



PREVENTIVE TREATMENT FOR POWER TRANSFORMER BY ANALYSIS OF DISSOLVED GAS AND USING FUZZY LOGIC

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ABSTRACT

Transformer is one of the major and most important high-cost components of electrical power systems, so it is necessary to prolong their life span, reduce downtime and maintenance. There are many types of electrical and chemical diagnostic methods for monitoring insulation conditions for the transformer, like Doerneburg's and Roger's revised IEC-599r methods. This study introduces fuzzy logic, which handles vague, imprecise, and uncertain fault diagnoses for transformers. This work applies fuzzy logic for three methods: Doerneburg's, IEC 599r, and proposed methods by using MATLAB to measure the dissolved gas in the mineral oil of transformers to explain if the transformer is faulty or NOR., and when the transformer is faulty, what must be done for accumulation of gases. The results explain that the correct diagnosis for the three methods: Doernenburg's, IEC-599r, and the proposed method is 12%, 76%, and 92%, and the certainty is 83.3%, 90.3%, and 89.1%, respectively.

KEYWORDS

Dissolve gas analysis, Faults diagnosis, transformer, Fuzzy Logic.



1. INTRODUCTION

The infrastructure of electrical utilities is essential to providing a steady power supply to their customers. Power transformers are some of the most expensive and important pieces of equipment in the power system, and their reliability directly affects the safety of power operations (Sdood, H., 2013). Any issue with the power transformer might lead to the power supply being off, which would also mean large financial losses. Mechanical, electrical, or thermal stress can cause defects in transformer oil insulators. Power transformer fault categories that frequently arise include ARC, partial discharge, low-energy sparking, severe overloading, pump motor failure, and insulation system overheating (Elmabrouk, et.al..2020). Carbon monoxide (CO), ethylene (C₂H₄), acetylene (C₂H₂), ethane (C₂H₆), hydrogen (H₂), and methane (CH₄) The application of fuzzy logic for power transformer fault detection has been the subject of several studies. The fuzzy inference system (FIS) is a technology that was created to solve the problem of inconsistent DGA interpretations and related faults. 250 different situations were used to assess the accuracy of various DGA techniques in understanding the transformer state (Nitin, and Helonde, 2014). Research on classic DGA methods for fault detection in power transformers indicates a promising result: the approach can monitor the gases released by imminent faults and indicate the health of the transformer. Consequently, it exhibits a low susceptibility to initial mistakes and depends on expert evaluation (Ghani, et.al. 2022)- (Demirci and Taplamacioglu, 2023). Furthermore, the fuzzy inference system, a fuzzy logic tool, was presented in (Yousif, 2016) and used to detect and monitor multiple transformer faults. It has proven to be a very useful tool for transformer diagnosis and maintenance scheduling. MOVHammed et al. 2023, transformer failure detection method was presented in response to the fact that DGA can be ineffective in diagnosing certain situations. However, it has some drawbacks, including complexity, accuracy that depends on the quality of the input data, potential modelling errors, and challenges capturing real-world dynamics for fault diagnosis and optimization. Three techniques for identifying transformer defects were combined by Iregar and Lumbanraja 2012; however, their methods lacked a sufficient cooling system, resulting in an unintentional failure. Ahmed et al. 2013 , created a system that combines three different DGA techniques—Rogers, IEC, and Duval—into just one diagnosis scheme.

2. METHDOLOGY

2.1. Dissolved gas analysis (DGA):

There are several methods for identifying such fault gases. The most successful approach is DGA, as it has been acknowledged. A small amount of oil is sampled from the transformer to

determine the quantity of dissolved gases and to diagnose the defect causing the gases that have been identified (Siregar and Lumbanraja, 2023).

2.2. Fault diagnosis techniques

Doernenburg's ratio method and Roger's revised IEC-599r ratio method is used in this study and fuzzy logic is applied on it with proposed method.

The standard of concentrations of dissolved gas served as the foundation for defect diagnostics in the ratio techniques. $R_1 = CH_4/H_2$, $R_2 = C_2H_2 / C_2H_4$, $R_3 = C_2H_2/CH_4$, $R_4 = C_2H_6 / C_2H_2$, and $R_5 = C_2H_4 / C_2H_6$ are the five ratios that have been employed. Parts per million (PPM) of dissolved gas analysis (DGA) is used to extract the concentration of gases such as ethylene, ethane, and methane (Dhini,2018).

Each ratio method uses some of these ratios that may be not used by another ratio method. Doernenburg's ratio method used only four ratios (R_1 , R_2 , R_3 and R_4). The diagnosis values and the four ratios are shown in Table 1 for Doernenburg's ratio method and the diagnosis value. While Roger's ratio method uses three ratios only (R_1 , R_2 and R_5). The diagnosis values and the three ratios are shown in Table 2 for Roger's revised ratio method. (Nitin and Helonde, 2011).

Table 1. Doernenburg's method (Arakelian, 2002).

Fault	R_1	R_2	R_3	R_4
Thermal decomposition	> 1.0	< 0.75	< 0.3	> 0.4
Low intensity PRD (corona)	< 1.0	Not significant	< 0.3	> 0.4
high intensity PRD (ARC)	> 0.1 and < 1.0	> 0.75	> 0.3	< 0.4

Table 2. Roger's revised method (IEEE Power and Energy Society, 2019)

Fault	R_1	R_2	R_5
NOR.	< 0.1	0.1-1.0	< 0.1
Low intensity PRD	< 0.1	< 0.1	< 0.1
high intensity PRD	0.1-3.0	0.1-1.0	> 3.0
Low temperature thermal	< 0.1	0.1-1.0	0.1-3.0
Thermal fault $< 700\text{ }^{\circ}\text{C}$	< 0.1	> 1.0	0.1-3.0
Thermal fault $> 700\text{ }^{\circ}\text{C}$	< 0.1	> 1.0	> 3.0

3. SELECTION TOOL AND CASES

To develop of any system, there should be a suitable selection for development tool. The computer language is flexible and the users can develop his methodology program formulations. The chosen for language should be declarative and very simple. The MATLAB has these benefits. By the help for this interface a capability of explaining, training and tracing in system is greatly signified.

Through a review of the literature, fifty real data cases as shown in Table 3, were gathered. Papers involving actual DGA readings from actual power transformers used by power distribution companies worldwide were gathered online. Each DGA reading or sample had a

real fault that was found following an examination by real experts. Attempts were made to gather cases from the AL-Dorra Refinery Company and other energy distribution stations; however, these attempts were unsuccessful as it was discovered that they had not yet adopted the DGA method for maintaining their power transformers in Iraq.

Table 3. Data cases (PPM)

Cases	H2	CH4	C2H6	C2H4	C2H2	Co	Real Fault
1	317	335	58	580	642	0	ARC
2	245	44	0	23	52	219	ARC
3	233	23	161	10	0	231	PRD
4	0.3	55	10	135	4	252	OVH
5	160	53	28	6	0	190	NOR.
6	911	104	231	153	363	82	ARC
7	24	31.76	5.8	44	60	0.3	ARC
8	802	1391	301	2818	3002	0.4	ARC
9	21	42	32	7	1.3	191	OVH
10	86	30	10	35	29	131	DHE
11	22	35	62	1	0.2	48	NOR.
12	32	31	61	6	0.1	49	NOR.
13	99	97	46	162	0	0.09	OVH
14	63	17	13	83	0.8	453	OVH
15	7	22	4.23	8	0.3	390	OVH
16	81	618	325	2481	0.9	267	OVH
17	415	696	72	868	0.21	203	OVH
18	237	22	150	10.2	0.9	223	PRD
19	5	72	60	162	<1	193	OVH
20	46	42	2	71	80	0.1	ARC
21	6.3	12	5	1.8	0.1	216	OVH
22	496	1772.9	277	2437	2.8	292	OVH
23	443	206	42	223	263	160	ARC
24	17	14	160	70	2.02	157	NOR.
25	115	1416	298	2092	0.2	0	OVH
26	11	12	18	11	0.3	0.1	NOR.
27	1361	2551	1331	560	0.8	551	OVH
28	1773	3632	1071	8484	79	831	OVH
29	5.3	106	105	4	0.2	73	NOR.
30	11	63	6	3	0.9	0.1	OVH
31	36	78	124	6	0.2	0.1	OVH
32	22	22	25	96	0	158	OVH
33	9475	4065	352	6551	12996	554	ARC
34	232	21	162	11	1.8	230	PRD
35	237	22	150	10.2	0.9	223	PRD
36	1	66	11	149	5	177	OVH
37	39	34	57	2.7	0.2	53	NOR.
38	33	37	10	42	7	47	DHE
39	57	337	43	395	1.8	0	OVH
40	3	5	7	1	1	0.5	NOR.
41	6	13	5	2	0	216	OVH
42	23.9	25	23.22	3.5	0	104	OVH
43	230	3996	1724	5587	0.2	0	OVH
44	3	14	45	36	2	1	OVH
45	126	23	0	33	83	0	ARC
46	5	72	60	162	<1	193	OVH

Cases	H2	CH4	C2H6	C2H4	C2H2	Co	Real Fault
47	45	17	0.11	9	0	117	ARC
48	55	0.4	0	5	0	105	ARC
49	505	1055	294	1443	18	20	OVH
50	336	36	1.7	32.9	52	0.1	PRD

Where:

OVH : for overheat; PRD : for partial discharge; PRDLE : for partial discharge low energy; DHE : for discharge high energy and ND : for not diagnosable.

4. FUZZY DIAGNOSTIC SYSTEM:

Any real integer between 0 and 1 can be the truth value of a variable in fuzzy logic, a kind of many-valued logic. The system's inputs and outputs are mapped as non-linear and static. Since $i = 1, 2, 3, 4, \dots, n$, and $j = 1, 2, 3, 4, \dots, m$, let us suppose that the system (fuzzy) has input from U_i to U_n and output from Y_j to Y_m . Crisp values make up the input and output. Instead of being fuzzy sets, all of the values in the input and output are actual integers. The inference mechanism uses fuzzy rules at the rule base to find fuzzy conclusions, which are then converted into crisp outputs by the defuzzification block, as shown in Fig. 1 (Su, Q., and Austin 2000).

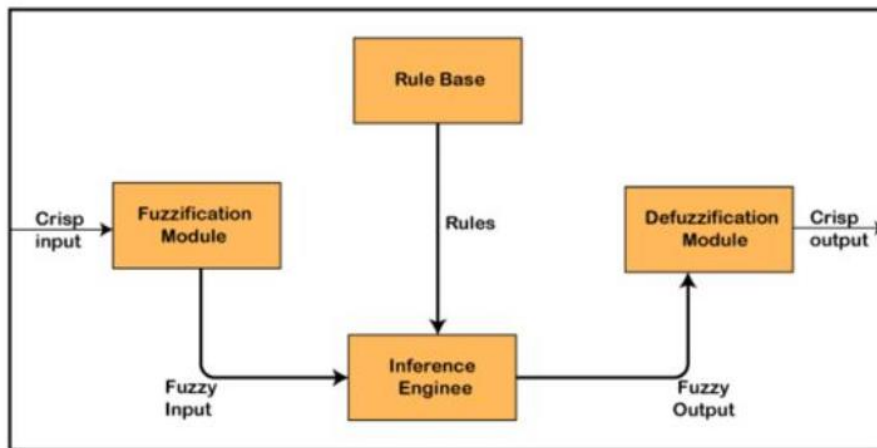


Fig. 1. Fuzzy System (Yang and Liao, 1999).

4.1. Fuzzification:

The fuzzy set is used to quantify the information of the base rule, and the mechanism of inference operates on a fuzzy set. Fuzzification is the conversion or transformation of the numeric system's input into a fuzzy set (Xu. and Wang, 1997).

4.2. Inference mechanism:

A fuzzy inference is a method that interprets values at the input vector based on several sets of rules and assigns values to the output vector. Fuzzy inference is the process of mapping the given input to the output by using fuzzy logic.

4.3. Defuzzification

A defuzzification is a driving the value of the fuzzy set. A typical technique of the defuzzification for an implied fuzzy set is a center of gravity is given by

$$U_{\text{crisp}} = \frac{\varepsilon B_i \int \mu(i)}{\varepsilon \int \mu(i)} \quad (1)$$

Where B_i : the center of membership function, $\int \mu(i)$: the area under the function on $\mu(i)$. s U_{crisp} : a numerical output. (IEEE, 2009).

5. PROPOSED METHOD:

The program whose systematic diagram of proposed method is given in Fig. 2 is arranged as follows:

- 1- It prompts the user to enter the value of the levels of gases concerned in the fault diagnostic procedure of transformer (input step).
- 2- then the two methods are incorporated after fuzzifying the level of gases (fuzzification step).
- 3- the rules of each method are applied separately as the rule base using fuzzy logic in the inference mechanism (analysis or processing step).
- 4-The process reach the end after defuzzifying the output to get crisp value indicting a certain fault (defuzzification step).
- 5- the final results are displayed all together on the same screen, each method suggests a fault along with a percentage indicating its certainty or its confidence in its diagnosis. If however the certainty of the diagnosis is determined as zero the then the system proceeds in such a way as to give a NOT Diagnosable (ND)result which means that the system was not able to determine the fault responsible for these gases in the sample.

The proposed method has used three ratios (R1, R2, and R5) as follows:

1. For ratio R1, four fuzzy subsets of the trapezoidal type have been assigned: very low (VL), low (L), medium (M), and high (H).
 - 2: The ratio R2 for fuzzy subsets of the trapezoidal membership function used in this study has been assigned very low (VL), low (L), medium (M), and high (H).
- For ratio R5, five fuzzy subsets of the trapezoidal type have been assigned: low (L), medium (M), high (H), very high (VH), and very very high (VVH).

6. RESULTS AND DISCUSSION:

When imputing the data cases to developed system several points can be observed through individual analysis of all fifty data cases that have been used in this new developed system.

In the first method, revised version IEC_599r as shown in Fig.3 the inference approach achieves the detection results by assuming 3-dimebtions space patron (I , j, K) and more than three fuzzy subsets had to be used . For ratio R2 four fuzzy subsets have been used Very Low (VL), Low (L), Medium (M), and High (H). The same number and assignments of fuzzy subsets have been used for ratio R1

whereas for ratio R5 six fuzzy subsets have been used or assigned as Very Low (VL), Low (L), Medium (M), High (H), Very High (VH) and Very Very High (VVH)).

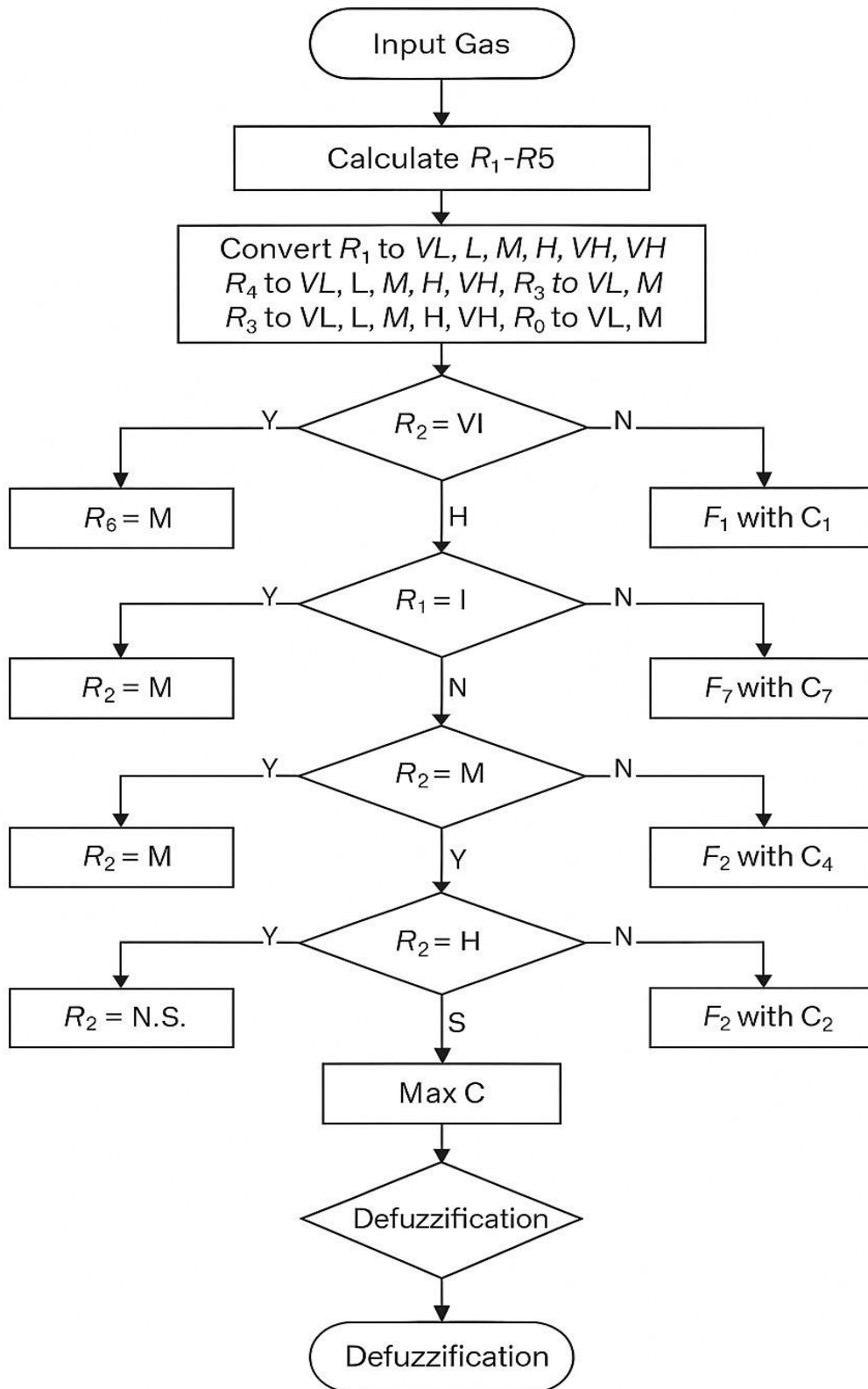


Fig.2. Systematic Diagram of the Proposed System

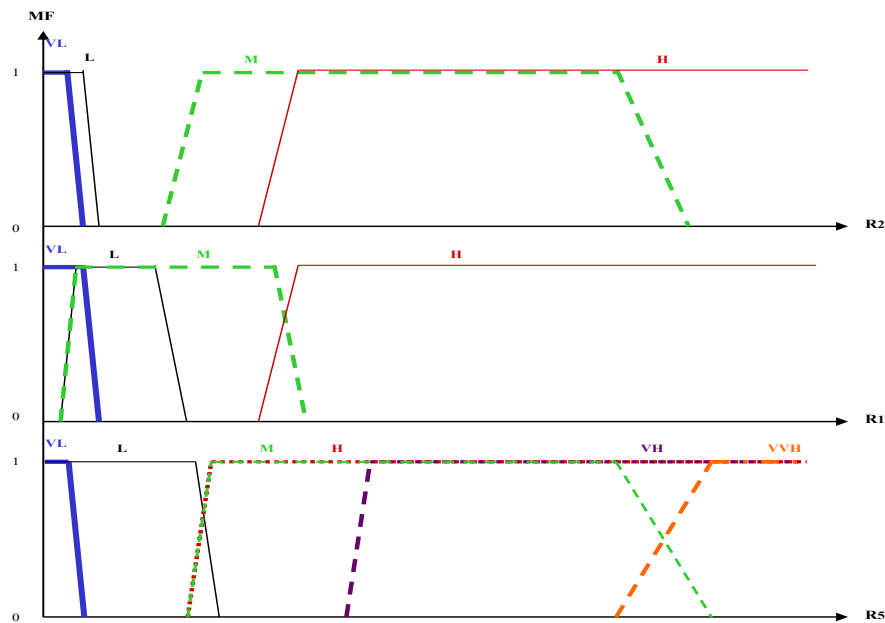


Fig.3. Fuzzy Relations Based on Roger's Method IEC_599r

MF: Membership Function

Likewise, the second method Doernenburg's which uses four ratios (R1, R2, R3, R4) have been incorporated making the general form of a rule look a little bit different. The third method that has been implemented in this study is the proposed method.

The results of Roger's revised method IEC599r and Doernenburg's method in the Table 4 and 5 respectively.

Table 4. Results of IEC_599r Method

Cases	Actual Fault	Correct	Certainty	Incorrect	ND
1.	ARC	DHE	26.83		
2.	ARC	DLE	100		
3.	PRD	PRD	100		
4.	OVH	OVH > 700	100		
5.	NOR.			OVH < 300	
6.	ARC	ARC	100		
7.	ARC				ND
8.	ARC	DHE	100		
9.	OVH	OVH < 300	100		
10.	DHE	DHE	100		
11.	NOR.			OVH < 300	
12.	NOR.			OVH < 300	
13.	OVH	OVH 300-700	52.92		
14.	OVH	OVH	100		
15.	OVH	OVH 300-700	100		
16.	OVH	OVH > 700	100		
17.	OVH	OVH > 700	100		
18.	PRD	PRD	100		
19.	OVH	OVH 300-700	100		
20.	ARC	DHE	100		
21.	OVH	OVH < 300	66.67		
22.	OVH	OVH > 700	100		
23.	ARC	DHE	100		

Cases	Actual Fault	Correct	Certainty	Incorrect	ND
24.	NOR.			OVH < 300	
25.	OVH	OVH > 700	100		
26.	NOR.			OVH < 300	
27.	OVH	OVH < 300	100		
28.	OVH	OVH > 700	100		
29.	NOR.			OVH < 300	
30.	OVH	OVH < 300	66.67		
31.	OVH	OVH < 300	100		
32.	OVH	OVH > 700	93.48		
33.	ARC	DLE	100		
34.	PRD	PRD	100		
35.	PRD	PRD	100		
36.	OVH	OVH > 700	100		
37.	NOR.			OVH < 300	
38.	DHE			OVH > 700	
39.	OVH	OVH > 700	100		
40.	NOR.			OVH < 300	
41.	OVH	OVH < 300	66.67		
42.	OVH	OVH < 300	100		
43.	OVH	OVH 300-700	100		
44.	OVH	OVH < 300	100		
45.	ARC	DLE	100		
46.	OVH	OVH < 300	66.67		
47.	ARC				ND
48.	ARC	ARC	100		
49.	OVH	OVH > 700	100		
50.	PRD	DLE	57.79		

Table 5. Results of Doernenburg's Method

Cases	Real Fault	Correct	Certainty	Incorrect	ND
1.	ARC				ND
2.	ARC				ND
3.	PRD				ND
4.	OVH				ND
5.	NOR.				ND
6.	ARC				ND
7.	ARC				ND
8.	ARC				ND
9.	OVH				ND
10.	DHE				ND
11.	NOR.				ND
12.	NOR.	NOR.	100		
13.	OVH				ND
14.	OVH				ND
15.	OVH				ND
16.	OVH				ND
17.	OVH				ND
18.	PRD				ND
19.	OVH				ND
20.	ARC				ND
21.	OVH				ND
22.	OVH	THERMAL	100		
23.	ARC				ND
24.	NOR.				ND

Cases	Actual Fault	Correct	Certainty	Incorrect	ND
25.	OVH				ND
26.	NOR.				ND
27.	OVH	Thermal	100		
28.	OVH	Thermal	100		
29.	NOR.				ND
30.	OVH				ND
31.	OVH				ND
32.	OVH				ND
33.	ARC	ARC	100		
34.	PRD				ND
35.	PRD				ND
36.	OVH				ND
37.	NOR.				ND
38.	DHE				ND
39.	OVH				ND
40.	NOR.				ND
41.	OVH				ND
42.	OVH				ND
43.	OVH				ND
44.	OVH				ND
45.	ARC				ND
46.	OVH	Thermal	22.94		
47.	ARC				ND
48.	ARC				ND
49.	OVH				ND
50.	PRD				ND

- The Doernenburg's method did not manage to get a satisfactory result, as it has diagnosed correctly only 5 cases out of 50 which means 10.2% and that was expected, as this method has many validation tests before reaching the final decision, showing this fact is another reason for involving this method in the final program.
- The new revised method IEC_599r which has achieved about 72% (36 out of 50 data cases), and this is probably because the latter does not have a code for the NOR. condition and so has failed to diagnose such a condition, thereby decreasing its percentage of correct diagnosis.
- Proposed Method [Table 6](#) which is a combination of the advantages of both of the Doernenburg's ratio method and the IEC_599r ratio method, [Table 7](#) explain the results of proposed method which has successfully yielded the best percentage of correct diagnosis which is 84% (41 of 50 data cases); [Table 8](#) shows the comparison between the three methods of DGA in percentage correct, percentage of certainty, percentage incorrect, and percentage of NOT diagnosis, which represent the accuracy of the work.

Table 6. The Proposed Method

Characteristic Fault	C2H2/C2H4 (R2)	CH4/H2 (R1)	C2H4/C2H6(R5)
NOR.	<0.1	0.1-1	<1
Partial Discharge	Not significant	<0.2	<1
Discharge of Low Energy	>1	0.1-0.5	>1

Characteristic Fault	C2H2/C2H4 (R2)	CH4/H2 (R1)	C2H4/C2H6(R5)
Discharge of High Energy	0.5-3.5	0.1-1	>2
Thermal Fault T < 300°C	<0.2	Not significant	<1
Thermal Fault 300°C < T < 700°C	<0.1	>1	1-3
Thermal Fault T > 700°C	<0.2	>1	>3

Table 7. Results of the Proposed Method

Cases	Real Fault	Correct	Certainty	Incorrect	ND
1.	ARC	DHE	65.06		
2.	ARC	DLE	100		
3.	PRD	PRD	100		
4.	OVH	OVH > 700	100		
5.	NOR.	NOR.	100		
6.	ARC	PRD	100		
7.	ARC				ND
8.	ARC	DHE	100		
9.	OVH	OVH < 300	100		
10.	DHE	DHE	100		
11.	NOR.			OVH < 300	
12.	NOR.	NOR.	55.4		
13.	OVH	OVH 300-700	19.85		
14.	OVH	OVH	100		
15.	OVH	OVH 300-700	100		
16.	OVH	OVH > 700	100		
17.	OVH	OVH > 700	100		
18.	PRD	PRD	100		
19.	OVH	OVH 300-700	100		
20.	ARC	DHE	100		
21.	OVH	OVH 150-300	67.1		
22.	OVH	OVH > 700	100		
23.	ARC	DHE	100		
24.	NOR.			OVH < 300	
25.	OVH	OVH > 700	100		
26.	NOR.	NOR.	100		
27.	OVH	OVH < 300	100		
28.	OVH	OVH > 700	100		
29.	NOR.			OVH < 300	
30.	OVH	OVH < 300	66.67		
31.	OVH	OVH < 300	100		
32.	OVH	OVH > 700	60.71		
33.	ARC	DLE	100		
34.	PRD	PRD	100		
35.	PRD	PRD	100		
36.	OVH	OVH > 700	100		
37.	NOR.	NOR.	81.2		
38.	DHE	DHE	37.14		
39.	OVH	OVH > 700	100		

Cases	Real Fault	Correct	Certainty	Incorrect	ND
40.	NOR.			OVH 300-700	
41.	OVH	OVH 150-300	65.7		
42.	OVH	OVH < 300	100		
43.	OVH	OVH > 700	100		
44.	OVH	OVH < 300	100		
45.	ARC	DLE	100		
46.	OVH	OVH < 300	22.94		
47.	ARC	ARC	100		
48.	ARC	ARC	100		
49.	OVH	OVH > 700	100		
50.	PRD	DLE	57.79		

- This proposed method is an effort that has been made to contribute to the problem of power transformer incipient fault diagnosis and hence to the power transformer reliability, which would in turn mean the reliability of the power distributing utility as a whole.
- This effort was made possible by using the advantages of both of the Doernenburg's ratio method and the revision IEC_599r so that a high percentage of correct diagnosis is ensured which is the most important advantage as far as fault diagnosis is concerned.

Table 8. Final Results

Method%	DOERNEN-BURG	IEC 599r	PROPOSED
Correct	12	76	92
Certainty	83.3	90.3	89.1
ND	48	12	4

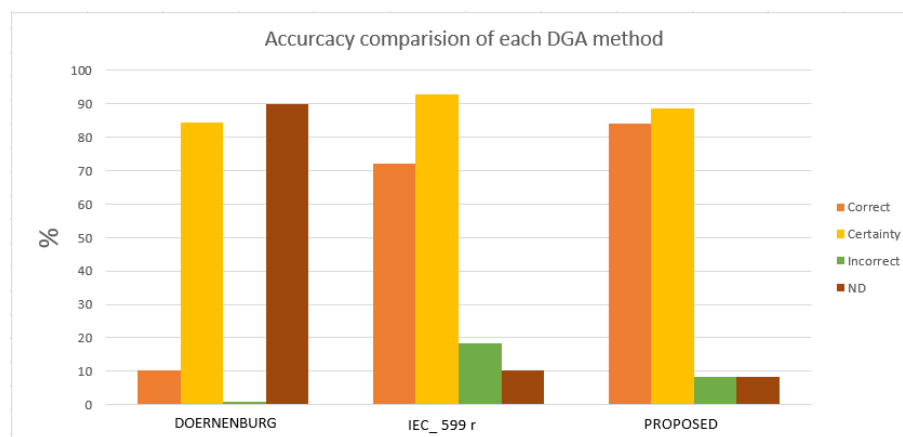


Fig. 4. Comparison of all DGA methods

The percentage accuracy comparison of the three DGA techniques is shown in Fig.4. It is mentioned that the percentage accurate sample for the DOERNENBURG, IEC 599r, and suggested ratio approaches is 10.2%, 72%, and 84%, respectively. The aforementioned three approaches have percentage confidence values of 84.59%, 92.92%, and 88.8%, respectively. The DOERNENBURG ratio method's incorrect percentage is 0%, while the IEC_599r and suggested ratio techniques' respective percentages are 18.37% and 8.16%, respectively. Lastly,

for the methodologies employed in this work, the proportion of non-diagnosis cases is 90%, 10.2%, and 8.16%.

This suggested approach has successfully reduced the workload of an engineer by more than 84%. In addition, diagnosis can be made in a much shorter amount of time, reducing failure or downtime and raising overall power system reliability—a feature that is of utmost importance to any utility or power distribution company.

7. CONCLUSION:

The traditional and proposed methods developed and implemented for 50 cases in this study have been very successfully used for the detection of faults in different power transformers. The link between the variables is represented practically by the application of fuzzy logic. The fuzzy logic technique may also be used to diagnose several issues. Fuzzy logic may be used in DGA techniques to extend transformer life while correspondingly lowering maintenance costs. To improve this method's accuracy, additional transformer cases need to be examined in relation to real faults. To achieve adequate accuracy, suitable membership functions and regulations are also required.

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