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Research Article

Diagnose the Potential Faults of Transformer by Fuzzy Logic Inference Method

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Abstract: In the progress of a transformer working, under the effect of heat, the hydrogen-carbon element of the mineral oil is broken down to hydrogen and produces hydrogen gas, methane, ethane, ethylene, acetylene and some other gases. The density of these gas components may indicate some state of working and potential faults of the transformer. Based on the diagnostic method according to the codes of IEC-599 standard, in this paper we have proposed a diagnostic model according to fuzzy logic. From the results of the analysis of density of gas components in oil (DGA - Dissolved Gas Analysis), the inference system calculate to the total gas content, total flammable gas content and determine 8 cases fault diagnosed and a case is normal (no fault). Along with the conclusions about faults, corresponding reliability is calculated as a percentage. The diagnostic software has been coded completely on the web environment and has been tested with many actual data sets. The diagnosis results are reliable.

Keywords: Diagnose Transformer Faults, Dissolved Gas Analysis Measurement, Fuzzy Logic.

INTRODUCTION

Transformers are an important device in energy systems. Their reliability not only change the ability to supply electricity but also affect the economic performance of a certain consumer (for example furnaces, production lines, etc. in factory). For example, a fault of a distribution transformer can cause thousands of households to lose power. A fault of a voltage increase transformer may be the cause of a power outage of adjacent areas in that grid system.

Diagnosing the potential faults of a pressure transformer in the electrical system is a problem of concern to many scientists. In order to be able to provide information on possible future faults (potential faults) of transformers, in some published, diagnostic methods based on dissolved gas analysis in oil. There are also diagnostic methods based on frequency spectrum response of the transformer, diagnostic based on vibration of transformer. The method of dissolved gas analysis in oil requires to be specialized measuring devices and requires high accuracy. Based on these techniques, there are many modern techniques that allow better diagnostics (Tapan K. Saha 2003; Norazhar Abu Bakar, A. Abu-Siada and S. Islam 2014; Sherif S. M. Ghoneim, IEEE Member, Sayed A. Ward 2012; S. Saranya, Uma Mageswari, Natalya Roy, R. Sudha 2013; Sherif Ghoneim, Kamel A. Shoush 2014), but a common point of these methods is to rely on accurate measurement techniques. Therefore, the diagnostic results also depend heavily on the accuracy of the measurements. Methods for using fuzzy logic are also proposed (Sey Moiul Islam, Tony Wu, Gerard Ledwich 2000; N. K. DHOTE, J. B. HELONDE 2012; Er. Niti Sharma 2012; M. Suganya Bharathi, Dr. M. Willjuice Iruthayarajan, S. Sudalai Shunmugam, L.Kalaivani 2013; Hongzhong Ma, Zheng Li, P. Ju, Jingdong Han and Limin Zhang 2005). The common point of these methods is to inherit expert knowledge based on the rule base system. Another diagnostic method that can inherit expert knowledge in the form of statistic rules has been introduced (Zhenyaun Wang 2000; Fathiah Zakaria, Dalina Johari, Ismail Musirin 2012; Amin Samy, Sayed A. Ward, Mahmud N. Ali 2015; Michel B. Hell, Marcos F. S. V. D`Angelo and Pyramo P. Costa Jr. 2002; R. Naresh, Veena Sharma, and Manisha Vashisth 2008). This method was developed based on the use of artificial neural networks. In order to get

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accurate diagnosis results, it is necessary to have an experiment data set large enough to train the network and select a reasonable network structure. In fact, according to this approach, there are many network structures that can be selected with diversification diagnostic results. Large network training time is also a disadvantage of this method.

Diagnose potential faults of transformers based on DGA results

Potential faults of transformer

The potential faults of transformers can be classified into the following main types: electric arc, discharge or partial discharge, cellulose overheating, oil overheating. These faults may be due to one or some causes.

Figure 1. Type 1: Discharge electrically

Figure 1 is an electrical discharge that causes a fire and has no mechanical deformation. However, this is a quite serious incident state. Transformers in this situation are unable to continue working.

Figure 2. Type 2: Discharge electrically

Figure 2 shows the discharge causing a fire and mechanical deformation of several turns of wire. This is a very serious incident state. Transformers in this situation are unable to continue working and must be overcome.

Characteristics Of Generate Gas and Dissolved Gas Analysis

In the progress of a transformer working, under the effect of electricity and heat, the hydrogen-carbon element ($H-C$) of mineral oil can be broken down into hydrogen and $H-C$ fragments, which can be combined to create gases are hydro hen (H_2), methane (CH_4), ethane (C_2H_6), ethylene (C_2H_4), acetylene (C_2H_2), CO and CO_2. The amount of gas of each individual gas depends on the temperature near the point of effect.

Dissolved gas analysis in the transformer oil aims to detect soon local overheating, discharge of low energy, etc. The increase in these processes will lead to incident. The incident generated during this period is not detected by the gas relay. A small a number of gases formed continuously through small decomposition in oil or insulating material. To analyze dissolved gas in transformer oil, need to use a system of analyzers called TOGAS (Transformer Oil Gas Analysis System). From the results of dissolved gas analysis in transformer oil we can diagnose the damaged forms of transformers. The analysis of dissolved gas in oil without the need to disconnect the transformer power is called the online diagnostic method. This type of analysis includes conventional DGA, which is based on periodic oil sampling and modern techniques of online gas monitoring.

A type of fault can be caused by many reasons. This makes partitioning very difficult. Therefore, the actual operation usually only uses DGA to diagnose the original fault, not the final conclusion. Other tests and even the opening of the transformer may be necessary to localize the error and find the cause more accurately.

However, fault diagnosis by DGA is good enough to provide information on maintenance schedules and act as a preventive maintenance strategy. For this purpose, DGA has become a major tool for diagnosing potential faults of transformer. It includes much successful research in three main areas: ratio method, main gas method and artificial intelligence methods.

For the proportional method, many researchers have proposed many methods to diagnosis potential faults in transformers such as Dornemburg ratio, Roger ratio, main gas method and IEC-599 standard (Tapan K. Saha 2003; Norazhar Abu Bakar, A. Abu-Siada and S. Islam 2014).

Diagnose potential faults based on ratios according to IEC-599 standard

The Dornemburg and Rogers methods use four ratios, the ratio C_2H_6/CH_4 represents only the limited temperature range of cellulose disintegration without any help with fault detection. Therefore, in the IEC-599 standard and the proportion of Rogers's method development later were abolished.

An improvement of IEC-599 standard was launched in 1996 (IEC-599/2). It has become perfect at this time. Rogers ratio method and IEC-599 standard have been developed commonly in industry. However, in some cases, it does not give a final conclusion, meaning there are faults that these methods cannot be identified.

Table 1. Ratio of gas components and corresponding faults according to IEC-60599 (2015)

Lỗi		**R1 (CH_4/H_2)**	**R2 (C_2H_2/C_2H_4)**	**R5 (C_2H_4/C_2H_6)**
Normal		< 0.1	< 0.1	< 0.1
Partial discharges		< 0.1	NS[(a)]	< 0.2
Discharges of low energy		0.1 – 0.5	> 0.1	> 1
Discharges of high energy		0.1 – 1	0.6 – 2.5	> 2
Thermal fault	t < 300 °C	> 1, NS[(a)]	NS[(a)]	< 1
	300 °C < t < 700 °C	> 1	< 0.1	1 – 4
	t > 700 °C	> 1	< 0.2[(b)]	> 4

Note:

(a) NS: Non-Significant whatever the value

(b) If C_2H_2 increases strongly, it may overheat t > 1000 °C

From *Table 1*, according to IEC-599 standard, ranges were coded and represent faults according to diagnostic rules such as Table 2 and Table 3.

Table 2. Codes of ratios and corresponding ranges

Ranges of ratios	**Codes of ratios**		
	R1=$\frac{C_2H_2}{C_2H_4}$	R2=$\frac{CH_4}{H_2}$	R3=$\frac{C_2H_4}{C_2H_6}$
<0.1	0	1	0
0.1 – 1.0	1	0	0
1.0 – 3.0	1	2	1
>3.0	2	2	2

Note: denote R3 instead of the ratio of R5 in Table 1.

Table 3. Rule diagnosis of faults by code

Rule no	**R1=$\frac{C_2H_2}{C_2H_4}$**	**R2=$\frac{CH_4}{H_2}$**	**R3=$\frac{C_2H_4}{C_2H_6}$**	**Decision**
1	0	0	0	Normal ageing
2	0 (*)	1	0	Partial discharge of low energy density
3	1	1	0	Partial discharge of high energy density
4	1 or 2	0	1 or 2	Discharge of low energy
5	1	0	2	Discharge of high energy
6	0	0	1	Thermal fault <150 °C
7	0	2	0	Thermal fault 150° – 300 °C
8	0	2	1	Thermal fault 300° – 700 °C
9	0	2	2	Thermal fault > 700 °C

Develop the diagnostic tool according to fuzzy logic

Build the fuzzy diagnostic model

Based on IEC-599 standard, codes of ranges can be considered classic sets (explicit sets). Each line in Table 3 can be considered a diagnostic rule on the classical sets. For example, in line 3, we have the diagnostic rule statement as follows:

If (R1=1) và (R2=1) và (R3=0) then "Partial discharge of high energy density"

Where:

- *R1*, *R2* and *R3* are respectively the ratios defined in *Table 2* and *Table 3*.
- The codes *1* and *0* are the corresponding labels. It can be considered the name of the classical set.
-

For classical logic, it is possible to interpret the left of conditional clauses as follows:

If (R1=1) is true and (R2=1) is true and (R3=0) is true Then …

Hay:

If ($R1 \in 1$) and ($R2 \in 1$) and ($R3 \in 0$) Then …

Value of expressions ($R1 \in 1$), ($R2 \in 1$) và ($R3 \in 0$) is only "true" or "false" values. Thus, all expressions in the left are simultaneously "true", then through the "and" operator, we can get the decision at the output. With a small change of the ratios can give completely an other decision. Boundaries to decision that fault or no fault is just a threshold of value. To overcome this limitation, we can design fuzzy sets to represent the values of the ratios.

The fuzzy diagnostic model is built through 2 steps as follows:

Step 1: Design fuzzy sets

It can be seen that a major constraint is when using the classic (explicit) set to represent the continuous variability of real world quantities. To overcome this drawback, a proposed method is to use fuzzy set to represent. Designing fuzzy sets and labeling them is qualitative as follows Figure 3.

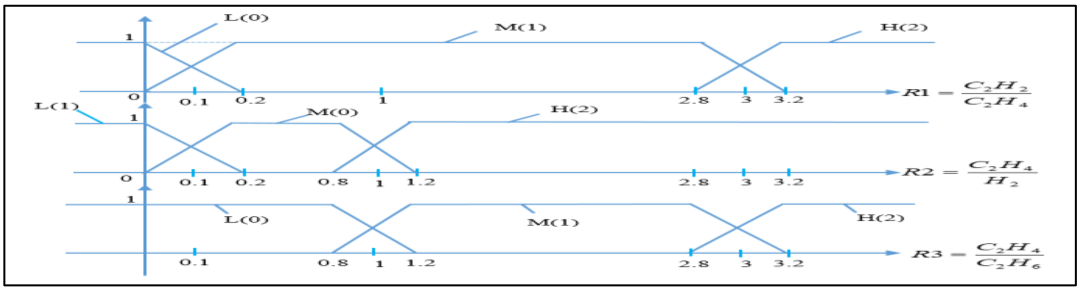

Figure 3. Fuzzy set of ratios

As shown in Figure 3, each ratio has 3 fuzzy sets with a trapezoidal function defined by 4 points *a*, *b*, *c* and *d*. When coding, we can consider fuzzy triangles as trapezoidal.

For example μ_L^{R1} =[0,0,0,0.1], μ_H^{R1}=[2.8,3.2,3.2,3.2]; and μ_M^{R1}=[0,0.2,2.8,3.2]

Re-label the corresponding fuzzy sets:

R1* and *R3	***R2***
'0' – L (Low), '1' – M (Medium) and '2' – H (High)	'1' – L (Low), '0' – M (Medium) and '2' – H (High)

Step 2: Convert the diagnostic rule system from classic logic to fuzzy logic

Table 4. The diagnostic rule table for 8 faults is rewritten according to the language label

Rule no	R1=$\frac{C_2H_2}{C_2H_4}$	R2=$\frac{CH_4}{H_2}$	R3=$\frac{C_2H_4}{C_2H_6}$	Decision
1	L	M	L	Normal ageing
2	*	L	L	Partial discharge of low energy density
3	M	L	L	Partial discharge of high energy density
4	M or H	M	M or H	Discharge of low energy
5	M	M	H	Discharge of high energy
6	L	M	M	Thermal fault <150 °C
7	L	H	L	Thermal fault 150° – 300 °C
8	L	H	M	Thermal fault 300° – 700 °C
9	L	H	H	Thermal fault > 700 °C

* *Insignificant*

In the above table, each line of diagnostic rule is interpreted as follows:

Rule 1: If (R1=L)and(R2=M)and(R3=L) Then "Normal ageing"

Rule 2: If (R1=L)and(R2=L) Then "Partial discharge of low energy density"
Rule 4: If ((R1=M)or(R1=H))and(R2=M)and((R3=M)or(R3=H)) Then "Discharge of low energy"

Where (R1=L) ⇔ $\mu_L(x)$, $x \in$ R1 (the membership degree of x in the R1 into the fuzzy set L).

Algorithm for diagnostic models

From the model of the above reasoning system, the calculation steps of the algorithm are described in detail as in the following algorithm:

Fuzzy_Diagnosis_Algorithm ()

Input: Gas components [ppm]: H_2 (hydrogen), CH_4 (methane), C_2H_2 (acetylen), C_2H_4 (ethylen), C_2H_6 (ethane); O_2, N_2, CO, CO_2 [ppm].

Output: Conclude the status of the transformer according to the diagnostic rule system and corresponding diagnostic reliability

METHOD:

1) ***If*** all values of gas components do not exceed the L1 threshold (Table 5) ***Then*** the conclusion is "Normal" (return).

Table 5. Threshold L1 according to IEC-599

Key gas	H_2	CH_4	C_2H_2	C_2H_4	C_2H_6	CO
Threshold L1 (concentration [ppm])	100	120	35	50	65	350

Else // One of the gas components exceeds the L1 threshold, next to step calculation

2) Calculate the value of the ratios $x = \frac{C_2H_2}{C_2H_4}$, $y = \frac{CH_4}{H_2}$, $z = \frac{C_2H_4}{C_2H_6}$

3) Calculate the membership degree vectors corresponding to each *Ri* (*i* = *1..3*) according to the formula in *Figure 4*:

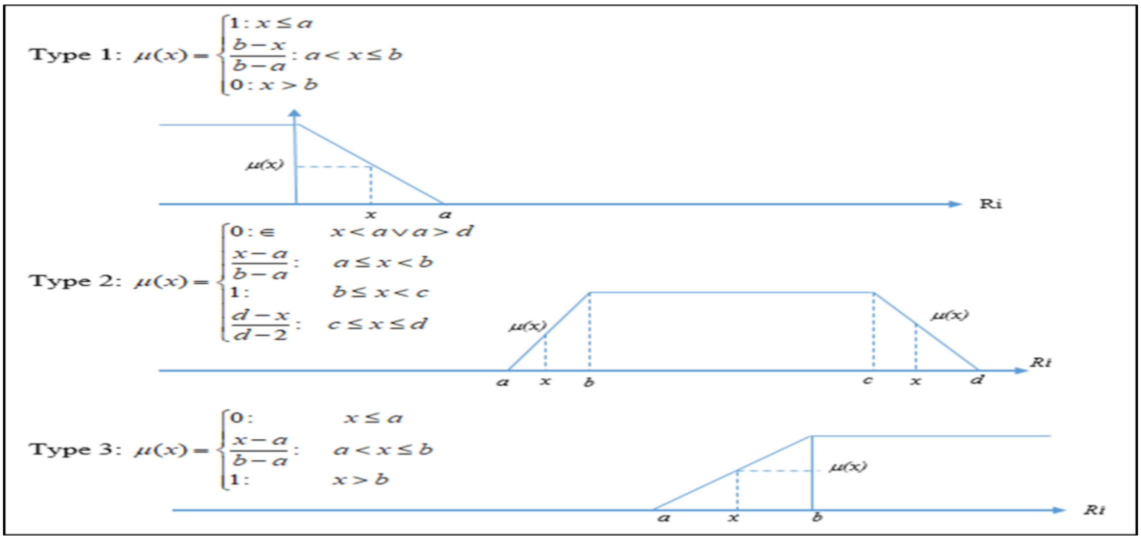

Figure 4. Formula to calculate the membership degree on fuzzy sets

The result is:

$$\mu^{R1} = [\mu_L(x), \mu_M(x), \mu_H(x)], x \in R1$$
$$\mu^{R2} = [\mu_L(x), \mu_M(x), \mu_H(x)], y \in R2$$
$$\mu^{R3} = [\mu_L(x), \mu_M(x), \mu_H(x)], z \in R3$$

4) ***For*** each rule in the rules table calculates the reliability of the decision as follows:
$r_i = min(\mu_X^{R1}, \mu_Y^{R2}, \mu_Z^{R3})$, $X, Y, Z \in \{L, M, H\}$, i is the index of the rule line.
For example, with the rule line *i* = *4*, the left is calculated by the following formula:

$$r_4 = max(min(\mu_M^{R1}, \mu_M^{R2}, \mu_M^{R3}), min(\mu_M^{R1}, \mu_M^{R2}, \mu_H^{R3}), min(\mu_H^{R1}, \mu_M^{R2}, \mu_M^{R3}), min(\mu_H^{R1}, \mu_M^{R2}, \mu_H^{R3}))$$

Table 6. Calculation of decision reliability of fuzzy diagnostic rule

Rule no	$x = \frac{C_2H_2}{C_2H_4}$	$y = \frac{CH_4}{H_2}$	$z = \frac{C_2H_4}{C_2H_6}$	Reliability
1	L	M	L	$r_1 = min(\mu_L(x), \mu_M(y), \mu_L(z))$
2	*	L	L	$r_2 = min(\mu_L(y), \mu_L(z))$
3	M	L	L	$r_3 = min(\mu_M(x), \mu_L(y), \mu_L(z))$
4	M or H	M	M or H	$r_4 = max\begin{pmatrix} min(\mu_M(x), \mu_M(y), \mu_M(z)), \\ min(\mu_M(x), \mu_M(y), \mu_H(z)), \\ min(\mu_H(x), \mu_M(y), \mu_M(z)), \\ min(\mu_H(x), \mu_M(y), \mu_H(z)) \end{pmatrix}$
5	M	M	H	$r_5 = min(\mu_M(x), \mu_M(y), \mu_H(z))$
6	L	M	M	$r_6 = min(\mu_L(x), \mu_M(y), \mu_M(z))$
7	L	H	L	$r_7 = min(\mu_L(x), \mu_H(y), \mu_L(z))$
8	L	H	M	$r_8 = min(\mu_L(x), \mu_H(y), \mu_M(z))$
9	L	H	H	$r_9 = min(\mu_L(x), \mu_H(y), \mu_H(z))$

5) Calculate the total amount of gas dissolved in the oil (total gas components in ppm)

$$Total = O_2 + N_2 + CO + CO_2 + H_2 + CH_4 + C_2H_2 + C_2H_4 + C_2H_6 \text{ [ppm]}$$

6) Display the results on the screen
   a. Display on the screen the decisions and corresponding reliability.
   b. **If** $Total > 10000$ notice "The total amount of dissolved gas in oil is not up to standard";
      Else notice "Total amount of dissolved gas in oil meets standard".

7) Report: Print out the summary report of the diagnosis in standard format.
8) Save to Data base.

End Fuzzy_Diagnosis_Algorithm

Experimental results

The diagnostic software has been fully installed and runs on the web environment, at http://mba.hopto.org/. The software is highly compatible, can run on many operating system platforms. Specifically, it can run on PC with Windows, iOS operating system of Mac; Can run with the appropriate interface on SmartPhone with both iOS and Android. Experiment with the data set (Hongzhong Ma, Zheng Li, P. Ju, Jingdong Han and Limin Zhang 2005), we get the diagnostic results as shown in *Table 7*.

Table 7. DGA sample and diagnosis results by different method

No.	H_2	CH_4	C_2H_4	C_2H_6	C_2H_2	Actual fault number	IEC method	Fuzzy method	Reliability[%]
1	200	700	740	250	1	8, 9	8	8, 9	60, 40
2	300	490	360	180	95	8	N	N	N
3	56	61	32	75	31	3	N	N	N
4	33	26	5.3	6	0.2	1	1	1, 4, 6	79.2, 20.8, 20.8
5	176	205.9	75.7	47.7	68.7	4	N	4	7.5
6	70.4	69.5	241.2	28.9	10.4	9	N	4, 5, 9	53.2, 21.6, 46.8
7	162	35	30	5.6	44	5	5	5	100
8	345	112.25	51.5	27.5	58.75	4	4	4	100
9	181	262	528	210	0	8	8	8	100
10	172.9	334.1	812.5	172.9	37.7	9	9	9	76.8
11	2587.2	7.882	1.4	4.704	0	2	2	2	98.5
12	1678	652.9	1005.9	80.7	419.1	5	5	5	100
13	206	198.9	612.7	74	15.1	9	N	4, 5, 9	58.6, 12.3, 41.4
14	180	175	50	75	4	7	1	1, 7	56.9, 43.1
15	34.45	21.92	44.96	3.19	19.62	5	5	5	100
16	51.2	37.6	52.8	5.1	51.6	5	5	N	N
17	106	24	28	4	37	5	5	5	100
18	180.85	0.574	0.188	0.234	0	2	2	2	98.4
19	27	90	63	42	0.2	8	8	8	98.4
20	138.8	52.2	62.8	6.77	9.55	5	5	5	76

Note: N – No decision

Observe the results table in Table 7 shows that IEC method (IECM) has 5 faults cannot be determined, while with the Fuzzy method (FM) there are only 3 faults. However, in the 16th data set, IECM determined the fault but FM did not. In this case, this is the weakness of FM compared to IECM.

With the 5th set of data, FM has indicated fault number 4 with reliability by 7.5%. This may understand that this decision is unreliable. But in data sets 6th and 13th, FM has indicated more faults other than actual faults.

The remaining results show that FM is well-diagnosed, accompanied by data on diagnostic reliability. This is the advantage of FM compared to IECM. Those data also indicates the development degree of the corresponding faults. Based on that, the operators will have specific plans in the maintenance and maintenance of transformers.

CONCLUSION

In this paper we have proposed a new diagnostic model and algorithm to diagnose potential faults of transformers. The diagnosis tool is made based on the ratio method DGA results. Specifically, we have built a diagnostic model based on fuzzy logical approach, developed from diagnostic rules according to IEC-599. It allows the description of the density of gas components to be consistent with reality, determining the total dissolved gas content and the total flammable gas content. With this fuzzy model calculation, potential errors are diagnosed with a degree of reliability. With this designed diagnostic algorithms, the software has been installed completely and running on the web environment. The software has been tested with many actual data sets and has the necessary adjust to make the diagnosis decision more reliable.

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REFERENCES

1. Saha, T. K. (2003). Review of modern diagnostic techniques for assessing insulation condition in aged transformers. *IEEE transactions on dielectrics and electrical insulation*, *10*(5), 903-917.
2. Bakar, N. A., Abu-Siada, A., & Islam, S. (2014). A review of dissolved gas analysis measurement and interpretation techniques. *IEEE Electrical Insulation Magazine*, *30*(3), 39-49.
3. Ghoneim, S. S., & Ward, S. A. (2012). Dissolved Gas analysis as a diagnostic tools for early detection of transformer faults. *Advances in Electrical Engineering Systems (AEES)*, *1*(3), 152-156.
4. Saranya, S., Mageswari, U., Roy, N., & Sudha, R. (2013). "Comparative Study Of Various Dissolved Gas Analysis Methods To Diagnose Transformer Faults", *International Journal of Engineering Research and Applications (IJERA)* www.ijera.com, 3 (3), 592-595.
5. Ghoneim, S., & Shoush, K. A. (2014). Diagnostic tool for transformer fault detection based on dissolved gas analysis. *IOSR J. Electr. Electron. Eng. www. iosrjournals. org*, *9*(5), 20-26.
6. Islam, S. M., Wu, T., & Ledwich, G. (2000). A novel fuzzy logic approach to transformer fault diagnosis. *IEEE Transactions on Dielectrics and electrical Insulation*, *7*(2), 177-186.
7. Dhote, N. K., & Helonde, J. B. (2012). Diagnosis of power transformer faults based on five fuzzy ratio method. *WSEAS Transactions on Power Systems*, *7*(3), 114-125.
8. Er. Niti Sharma (2012). "Power Transformer Diagnosis Using Fuzzy Logic", *International Journal of Latest Research in Science and Technology*, 1 (2), pp. 149-151.
9. SuganyaBharathi, M., Iruthayarajan, M. W., Shunmugam, S. S., & Kalaivani, L. (2013, February). Interpretation of dissolved gas analysis in transformer oil using fuzzy logic system. In *2013 International Conference on Power, Energy and Control (ICPEC)* (pp. 245-249). IEEE.
10. Ma, H., Li, Z., Ju, P., Han, J., & Zhang, L. (2005). "Diagnosis of power transformer faults on fuzzy three-ratio method", *International Power Engineering Conference*, Singapore, pp. 1-456. doi: 10.1109/IPEC.2005.206897.
11. Su, Q. (2000, December). A fuzzy logic tool for transformer fault diagnosis. In *PowerCon 2000. 2000 International Conference on Power System Technology. Proceedings (Cat. No. 00EX409)* (Vol. 1, pp. 265-268). IEEE.
12. Zhenyaun, W. (2000). "Artificial intelligence applications in the diagnostic of power transformer incipicent", Virginia.
13. Fathiah, Z., Dalina, J., & Ismail, M. (2012), "Artificial Neural Network (ANN) Application in Dissolved Gas Analysis (DGA) Methods for the Detection of Incipient Faults in Oil-Filled Power Transformer", *IEEE International Conference on Control System, Computing and Engineering*, 23 - 25 Nov. 2012, Penang, Malaysia.
14. Amin, S., Sayed, A. W., & Mahmud, N. A. (2015). "Conventional Ratio and Artificial Intelligence (AI) Diagnostic methods for DGA in Electrical Transformers", *International Electrical Engineering Journal (IEEJ)*, 6 (12), pp. 2096-2102.
15. Michel, B., Hell, M., D`Angelo, F. S. V., & Pyramo, P. Costa Jr. (2002). "Power Transformer Fault Diagnosis Based on Dissolved Gas Analysis Using a Fuzzy Neural Network Approach in a Real Data Base".
16. Naresh, R., Sharma, V., & Vashisth, M. (2008). An integrated neural fuzzy approach for fault diagnosis of transformers. *IEEE transactions on power delivery*, *23*(4), 2017-2024.