frequency of DGA testing, and monitoring the growth of DGA in the transformer oil.

4. CONCLUSION

The RF-based duval method was utilized to identify the condition of transformers using DGA test from the insulating oil samples of UIT JBM–East Java, Bali, and Madura transmission main unit transformers. To apply a RF model, three datasets were created. The outcomes demonstrate that the optimal leaf size and criterion for all DTM are typically 10 with an entropy criterion. Duval triangle 1 with 500 trees achieved 96% accuracy, duval triangle 4 with 50 trees achieved 99% accuracy, while duval triangle 5 with 100 trees achieved 97% accuracy. Interpretation using IEEE C57.106-2019 was performed to determine the condition of the transformers. The analysis revealed that transformers 1, 2, 5, and 6 exhibited abnormal conditions, which are categorized as DGA status 2 and DGA status 3. Implementing the duval triangle with a RF classifier resulted in the identification of a T1 in transformer 1. Transformer 5 showed a stray gassing (S) fault diagnosis, and transformers 2 and 6 exhibited O<250 °C. This research offers promising advancements for the field of power transformer fault diagnosis. The integration of the DTM with a RF classifier has demonstrated the potential to increase diagnostic accuracy, particularly in complex fault scenarios. This enhanced accuracy could lead to more informed maintenance strategies, ultimately improving power grid reliability. This means fewer disruptions, reduced costs associated with major repairs, and increased safety due to the proactive identification of potential transformer failures. The future research is expected to be accomplished using a RF model with a multi-method DGA model, which combining the results of the duval triangle, duval pentagon, roger ratio method, and International Electrotechnical Commission (IEC) ratio method.

ACKNOWLEDGMENT

This work is supported by research grant (Penelitian Produk Vokasi/P2V) provided by Direktorat Jenderal Pendidikan Vokasi, Kementerian Pendidikan, Kebudayaan, Riset, dan Teknologi Republik Indonesia, 2024.

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