Comparative Study and Analysis of DGA Methods for Mineral Oil Using Fuzzy Logic

N.A. Muhamad, B.T. Phung and T.R. Blackburn

Abstract: **Dissolved gas analysis (DGA) is one of the most useful techniques to detect the incipient faults in large oil-filled transformers. Various methods have been developed to interpret DGA results. Among them are the Key Gas, Rogers Ratio, Logarithmic Nomograph, Doernenburg, IEC Ratio and Duval Triangle. This paper used the DGA data from 69 different cases to test the accuracy and consistency of these methods in interpreting the transformer condition. The key gases considered for evaluation are hydrogen, methane, ethane, ethylene and acetylene. MATLAB programs with and without using Fuzzy logic were developed to automate the evaluation of each method. The difference on accuracy and consistency of each method using and not using Fuzzy logic is presented.**

***Index Terms*— DGA interpretation method, Fuzzy Logic, fault gases.**

I. Introduction

The DGA methods have been employed widely in the transformer industry for condition assessment. Stemming from breakdown or decomposition of the insulation oil, cellulose or paper, gases at various concentrations, such as 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), may be released and partly dissolved in the oil. The causes of the breakdown or decomposition of the insulation material are attributed to electrical and thermal stresses in the transformer. Principles have been developed in the DGA method for the judgment of the fault conditions according to the results from gas chromatographic analysis. Currently there are several methods developed to do the interpretation of the fault type from the dissolved gas data. In this paper, the six methods of interpretation of the fault gases of mineral oil are investigated and compared. They are: Key Gas, Rogers Ratio, Doernenburg, Logarithmic Nomograph, IEC Ratio and Duval Triangle. The study was done to evaluate the accuracy of each method in predicting the fault and the consistency of each method.

These methods commonly use the multiple numeric thresholds and gas ratio boundaries to classify features of the dissolved gas data as to membership in various intervals. The interval membership information is used to infer a diagnosis. When a fault is intermittent or of low intensity, some of the input features may fall near but outside the expected intervals, with the result that no diagnosis is obtained. There is a possibility to smooth these thresholds and ratio boundaries by using Fuzzy Logic [1-3].

Fuzzy Logic is known as one of the expert systems that can be used to diagnose the faults because of its ability in storing knowledge and using it to make decision [4]. Here, the final diagnosis rules are automatically determined and the membership functions of the corresponding fuzzy subsets are simultaneously adjusted. This can give better judgment on the diagnosis of transformer faults. In this paper, evaluation of DGA methods was firstly done using only basic coding and construction of Simulink block diagram. Then the same set of DGA data was evaluated using a Fuzzy Logic controller. The results are then analyzed and compared.

II. Testing Method

The data comprises 69 sets of 5 fault gases, obtained from published papers [4-7]. These were used to test each method. The five key gases are H_2, CH_4, C_2H_6, C_2H_4 and C_2H_2. Table 1 shows the set of data used and fault code for each type of faults used in this paper.

TABLE 1:
SET OF DATA USED IN ANALYSIS

Fault Type	Fault Type Code	Number of cases
Thermal fault at low temperature	F_1	1
Overheating and sparking	F_2	33
Arcing	F_3	22
Partial Discharge and Corona	F_4	8
Normal	F_5	5

The testing method should be the same for each DGA interpretation method in order to compare their accuracy and consistency. Each method diagnosis was grouped according to the faults type code for comparison. This is shown in Table 2.

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TABLE 2:
GROUPING FOR FAULT TYPE CODES

Method	F_1	F_2	F_3	F_4	F_5
Roger	Slight overheating <150°C Overheating 150°C-200°C Overheating 200°C-300°C	Conductor overheating Winding circulating current Core/tank circulating current.	Flashover. Arcing Continuous sparking.	PDs PDs with tracking	Normal
IEC	Thermal fault <150°C Thermal fault 150°C-300°C	Thermal fault 300°C-700°C Thermal fault > 700°C	Discharge of low energy Discharge of high energy	PDs of low energy density PDs of high energy density	Normal
Nomograph	Heating	Heating and Discharge	Arcing Arcing and heating	Arcing, heating and discharge Arcing and discharge	Normal (<L1)
Doernenburg	Thermal decomposition with very high ratio 4	Thermal decomposition	Arcing	Corona	Normal (< L1)
Duval	Thermal fault <300°C	Thermal fault 300°C-700°C Thermal fault > 750°C	Low energy discharge High energy discharge	PDs Mix thermal and electrical faults	Normal (< L1)
Key Gas	Principal gas: CH_4 and C_2H_6	Principal gas: C_2H_4	Principal gas: C_2H_2	Principal gas: H_2	Normal (< L1)

A. Basic coding and Simulink diagram (Without Fuzzy System)

The comparison for each method was done using MATLAB programming. A program was developed to run the test based on each method rules for diagnosing the faults. This involved several coding and Simulink block diagrams to run the test. An example is shown in Figure 1. In general, the diagrams consist of three main sections. The first section is for checking the limit value of the fault gases if applicable. The second section is for calculating the ratio and finding the ratio coding if applicable. The last section provides the diagnosis based on the ratio coding sequence or ratio value or fault gas value.

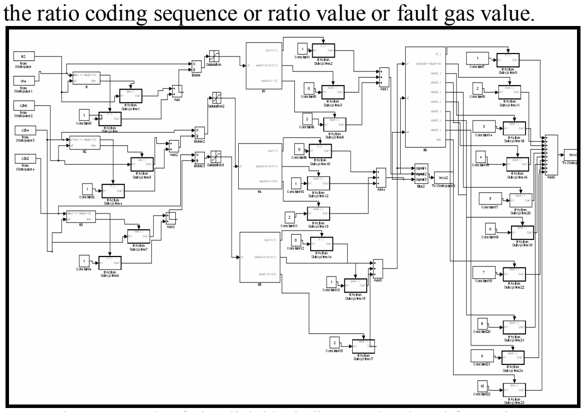

Fig 1: Example of Simulink block diagram developed for testing.

B. *Fuzzy diagnosis systems*

i. Roger's Ratio Fuzzy System

This fuzzy system consists of 4 ratio codes as inputs. The output comprises 13 interpretation results based on the 11 fault types shown in Table 3 plus one 'normal' and one 'no prediction' to cover those ratio code sequences not included in the table.

TABLE 3:
CLASSIFICATION OF FAULTS BASED ON ROGER'S RATIO CODES[5]

i	j	k	l	Diagnosis
0	0	0	0	Normal deterioration
5	0	0	0	Partial discharge
1-2	0	0	0	Slight overheating <150° C
1-2	1	0	0	Overheating 150° C-200° C
0	1	0	0	Overheating 200° C-300° C
0	0	1	0	General conductor overheating
1	0	1	0	Winding circulating currents
1	0	2	0	Core and tank circulating currents, overheated joints
0	0	0	1	Flashover without power follow through
0	0	1-2	1-2	Arc with power follow through
0	0	2	2	Continuous sparking to floating potential
5	0	0	1-2	Partial discharge with tracking (note CO)

The 4 ratios are classified as either Low (Lo), Medium (Med), High (Hi) or Very High (Vhi) according to membership intervals as defined below:

$$l = C_2H_2 / C_2H_4 = \{Lo, Med, Hi\}$$

$$i = CH_4 / H_2 = \{Lo, Med, Hi, Vhi\}$$

$$k = C_2H_4 / C_2H_6 = \{Lo, Med, Hi\}$$

$$j = C_2H_6 / CH_4 = \{Lo, Hi\}$$

$$i = \begin{cases} 5 & Lo & U < 0.1 \\ 0 & Med & 0.1 \le U \le 1.0 \\ 1 & Hi & 1.0 \le U \le 3.0 \\ 2 & Vhi & U > 3.0 \end{cases} \qquad l = \begin{cases} 0 & Lo & U < 0.1 \\ 1 & Med & 0.1 \le U \le 3.0 \\ 2 & Hi & U > 3.0 \end{cases}$$

$$k = \begin{cases} 0 & Lo & U < 1.0 \\ 1 & Med & 1.0 \le U \le 3.0 \\ 2 & Hi & U > 3.0 \end{cases} \qquad j = \begin{cases} 0 & Lo & U < 1.0 \\ 1 & Hi & U \ge 1.0 \end{cases}$$

The membership boundaries are fuzzified by using the following functions:

a) Triangular function

$$T(u; a, b, c) = \begin{cases} 0 & for \quad u < a \\ (u-a)/(b-a) & for \quad a \le u \le b \\ (c-u)/(c-b) & for \quad b \le u \le c \\ 0 & for \quad u > c \end{cases}$$

b) Trapezoidal function

$$\text{Trapezoid}\,\Pi\,(u; a, b, c, d) = \begin{cases} 0 & for \quad u<a \\ (u-a)/(b-a) & for \quad a \le u < b \\ 1 & for \quad b \le u \le c \\ (d-u)/(d-c) & for \quad c < u \le d \\ 0 & for \quad u > d \end{cases}$$

c) Linear function declining (L-function)

$$
\mathrm{L}\,(u;\, a,\, b\,) = \begin{cases} 1 & \textit{for} \quad u < a \\ (u-a)/(b-a) & \textit{for} \quad a \le u \le b \\ 0 & \textit{for} \quad u > b \end{cases}
$$

d) Linear function increasing (Γ -function)

$$
\Gamma\,(u;\, a,\, b\,) = \begin{cases} 0 & \textit{for} \quad u < a \\ (u-a)/(b-a) & \textit{for} \quad a \le u \le b \\ 1 & \textit{for} \quad u > b \end{cases}
$$

An example of fuzzy membership function for the Roger's 4 ratio input classifications is illustrated in Figure 2.

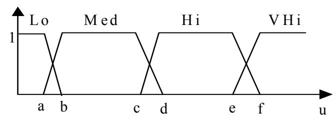

Fig 2: Input code i membership function for Roger's Ratio Method

Fuzzy inference consists of two components which are the antecedent (IF part) and the consequent (THEN part). Here, the fuzzy inference rules are based on the fault interpretations given in Table 3. 18 inference rules can be derived out of the total of 72 possible rules (4x3x3x2). With the fuzzy logic technique, the partial membership may improve the number of matched cases as compared to the ordinary crisp set theory. The following are some examples of the fuzzy rules:

Rules 1: IF i=Med AND j=Lo AND k=Lo AND l=Lo THEN Faults(1)
Rules 3: IF i=Hi AND j=Lo AND k=Lo AND l=Lo THEN Faults(3)
Rules 4: IF i=VHi AND j=Lo AND k=Lo AND l=Lo THEN Faults(3)

The output of the fuzzy inference can be obtained using the Mamdani's Max-Min composition technique. Here the logical 'AND' is replaced with the minimization operator and the logical 'OR' is replaced with the maximization operator [3]. Based on the Roger's ratio rules, the following are some examples of the diagnosed equations:

Fault(1)=min[i=Med ,j=Lo, k=Lo, l=Lo]
Fault(3)=max{ min[i=Hi, j=Lo, k=Lo, l=Lo],
min[i=Med, j=Lo, k=Lo, l=Lo]}

ii. IEC Ratio Fuzzy System

This system has 3 ratios as inputs and 10 conditions as outputs (including "no prediction" output and the 9 conditions from Table 4). The 3 ratios are simplified and classified as either Low (Lo), Medium (Med) or High (Hi) according to membership intervals as defined below:

$l = C_2H_2 / C_2H_4$ ={Lo, Med, Hi}

$i = CH_4 / H_2$={Lo, Med, Hi}

$k = C_2H_4 / C_2H_6$ = {Lo, Med, Hi}

$$
l = \begin{cases} 0 \quad Lo & U < 0.1 \\ 1 \quad Med & 0.1 \le U \le 3.0 \\ 2 \quad Hi & U > 3.0 \end{cases} \qquad i = \begin{cases} 1 \quad Lo & U < 0.1 \\ 0 \quad Med & 0.1 \le U \le 1.0 \\ 2 \quad Hi & U > 1.0 \end{cases}
$$

$$
k = \begin{cases} 0 \quad Lo & U < 1.0 \\ 1 \quad Med & 1.0 \le U \le 3.0 \\ 2 \quad Hi & U > 3.0 \end{cases}
$$

TABLE 4
CLASSIFICATION OF FAULTS BASED ON IEC RATIO CODES [5]

l	i	k	Characteristic fault
0	0	0	Normal ageing
*	1	0	Partial discharge of low energy density
1	1	0	Partial discharge of high energy density
1-2	0	1-2	Discharge of low energy (Continuous sparking)
1	0	2	Discharge of high energy (Arc with power flow through)
0	0	1	Thermal fault <150^0 C
0	2	0	Thermal fault 150^0-300^0 C
0	2	1	Thermal fault 300^{0}C-700^0 C
0	2	2	Thermal fault >700^{0}C

The types of fuzzy membership functions used are the same as the previous method. Only 11 inference rules out of 27 possible rules (3x3x3) can be derived. The inference and diagnosis vector for this method was developed using the same technique as for the Roger's Ratio method.

iii. Doernenburg Ratio Fuzzy System

This method first checks the measured concentrations of the key gases against the limits L1 as specified in Table 5(A). If all are within the limits then the diagnosis would be "normal". Otherwise, it indicates a fault condition, and 4 ratios are then calculated based on the gas concentrations and used to classify the fault.

TABLE 5:
CONCENTRATION L1 (A) AND FAULT DIAGNOSIS FOR DOERNENBURG RATIO METHOD (B) [8]

Key Gas	Concentrations *L*1 (ppm)
Hydrogen (H_2)	100
Methane (CH_4)	120
Carbon Monoxide (CO)	350
Acetylene (C_2H_2)	35
Ethylene (C_2H_4)	50
Ethane (C_2H_6)	65

(A)

Suggested Fault Diagnosis	Ratio 1 (R1) CH_4/H_2 Extracted From	Oil Gas Space	Ratio 2 (R2) C_2H_2/C_2H_4 Extracted From	Oil Gas Space	Ratio 3 (R3) C_2H_2/CH_4 Extracted From	Oil Gas Space	Ratio 4 (R4) C_2H_6/C_2H_2 Extracted From	Oil Gas Space
1–Thermal Decomposition	>1.0	>0.1	<0.75	<1.0	<0.3	<0.1	>0.4	>0.2
2–Corona (Low Intensity PD)	<0.1	<0.01	Not Significant		<0.3	<0.1	>0.4	>0.2
3–Arcing (High Intensity PD)	>0.1 <1.0	>0.01 <0.1	>0.75	>1.0	>0.3	>0.1	<0.4	<0.2

(B)

The 4 ratios give 8 different input parameters as referred to Table 5(B) (4 for first column and 4 for second column) and 5 conditions (normal, thermal, corona, no prediction and arcing) as output parameter. The input ratios are classified as either Low, Medium or High according to membership intervals as defined below:

$R1 = CH_4 / H_2$
$R2 = C_2H_2 / C_2H_4$
$R3= C_2H_6 / CH_4$

R4= C_2H_6/C_2H_6

R11 ={Lo, Med, Hi} R12 ={Lo, Med, Hi}
R21 ={Lo, Hi} R22 ={Lo, Hi}
R31 ={Lo, Hi} R32 ={Lo, Hi}
R41 ={Lo, Hi} R42 ={Lo, Hi}

$$R11=\begin{cases}0 & Lo & U < 0.1\\ 1 & Med & 0.1 \le U \le 1.0\\ 2 & Hi & U > 1.0\end{cases} \qquad R12=\begin{cases}0 & Lo & U < 0.01\\ 1 & Med & 0.01 \le U \le 0.1\\ 2 & Hi & U > 0.1\end{cases}$$

$$R21=\begin{cases}0 & Lo & U < 0.75\\ 1 & Hi & U > 0.75\end{cases} \qquad R22=\begin{cases}0 & Lo & U < 1.0\\ 1 & Hi & U > 1.0\end{cases}$$

$$R31=\begin{cases}0 & Lo & U < 0.3\\ 1 & Hi & U > 0.3\end{cases} \qquad R32=\begin{cases}0 & Lo & U < 0.1\\ 1 & Hi & U > 0.1\end{cases}$$

$$R41=\begin{cases}0 & Lo & U < 0.4\\ 1 & Hi & U > 0.4\end{cases} \qquad R42=\begin{cases}0 & Lo & U < 0.2\\ 1 & Hi & U > 0.2\end{cases}$$

The fuzzifying membership functions are the same types used in the Roger's Ratio method. The fuzzy inference rules are based on the fault interpretation shown in Table 5(B). In this case, only 6 fuzzy inferences (3 for first column and 3 for second column) can be derived out of the total of 48 possible rules (3x2x2x2 + 3x2x2x2).

iv. Duval Triangle Ratio Fuzzy System

This system consists of 3 gas percentages as the inputs and the 7 regions in the Duval triangle as the outputs. Similar to the approach used in the previous method, at least one of the gas values must exceed a specified limit (L1) in order to be considered as having a fault. Table 6 lists the gas limiting values for the Duval Triangle method.

TABLE 6:
L1 LIMITS FOR DUVAL TRIANGLE METHOD[9]

Gas	L1 Limits
H_2	100
CH_4	75
C_2H_2	3
C_2H_4	75
C_2H_6	75
CO	700
CO_2	7,000

The 3 gas percentages are divided into intervals: Z0 to Z7 for CH_4 percentage, S0 to S6 for C_2H_4 percentage, and P0 to P7 for C_2H_2 percentage. These are shown in Figure 3 and defined as follows:

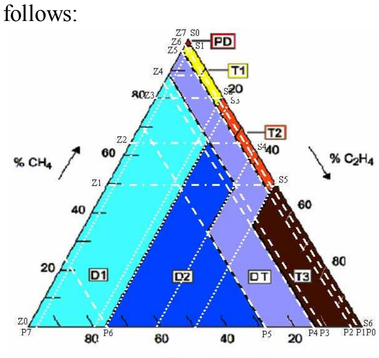

Fig 3: Duval Triangle classification.

$$\%\,CH_4=\begin{cases}Z1 & U < 50\\ Z2 & 50 \le U < 63\\ Z3 & 63 \le U < 80\\ Z4 & 80 \le U < 88\\ Z5 & 88 \le U < 96\\ Z6 & 96 \le U < 98\\ Z7 & U \ge 98\end{cases} \qquad \%\,C_2H_4=\begin{cases}S1 & U < 2\\ S2 & 2 \le U < 20\\ S3 & 20 \le U < 23\\ S4 & 23 \le U < 37\\ S5 & 37 \le U < 50\\ S6 & U \ge 50\end{cases}$$

$$\%\,C_2H_2=\begin{cases}P1 & U < 2\\ P2 & 2 \le U < 4\\ P3 & 4 \le U < 12\\ P4 & 12 \le U < 14\\ P5 & 14 \le U < 28\\ P6 & 28 \le U < 77\\ P7 & U \ge 77\end{cases}$$

The types of fuzzy membership function used for this method are the same as for previous methods. Based on membership functions of the inputs, this system can have up to 294 rules (7x6x7). However as the total % CH_4 + % C_2H_4 + % C_2H_2 must be 100, some rules are not used. The rules were developed based on the regions shown in Figure 4.

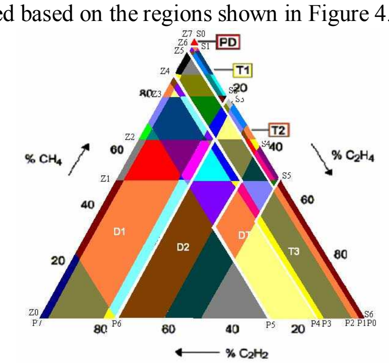

Figure 4: Regions used to develop Duval Triangle Fuzzy system

Only 70 rules were created for this method. These are based on the rules covering each region in Figure 4 as listed below:

D1 = 24 rules	D2 =7 rules
DT=13 rules	T1 = 10 rules
T2 = 11 rules	T3 = 4 rules
PD = 1 rules	Total = 70 rules

The rule components and the output inferences of this method were derived using the same technique as the previous method.

v. *Key Gas Fuzzy System*

This system is based on the values of the fault gases when at least one exceeds the threshold value. Here all five key gases were used as inputs and the output is the 5 fault types as classified in Table 2. The membership of the fuzzy set "Lo" "Med" or "Hi" was used for each fault gas.

vi. *Logarithmic Nomograph Fuzzy System*

This method combines the fault gas ratio concept with the Key Gas threshold value. It consists of a series of vertical logarithmic scales representing the concentrations of the individual gases. Straight lines are drawn between adjacent scales to connect the points representing the values of the individual gas concentration. The diagnostic criteria for determining the type of fault are based on the slopes of these lines. There are 28 fuzzy inference rules (2x2x7 which is type of slope multiplied with type of faults and number of vertical axes). The membership functions are the linear type L-function and Γ-function.

III. RESULTS

Each method was tested against all the 69 cases in the data set. The percentages of successful prediction and consistency are calculated using the following formulas:

$$S_{Fn} = \frac{R_{Fn}}{Number\ of\ cases\ of\ Fn} \times 100 \qquad (1)$$

$$C_{Fn} = \frac{\sum_{n=1}^{n=5} S_{Fn}}{Number\ of\ fault\ types} \times 100 \qquad (2)$$

where:

F_n = fault type code (n=1,2,3,4,5)

TABLE 7:
RESULT ANALYSIS FOR EACH TYPE OF FAULTS WITHOUT FUZZY (WF) AND WITH FUZZY SYSTEM (FS).

Method	Faults Code	Number of predictions (P)		Number of correct predictions (R)		% Successful prediction (S)		Consistency (C)	
		WF	FS	WF	FS	WF	FS	WF	FS
Roger	F_1	1	1	0	0	0%	0%	26%	30%
	F_2	13	16	13	16	39%	48%		
	F_3	13	17	12	14	55%	64%		
	F_4	3	3	3	3	38%	38%		
	F_5	1	1	0	0	0%	0%		
IEC	F_1	1	1	0	1	0%	0%	29%	40%
	F_2	14	26	14	26	42%	79%		
	F_3	17	19	15	18	68%	82%		
	F_4	1	3	1	3	13%	38%		
	F_5	1	1	1	0	20%	0%		
Nomograph	F_1	6	6	0	0	0%	0%	68%	68%
	F_2	23	23	21	21	64%	64%		
	F_3	19	19	17	17	77%	77%		
	F_4	15	15	8	8	100%	100%		
	F_5	6	6	5	5	100%	100%		
Doernenburg	F_1	0	0	0	0	0%	0%	36%	63%
	F_2	15	23	15	21	45%	64%		
	F_3	9	13	8	13	36%	59%		
	F_4	1	1	0	1	0%	13%		
	F_5	6	15	5	5	100%	100%		
Duval	F_1	2	2	1	1	100%	100%	82%	84%
	F_2	31	31	29	28	88%	85%		
	F_3	26	26	21	22	95%	100%		
	F_4	4	4	2	3	25%	38%		
	F_5	6	6	5	5	100%	100%		
Key Gas	F_1	2	2	1	1	100%	100%	77%	77%
	F_2	48	48	33	33	100%	100%		
	F_3	11	11	10	10	45%	45%		
	F_4	3	3	3	3	38%	38%		
	F_5	5	5	5	5	100%	100%		

The results are presented in Table 7. For systems without fuzzy logic, it clearly shows that those methods which take into account the limit value of fault gases before doing diagnosis have better success in predicting the normal condition. On the other hand, methods that have no limit values of fault gases always fail to predict the normal condition. This affects the consistency result. Note the low consistency value (<50%) with some of the methods. It is found that the Duval Triangle method is the most consistent method followed by the Key Gas, Nomograph, Doernenburg, IEC Ratio and lastly the Roger Ratio method (when tested without using fuzzy logic).

By applying fuzzy logic, the analysis shows that the consistencies of most methods are improved. The exceptions are the Nomograph and the Key Gas method where consistencies remain at the same values. The Duval Triangle method is still the most consistent method with 2% consistency improvement followed by Key Gas with no improvement, Nomograph with no improvement, Doernenburg with 27% improvement, IEC with 11% improvement and lastly Roger's method with 4% improvement.

It was also found that for both types of systems, the best methods for predicting fault types F1 and F2 are the Duval Triangle and the Key Gas method. The Duval Triangle method also is the best method for predicting fault types F3 and F5. Other than the Duval Triangle, the Nomograph is the best method for predicting fault types F5 and F4.

In addition to consistency, the accuracy of each method is another parameter used for comparison. Here, the accuracy is calculated in two different ways: A_p when considering only the predicted cases T_p, and A_T when considering the total number of cases T_C. Their formulas are:

$$A_P = \frac{T_R}{T_P} \times 100 \qquad (3)$$

$$A_T = \frac{T_R}{T_C} \times 100 \qquad (4)$$

TABLE 8:
COMPARISON OF ACCURACY VALUES.

	Roger		IEC		Nomograph		Doernenburg		Duval		Key Gas	
	WF	FS	WF	FS	WF	FS	WF	FS	WF	FS	WF	FS
Total cases, T_C	69	69	69	69	69	69	69	69	69	69	69	69
No predictions, T_{NP}	38	31	35	19	0	0	38	15	0	0	0	0
Number of predictions, T_P	31	38	34	50	69	69	31	54	69	69	69	69
Correct predictions, T_R	28	33	31	47	51	51	28	40	58	57	52	52
Incorrect predictions, T_W	3	5	3	3	18	18	3	14	11	10	17	17
Accuracy (predicted cases), A_P	90%	87%	91%	94%	74%	74%	90%	74%	84%	86%	75%	75%
Accuracy (total cases), A_T	41%	48%	45%	68%	74%	74%	41%	58%	84%	86%	75%	75%

The results are summarized in Table 8. Without using fuzzy logic, the results based on the predicted cases show that all methods have accuracy more than 70 percent. The most accurate is the IEC Ratio method followed by the Roger Ratio, Doernenburg, Duval Triangle, Key Gas and Nomograph method. As can be seen from the table, those methods that used specific code in their diagnosis have high accuracy (>90%). On the other hand, methods that use direct interpretation based on each value of fault gases are less accurate. However, the accuracy based on the total number of cases shows a different trend. Because of the high number of cases with no prediction, the accuracy drops significantly (<70%) for methods that used specific codes in the diagnosis.

When fuzzy logic was applied, the accuracy based on the total number of cases improves as the number of 'no predictions' is now smaller. The accuracy of the Roger Ratio method has increased by 7%, IEC method by 23%, Doernenburg by 17% and Duval Triangle by 2%. As Nomograph and Key Gas are the two methods that use direct values of fault gases, the application of fuzzy logic does not affect their accuracy values.

IV. CONCLUSION

In this paper, a comprehensive investigation of various methods for interpreting DGA results was carried out and the possibility of improving the diagnosis with the aid of fuzzy logic was explored. The results show that those methods using specific codes in their interpretation have higher value of accuracy for predicted cases in both systems (with or without fuzzy logic) when compared to others. However, the accuracy is somewhat worsened when fuzzy system was applied. This is because the number of predictions when using fuzzy system is increased and this increases the possibility of incorrect predictions. However, there are some improvements on the accuracy based on total cases and the consistency when using fuzzy system for these methods even though the values are still less than other methods.

The reversed results were found for those methods that use direct values of fault gases in their interpretation as against methods that use specific codes. These methods have higher consistency and accuracy based on total cases but have low values of accuracy based on predicted cases as compare to other methods in both systems. This is expected because they attempt to provide predictions for all cases. But as they have all the interpretations, the prediction is likely to be incorrect for certain cases. Indeed for these methods, the application of fuzzy system does not improve the diagnosis results. This is because these methods are direct methods and do not have multiple numeric thresholds and gas ratio boundaries that can be improved by applying fuzzy membership function.

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