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Enhancing the Diagnostic Accuracy of DGA Techniques Based on IEC-TC10 and Related Databases

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ABSTRACT Investigating and enhancing the accuracy of widespread dissolved gas analysis (DGA) techniques based on IEC-TC10 and related databases was implemented. The current work aimed to help the experts to diagnose the transformers' faults accurately. The major drawback of the dissolved gas techniques is no decision diagnosis for the cases that lie out of the specified codes of the traditional DGA methods. In this article, fuzzy logic (FL) and artificial neural network (ANN) were applied to the standard DGA techniques such as the Dornenburg ratio method, Rogers ratio method, and IEC Standard Code 60599. This paper provided a new concept using artificial intelligence for enhancing the diagnostic accuracy of the conventional DGA method such as Dornenburg ratio, Rogers' ratio, and IEC standard which suffer from a poor diagnostic accuracy and fail to interpret the cause of the faults in most cases. In this article the FL and ANN accuracy results were compared with that of other diagnostic techniques in the literature. The results revealed that the artificial intelligence methods improve the diagnostic accuracy of the conventional DGA techniques from 41.95, 76.76, and 51.44% to 58.97 (ANN), 89.02 (FL), and 62.67% (FL) for Rogers, Dornenburg, and IEC standard code, respectively.

INDEX TERMS Dissolved gas analysis, fault diagnosis, power transformer oil, heptagon graph DGA, and Duval triangle.

I. INTRODUCTION

Power transformers are the most expensive and vital equipment in the electric power system due to their power transformation functions. Moreover, it serves as a crucial link between power plants and the distribution electric power system [1]. Therefore, any failure of power transformers affects the stability and reliability of energy delivery of the whole power system and would lead to a blackout, which causes economic problems. Hence, condition assessment of power transformer is a necessary task; it is a well-accepted method that helps in improving the detection of the power transformer faults [2]–[4]. Therefore, reliable and economic transformer insulation condition monitoring and diagnostic techniques are necessary to conduct a comprehensive and efficient transformer condition assessment.

Dissolved Gas Analysis (DGA) is one of the most effective monitoring tools for the oil-immersed transformer. It provides valuable information about the oil and paper insulation condition and helps to identify the incipient fault types within the transformer [5]–[7]. It uses various dissolved gases in the transformer oil generated by the oil and paper insulation decomposition. DGA has gained worldwide acceptance as a technique for the detection of incipient faults in transformers. Due to the thermal and electrical stresses, the power transformer's insulation decomposes, generating gases that dissolve in the oil and reduce its dielectric strength. Gases generated through oil decomposition include hydrogen (H_2), methane (CH_4), acetylene (C_2H_2), ethylene (C_2H_4), and ethane (C_2H_6).

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On the other hand, carbon monoxide (CO) and carbon dioxide (CO_2) are generated due to paper decomposition. Through the analysis of the type, amount, and gassing rate of generated gases, various techniques for interpretation of DGA data have been developed, e.g., the key gas, Dornenburg ratio, Rogers's ratio, IEC ratio, Duval triangle, and artificial intelligence-based techniques to diagnose incipient faults based on DGA [8]–[14]. Rogers used IEEE and IEC Codes [8] to interpret faults in the power transformers using the dissolved gas analysis in the transformer oil [9].

According to specific codes, the conventional ratio techniques for fault diagnosis used certain ratios of dissolved gas concentrations for fault diagnosis. The ratio techniques were first proposed by Dornenburg [10] and modified by Rogers [11] before they were revised in IEC standard 60599 [12]. The codes are generated by calculating ratios of gas concentrations and comparing the ratios with predefined values derived by experience and continually modified. Diagnosis is made when a code combination matches the code pattern of the fault type. The major drawback of this technique's accuracy is no decision is associated with some cases that lie out of the specified codes.

On the other hand, the Duval triangle technique [14] is characterized by simplicity in application and evaluating fault types and severity. Still, the essential drawback of Duval is using only three hydrocarbon gases (methane, ethylene, acetylene). Furthermore, it does not consider the concentrations of hydrogen (H_2) and ethane (C_2H_6) despite their importance in diagnosing certain fault types especially low-temperature thermal fault and partial discharge, which reduces the accuracy of Duval techniques.

In recent years, artificial intelligence-based techniques have been extensively studied by many researchers for transformer fault diagnosis [15]–[22]. These techniques include expert systems, fuzzy logic, artificial neural network, or hybrid system. Artificial intelligence techniques are constructed either on knowledge-based training using DGA data. However, these techniques are too complicated for practical implementation on a wide range. In addition, they are highly dependent on the training data set, which may reduce their accuracy. The drawbacks must be avoided to increase the DGA accuracy. Several ways for different DGA diagnostic techniques can be presented. DGA techniques were used, such as the Heptagon graph, three ratios using five main diagnosis gases H_2, CH_4, C_2H_6, C_2H_4, and C_2H_2. On the other hand, the modified Duval Triangle technique using a new 3-ratio percentage of DGA based on the consideration of all five hydrocarbon combustible gases can be presented [23]–[25].

In this article, Fuzzy logic and Artificial Neural Network models based on DGA ratio techniques are implemented to study their intrinsic advantages and drawbacks that can affect the accuracy of DGA interpretation by using an actual database. Furthermore, this paper systematically discusses the accuracy of the different conventional, Fuzzy Logic, Artificial Neural network-based DGA ratio techniques, and DGA techniques suggested by [23]–[25] to detect and identify transformer malfunctions in each fault type. These techniques are implemented for fault diagnosing and decision-making for oil-immersed transformers and summarize existing problems. The overall accuracy, fault type zone boundaries, and each gas ratio development of the suggested techniques have been determined based on many actual cases. These cases were visually inspected in transformers over the last 30 years as reported by EEHC, IEC TC10, and related databases surveyed from real incident cases of the mineral oil-filled transformers. The dissolved gas analysis databases have been tested to confirm or re-adjust these boundaries of each fault zone slightly with maximum accuracy whenever possible. The classification performance of these suggested DGA techniques and Fuzzy logic and artificial neural network-based DGA ratios techniques are verified compared to the other conventional DGA techniques. This comparison proved the Heptagon graph; three ratios using five main diagnosis gases and modifications done on Duval Triangle technique [23]–[25] have good diagnostic accuracy.

Although some of the conventional methods have been standardized, they have some limitations in the field applications. Various DGA standard interpretation methods may lead to different results, which makes the final decision difficult. Several solutions are proposed in the literature based on the combination of more than one technique for improving the accuracy of the DGA techniques To overcome these limitations [26], [27]. For example, A Ward *et al.* [26] used novel combined techniques based on DGA and partial discharge sensors to improve the final decision accuracy

II. CONVENTIONAL DGA INTERPRETATION TECHNIQUES

One of these techniques is the Doernenburg method which identifies transformer incipient fault conditions based on the DGA results by analyzing four different gas concentration ratios of (CH_4/H_2), (C_2H_2/C_2H_4), (C_2H_2/CH_4), and (C_2H_6/C_2H_2). A significant amount of gas is needed to validate its use. Nevertheless, it is capable of identifying the thermal decomposition fault, low energy partial discharges (PD), and high energy discharges (arcing) [9], [10]. The major drawback of this technique is its low accuracy caused by no decision associated with some cases that lie out of the specified codes.

Rogers's ratio method is the most common gas ratio technique that distinguishes between thermal and electrical fault types in the oil-immersed transformer compared to the Doernenburg ratio technique. This method is based on Halstead's thermal equilibrium knowledge and the thermal degradation principles included in IEEE Standard C57.104-2008. It is a simple scheme that uses four gas ratios, namely CH_4/H_2, C_2H_6/CH_4, C_2H_4/C_2H_6, and C_2H_2/C_2H_4, which are associated with specific ranges to diagnose the incipient fault types and the normal aging condition in the mineral oil transformers [8], [9], and [11].

IEC Technique is originated from the Rogers technique; it uses the same three gas ratios of the revised Rogers ratio technique, but it refers to different gas ratio ranges of code and interpretations in the fault diagnosis scheme. It excluded the C_2H_6/CH_4 ratio referring only to a limited temperature range of decomposition faults, and did not further identify the incipient fault. Based on the output pattern, the incipient fault conditions detectable in this technique can be divided into nine different types as illustrated in reference [12]. The problem of no decision associated with some cases can be considered in this technique.

Duval Triangle technique uses only the concentrations of methane (CH_4), ethylene (C_2H_4), and acetylene (C_2H_2). These gases are generated by the increasing energy levels necessary to generate gases in transformers during their service [7], [14]. Unfortunately, neglecting the hydrogen (H_2) and ethane (C_2H_6) concentrations despite their importance in diagnosing certain fault types reduces the technique accuracy.

Heptagon graph technique for interpretation of oil-immersed transformers, including cellulose degradation, is a graphical technique in the form of an equilateral heptagon shape with its heads representing the percentage concentration of each individual gas (combustible and non-combustible gases) to the total dissolved gases. The corresponding point for a certain faulty case was determined by the center of mass of all heptagon heads. First, the knowledge related to each fault type was extracted from previous DGA techniques and field experience. Then, this knowledge was used to estimate the normal concentration limits of dissolved gases and the preliminary positions of boundaries between fault regions within the heptagon [23]. The proposed heptagon is based on the concentrations of seven dissolved gases. One advantage of this method over the others is that it considered the presence of carbon monoxide (CO) and carbon dioxide (CO_2) concentrations generated due to paper decomposition. This method can distinguish between high, medium, and low concentrations of cellulose degradation in oil transformers. By the use of this technique Mix of electrical and thermal faults can be defined and determined. Due to the ability of this method to recognize the different fault types, its accuracy is high compared with the others.

The three ratios technique (TRT) is proposed using a new 3-gas ratios concentration of DGA to overcome the conflict of the conventional interpretation techniques. Five main diagnosis gases H_2, CH_4, C_2H_6, C_2H_4, and C_2H_2 are selected from the dissolved gases generated by faults in transformers to create an accurate and reliable technique of DGA diagnosis, which are represented in three different types of gas ratios that are capable of clear fault distinction [24]. The proposed TRT diagnosis technique can also perform a detailed diagnosis of the internal transformer fault types defined by IEC 60599. The diagnosis coding rule of TRT technique is given in [24]. Using main five diagnosis gases in this technique improved its accuracy.

Composite Triangle Technique (CTT) presented a graphical triangle technique using new three gas concentration ratios. These ratios were converted to new three ratio percentages of DGA based on considering all five combustible gases. The aim of that was to overcome the conflict takes place in other traditional techniques. The accuracy of the composite triangle technique was evaluated using a practical DGA database obtained from different transformers of different rating life spans reported by IEC TC 10 and related databases surveyed from actual incipient cases.

More details of the composite graphical triangle technique using new 3-gas concentration ratios are presented in reference [25].

III. ARTIFICIAL INTELLIGENCE BASED ON DGA RATIO TECHNIQUES

A. FUZZY LOGIC MODELS BASED ON DGA RATIO TECHNIQUES

Fuzzy Logic Models are employed in the present article to combine Fuzzy Logic and the conventional DGA ratio techniques; they use the degree an object belongs as the interval membership information to a fuzzy set. It fuzzifies the coding boundary to smooth these thresholds and ratio boundaries. It means that the membership function value ranging between 0 and 1. It helps to overcome the drawbacks of the conventional DGA ratio techniques that can't diagnose any matching and multi-fault codes for diagnosis and to indicate a probable diagnosis established in the conventional techniques. Each input pattern was fuzzified into several triangular combinations, and the output fault types of each model are divided into seven sets of membership functions MF. The membership boundaries of the fuzzy input ratios and the output fault types are fuzzified using triangular membership functions.

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

where T is the Membership function, u, a, b, and c are the limits of each membership function. Each fuzzy logic model for a certain technique is developed under the fuzzy inference flowchart shown in Fig. 1.

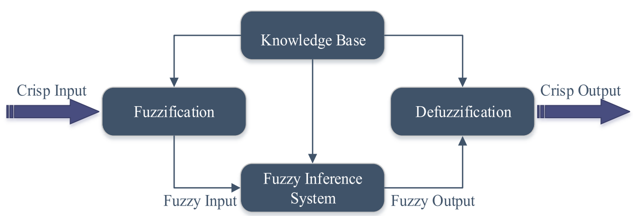

FIGURE 1. Fuzzy logic model flow chart.

Three fuzzy logic models were developed for all DGA conventional ratio techniques using the fuzzy inference system (FIS). The input and output membership functions are triangular functions. They are defined on the corresponding ranges as shown in Fig. 2 for the Doernbourg Ratio method, Fig. 3 for Rogers Ratio, and Fig. 4 for the IEC Ratio technique. It has to be noted that the colors' membships refer to the ratio code and their limits.

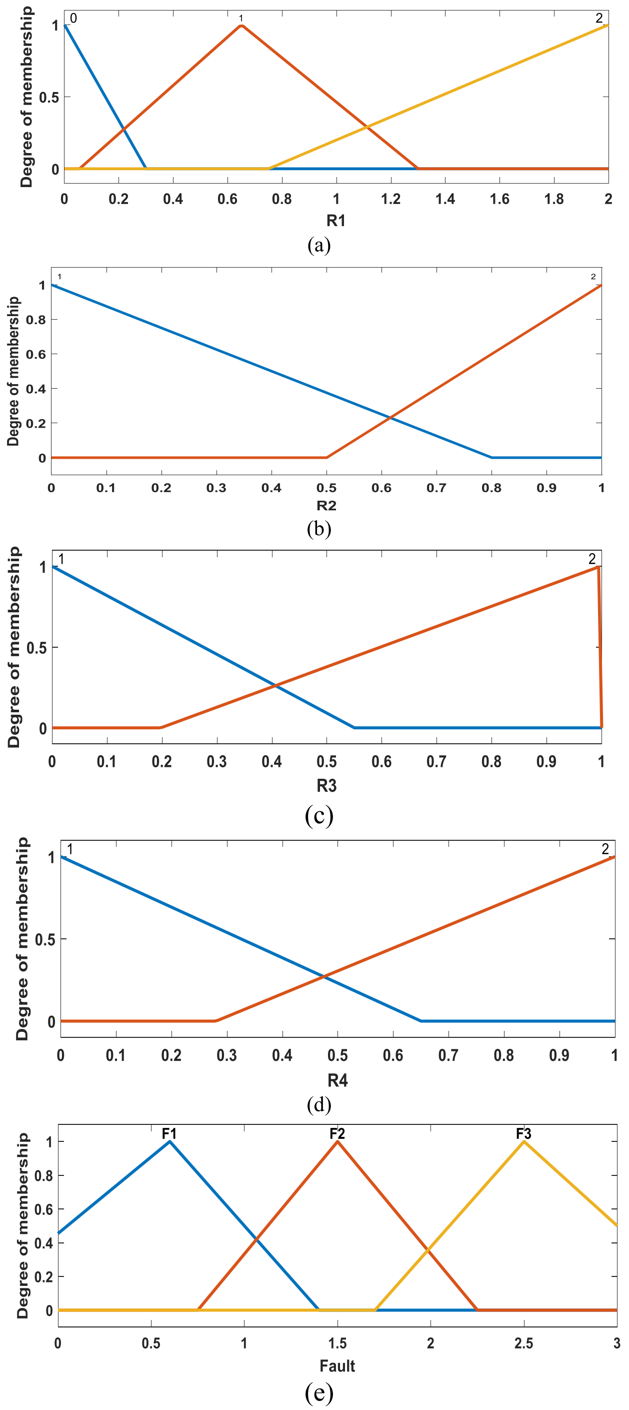

FIGURE 2. **Fuzzy logic model of Doernbourge ratio.**

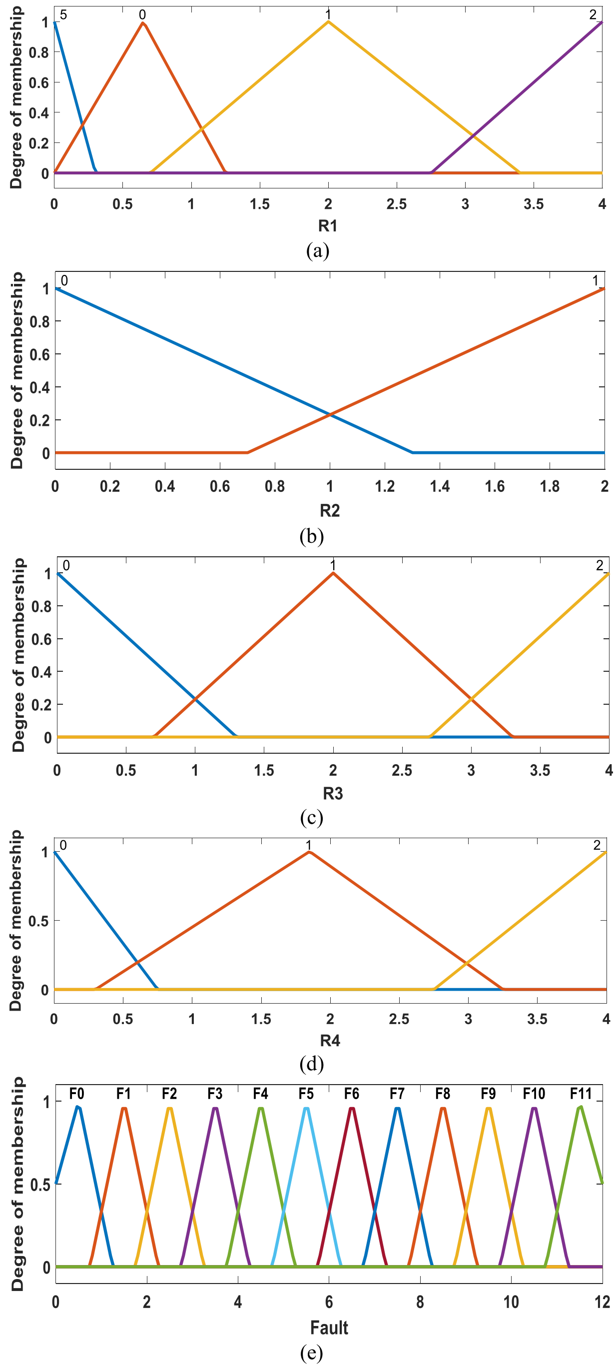

FIGURE 3. **Fuzzy logic model of Rogers ratio.**

Based on these membership boundaries, a set of fuzzy rules for each DGA technique has been developed in the form of (IF-THEN) statements relating the input patterns to the output fault types. It discriminates between the entire topology of the uncertainty levels of the particular parameter based on the transformer's diagnostic.

The desired output is computed after de-fuzzification based on the center of gravity. The output of the fuzzy inference can be obtained using the Fuzzy Inference System. About 734 oil samples have been collected from different oil-immersed transformers and used in testing the conventional DGA techniques and the developed fuzzy logic model for each technique.

The samples are classified according to IEC code as 305 cases with normal or no-fault, 237 cases with thermal faults (32 for T1, 65 for T2, and 140 for T3), 24 cases with partial discharge and 161 cases represent energy discharges (sparking and arcing) (73 for D1 and 88 for D2).

B. ARTIFICIAL NEURAL NETWORK MODELS (ANNMs) BASED ON DGA RATIO TECHNIQUES

ANNMs are used in transformers fault diagnostic systems, including input code boundary features, network topology, fault types outputs, and training network patterns. In the current study, the Feed-forward back propagation-based artificial neural nets are used for transformers faults classification to identify complicated relationships among the input dissolved gas contents patterns and corresponding fault types. Furthermore, the Feed-forward back propagation determines the optimal connection weights and bias terms to achieve the most accurate diagnosis model for the conventional DGA Ratio technique.

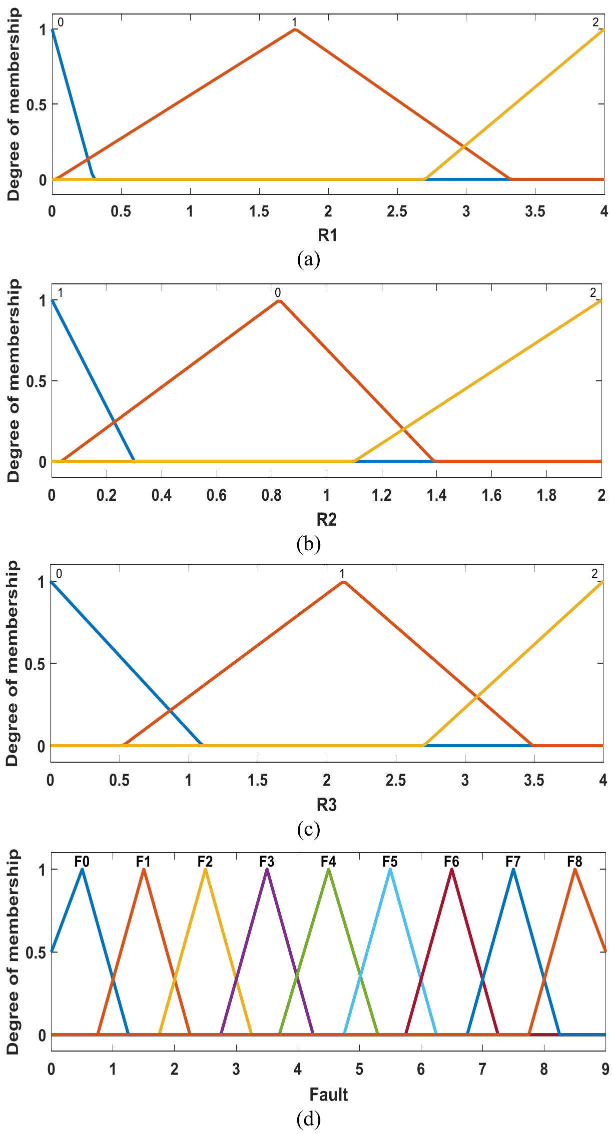

FIGURE 4. Fuzzy logic model of IEC ratio.

Fig. 5 illustrates the construction of the Feed-forward back propagation neural network explaining the input layer neurons, hidden layer neurons and the output layer neurons. Neurons in input layer consider as buffers for distributing the input signals x_i ($i = 1, 2 \ldots n$) to neurons in the hidden layer. Each neuron j in the hidden layer sums up its input signals x_i after weighting as w_{ji} from the input layer and then computes the output y_j as a function f of the sum. The output of the ANN can be determined as in Eqn. 2 [28].

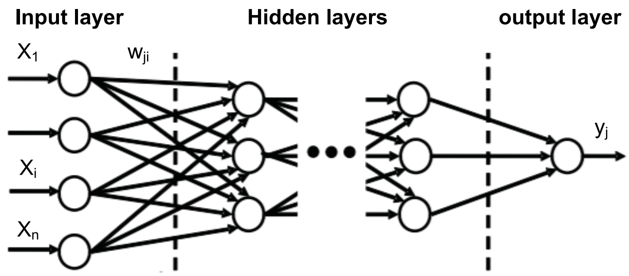

FIGURE 5. Feed-forward back propagation neural network.

$$y_j = f\left(\sum_{i=1}^{n} w_{ji} x_i\right) \tag{2}$$

f is a simple threshold function or a sigmoidal, hyperbolic tangent or radial basis function.

The change of the weight (Δw_{ji}) of a connection between neurons i and j can be computed as follows:

$$\Delta w_{ji} = \eta \delta_j x_i \tag{3}$$

η refers to the learning rate, δ_j is a factor depends on whether j refers to the hidden or output neuron.

For output neurons, δj can be expressed as,

$$\delta_j = \left({}^{\partial f}\!/_{\partial net_j}\right)\left(y_j^t - y_j\right) \tag{4}$$

For hidden neurons

$$\delta_j = \left({}^{\partial f}\!/_{\partial net_j}\right)\left(\sum\nolimits_q w_{qj}\delta_q\right) \tag{5}$$

The $\mathrm{net_j}$ refers to the total weighted sum of input signals to neurons j and $\mathrm{y_j^t}$ expresses the target output for neuron j.

When the target output of the hidden layer is missed as in Eqn. 5, for hidden layer j, the difference between the target and actual output can be replaced by the weighted sum of the δ_q terms already obtained for neurons q connected to the output of j.

The definition of output fault types based on interpretation results and input code boundary patterns must train the Neural Network-based technique. These parameters (input and output patterns) constitute a Neural Network training set. The input patterns of the artificial neural network are weighted, such each input pattern is multiplied by a weighting factor called the connection strength weight. Moreover, the connection strength weights are adjusted during the neural network training procedure to minimize the difference between the required fault type output and the actual output of the neural network for the same input patterns. The output classification of each DGA ratio technique to minimize the neurons number of the output layer is presented as follows:

(T3): represents the "Thermal faults of T > 700 °C".

(T2): represents the "Thermal faults of300 < T < 700 °C".

(T1): represents the "Thermal faults 150 < T < 300 °C".
(D1): represents the "Low energy discharge".
(D2): represents the "High energy discharge".
(PD): represents the "Partial discharge".
(DT): represents the "Mix of electrical and thermal fault".
(CCD): represents the "Concentration of cellulose degradation".
(HCCD): represents the "High concentration of cellulose degradation".
(MCCD): represents the "Medium concentration of cellulose degradation".
(LCCD): represents the" Low concentration of cellulose degradation".
(NO): means" no fault".

Feed-forward back-propagation neural network-based artificial neural design and training steps are:

Step 1: Create the input patterns and output incipient fault type patterns and then create the network object as a feed-forward network.

Step 2: After the test is done with several parameters, the appropriate feed-forward back-propagation network architecture can be obtained with a minimal error rate. Consequently, the optimal parameters are utilized for training the network model. Back-propagation training with an adaptive learning rate is implemented in the function trained for IEC and roger techniques while in the function trains for Dornenburg technique. Moreover, the transfer function for IEC and Doernenburg techniques is Tangent sigmoid, while the transfer function for roger technique is log-sigmoid.

Step 3: A total of 734 oil samples were collected from different oil-immersed transformers DGA results are tested to demonstrate the effectiveness of the proposed ANN-based DGA technique for fault diagnosis.

On the other hand, the main advantage of using artificial intelligence, whether Fuzzy logic or Neural networks, is that artificial intelligence automatically recognizes the fault type pattern and learns what to give due to similar diagnoses to the datasets they are trained. But they are trained with limited specific datasets obtained in specific diagnoses. So, the consistency and accuracy of their classification may decreases when they operate in different diagnoses. Besides that, these artificial intelligence-based DGA techniques are too complicated for practical implementation on a wide range.

IV. RESULTS OF ACCURACY COMPARISON AND EVALUATION

A. COMPARISON BETWEEN THE MENTIONED DGA TECHNIQUES

The mentioned techniques are implemented and verified using practical DGA data obtained from 734 samples that have been collected from different transformers of different ratings and different life spans as reported by IEC TC 10, Egyptian Electricity Holding Company, and related databases [29]–[36]. The incipient fault types in these cases are determined based on visual inspections and the other fault diagnosis methods. Then, by comparing the results of the used techniques and visual inspections reported by the related database, the techniques are evaluated. This contribution presents a study on various conventional approaches to fault types diagnosing and decision making of the oil-immersed transformer.

B. UNIFIED CLASSIFICATION OF FAULT TYPES

All of the mentioned diagnostic techniques depend on personal experience more than standard mathematical formulation. So, the results of these interpretation techniques do not necessarily lead to the same conclusion for the same tested oil sample.

Therefore, an accuracy comparison has to be carried out for each DGA diagnostic technique, based on standardizing DGA results quantification and classification to prevent the comparison from being misleading to mitigate this issue. Therefore, each interpretation technique is grouped according to the incipient fault types and their severity assigned with fault codes (T1, T2, T3, PD, D1, and D2) to compare their accuracy as in Tables 1 and 2.

C. COMPARISON BASED ON EACH INDIVIDUAL FAULT TYPE

The comparison of traditional techniques depends on the consistency of each fault type and their severity of each technique. The consistency is the value of a reliable indicator for comparing the different techniques because it does not depend on the number of cases of each fault and normal cases. Each technique is tested using the 734 cases in the dataset. The overall percentage accuracy of each technique is calculated based on the total successful predictions by using the following formulas [24]:

$$S_{Fj} = \frac{P_{Fj}}{Total\ number\ of\ the\ device\ operation\ for\ each\ F_j} \times 100 \tag{6}$$

$$C_{Fj} = Fj\frac{\sum_{j=1}^{j=n} \boldsymbol{SFj}}{n} \times 100 \tag{7}$$

where; $\boldsymbol{F_j}$ **:** Fault types, $\boldsymbol{S_{Fj}}$ **:** the percentage of successful predictions of particular fault type, $\boldsymbol{P_{Fj}}$: number of successful predictions, ***j:*** number of fault detectable by each technique (j = 1, 2, 3, 4 . . . . . . n), $\boldsymbol{C_{Fj}}$ **:** the overall average percentage of successful predictions of all faults in a particular technique.

The overall percentage of successful predictions of a certain fault type is calculated based on the above equations. In contrast, the average overall percentage of successful predictions of all fault types in a particular technique is calculated based on IECTC10 and related databases. Doernenburg ratio, Rogers ratio, IEC ratio, Duval triangle, TRT ratio, CTT triangle, Heptagon techniques are compared. Table 3, illustrates the calculated percentage of successful predictions of particular fault type for unified classification of the incipient fault types for conventional techniques (SF_i). As it

TABLE 1. Grouping of the incipient fault types codes for conventional DGA interpretation techniques.

Technique	Fault Types					
	T1	T2	T3	PD	D1	D2
Duval	Thermal fault <300 °C	Thermal Fault 300-700 °C	Thermal fault>700 °C	Partial Discharges	Low energy discharge mix thermal and electrical fault	High energy discharge
Doernenburg	Thermal decomposition			Partial Discharges	energy discharge (Arcing)	
Rogers	Thermal fault of low temperature range <150 °C Thermal fault of temperature range 150-200 °C Thermal fault of temperature range 200-300 °C	Winding circulating current Core/tank circulating current.	Insulated conductor overheating	Partial discharge with low energy Partial discharge with tracking	Continuous Sparking. Flashover	Arc with power follows through
IEC	Thermal fault of low temp <150 °C Thermal fault of low temp between 150-300 °C.	Thermal fault of medium temp between 300-700 °C	Thermal fault of high temp >700 °C	PD with high energy density , PD with low energy density	Discharges with low energy, Continuous sparking	Discharge with high energy, Arcing

TABLE 2. Fault types detected by conventional techniques.

Technique	Fault types											
	T			PD		D1		DT	CCD			NO
	T1	T2	T3	PD1	PD2	D1	D2	DT	HCCD	MCCD	LCCD	NO
Doernenburg [10]	+			+		+		-	-	-	-	+
Rogers[9]	+	+	+	+	+	+	+	-	-	-	-	-
IEC[12, 13]	+	+	+	+	+	+	+	-	-	-	-	-
Duval[1, 14]	+	+	+	+		+	+	+	-	-	-	+
TRT [24]	+	+	+	+	+	+	+	+	-	-	-	+
CTT[25]	+	+	+	+	+	+	+	+	-	-	-	+
Heptagon[23]	+	+	+	+		+	+	+	+	+	+	+

+: This technique capable of detecting this fault type.

- : This fault is not determined.

is seen from the results summarized in Table 3, the percentage of successful predictions of thermal fault T1 of the TRT ratio, CTT triangle, and Heptagon graph techniques are the most consistent techniques with 100% accuracy for 734 cases, followed by the IEC technique which has 56.25%. In contrast, IEC-based fuzzy accuracy is 62.50%, and IEC-based neural network is 65.63%. It is also observed that Duval triangle technique has close accuracy percentages of 53.13% because it did not consider the concentrations of two combustible gases, namely ethane (C_2H_6) and hydrogen (H_2).

As a result, Duval triangle exhibits a lower accuracy in diagnosing certain fault types, for which these gases are the key gases, such as low overheating and corona discharge. Whereas Rogers technique has the lowest accuracy of the conventional techniques with 43.75%, Rogers's accuracy is 50.00%. Rogers-based neural network is 65.63%. because it is based on four ratios, which increases the rate of misjudgment due to no decision of some cases resulting in the incompleteness of the possible ratio combinations that lead to uncertainty.

On the other hand, for the thermal fault (T2), Duval triangle has better performance than the conventional techniques with 67.69% accuracy, followed by IEC and Rogers's ratio, which have close accuracy percentages of 43.08% 27.69%, respectively, for the 734 cases. The accuracy of the IEC and Rogers's ratio techniques based on fuzzy logic is 50.77% and 27.69%, respectively. The accuracy of this techniques-based neural network is 49.23% and 50.77%, respectively. The TRT ratio and CTT triangle techniques have the best performance for the thermal fault (T3) with 100 % accuracy; moreover, the Duval triangle technique has 97.14% accuracy. At the same time, Rogers' technique received the worst accuracy of traditional diagnostic techniques for diagnosing the thermal fault (T3). TRT ratio and CTT triangle techniques have the best result for detecting low energy electrical discharge faults (D1) with 100% accuracy, followed by Duval triangle which has the maximum accuracy of conventional techniques

TABLE 3. The successful percentage predictions of techniques for unified classification of particular fault types.

Technique		Fault code	Correct prediction and% Successful	T			PD	D		CCD			Accu. %
				T1	T2	T3		D1	D2	HCCD	MCCD	LCCD	
Rogers	Conventional	Correct predictions	28	14	18	46	12	32	76	◙	◙	◙	41.95
		Successful %	9.18	43.75	27.69	32.86	50.00	43.84	86.36	◙	◙	◙	
	Neural Network	Correct predictions	81	21	33	83	13	47	79	◙	◙	◙	58.97
		Successful %	26.56	65.63	50.77	59.29	54.17	64.38	89.77	◙	◙	◙	
	Fuzzy logic	Correct predictions	41	16	18	114	16	53	76	◙	◙	◙	56.89
		Successful %	13.44	50.00	27.69	81.43	66.67	72.60	86.36	◙	◙	◙	
Doernburge	Conventional	Correct predictions	305	171			13	130		◙	◙	◙	76.76
		Successful %	100	72.15			54.16	80.74		◙	◙	◙	
	Neural Network	Correct predictions	305	225			13	158		◙	◙	◙	86.81
		Successful %	100	94.94			54.16	98.14		◙	◙	◙	
	Fuzzy logic	Correct predictions	305	188			22	137		◙	◙	◙	89.02
		Successful %	100.00	79.32			91.67	85.09		◙	◙	◙	
IEC	Conventional	Correct predictions	68	18	28	78	12	38	71	◙	◙	◙	51.44
		Successful %	22.30	56.25	43.08	55.71	50.00	52.05	80.68	◙	◙	◙	
	Neural Network	Correct predictions	91	21	32	90	13	48	79	◙	◙	◙	59.81
		Successful %	29.84	65.63	49.23	64.29	54.17	65.75	89.77	◙	◙	◙	
	Fuzzy logic	Correct predictions	83	20	33	88	19	52	76	◙	◙	◙	62.87
		Successful %	27.21	62.50	50.77	62.86	79.17	71.23	86.36	◙	◙	◙	
Duval Triangle		Correct predictions	305	17	44	136	16	72	84	◙	◙	◙	82.67
		Successful %	100.00	53.13	67.69	97.14	66.67	98.63	95.45	◙	◙	◙	
Heptagon Technique		Correct predictions	107	19	38	134	24	69	81	11	61	171	97.83
		Successful %	100.00	100.0	95.00	95.71	100.0	94.52	93.10	100.0	100.00	100.00	
TRT Technique		Correct predictions	305	32	65	140	24	73	87	◙	◙	◙	99.84
		Successful %	100.0	100.0	100.0	100.0	100.0	100.0	98.86	◙	◙	◙	
CTT Technique		Correct predictions	305	32	65	139	24	73	87	◙	◙	◙	99.74
		Successful %	100.0	100.0	100.0	99.29	100.0	100.0	98.86	◙	◙	◙	

◙ This fault is not determined

about 98.63%. Nevertheless, IEC ratio and Rogers's ratio techniques are weak in detecting D1. On the other hand, TRT ratios and Heptagon graph techniques have the best results for detecting partial discharge faults (PD), and after that, the CTT triangle can be a suitable option.

It can be concluded from Table 3 that the electrical discharge (D2) fault is the easiest fault to be detected, and the suitable technique for diagnosing D2 is effectively TRT ratio and CTT triangle techniques with 98.86% accuracy. On the other hand, the accuracy of the Heptagon graph technique for D2 is close to the Duval triangle, with accuracy percentages of 93.10% and 95.45%, respectively.

On the other hand, all conventional techniques cannot detect the degree of cellulose degradation (CCD) except the Heptagon graph technique. It has an accuracy of 100% for all levels of cellulose degradation. But this fault can appear in the incipient fault types T1 and T2 of the other techniques since most inspected cases of thermal faults in paper have

TABLE 4. The successful percentage predictions of techniques for unified classification of particular fault types based on main fault types.

Technique		Successful (%)				Accuracy (%)
		Thermal Decomposition	Partial Discharge	Arcing	Normal Aging	
Conventional Techniques	Doernenburg	72.15	54.16	80.74	100	76.76
	Heptagon	98.98	100.00	100.00	100.00	99.75
	(TRT) Technique	100.00	96.67	99.38	100.00	99.01
	(CTT) Triangle	100.00	95.65	98.41	100.00	98.52
	Rogers	59.65	50.00	78.75	9.18	49.40
	IEC	66.48	50.00	74.57	22.30	53.34
	Duval	84.48	84.21	96.87	100	91.39
Fuzzy logic	Doernenburg	79.32	91.67	85.09	100	89.02
	Rogers	92.28	66.67	86.87	13.44	64.82
	IEC	78.11	79.17	92.50	27.21	69.25
Neural Network	Doernenburg	94.94	54.16	98.14	100	86.81
	Rogers	83.26	54.17	88.75	26.56	63.19
	IEC	90.56	54.17	89.37	29.84	65.99

been observed in these zone boundaries. Such degradations affect the insulation paper and may reduce the transformer life in the long term, more precisely identified by furans formation in HCCD degradation. The present analysis shows that the TRT Ratio technique is the most consistent, followed by the CTT triangle, Heptagon graph, Duval Triangle, Doernenburg Ratio, IEC Ratio, and the Roger Ratio technique. But heptagon graph technique is the first one for distinguishing between thermal faults either in oil or cellulose. It is found that those techniques that take into consideration the limit value of fault gases before making the incipient diagnosis have better success in predicting the normal condition. While techniques with no limit value of faults gases always fail to predict the normal condition, the accuracy results.

D. COMPARISON BASED ON MAIN FAULTS

In this section, to measure each technique's performance, the accuracy of the thermal decomposition, partial discharge, and electrical discharge arcing main fault types are investigated. The consistencies of the conventional techniques are calculated based on IEC TC 10, Egyptian Electricity Holding Company, and related databases, and the results are summarized in Table 4. For the main fault type's detection, the TRT ratio, CTT triangle, and Heptagon techniques have better performance than conventional techniques, and their results are more reliable. In addition, they have a high accuracy of more than 98% compared to the Duval triangle with 91.39% accuracy, while Rogers's ratio is the weakest one.

The average of the overall percentages of successful predictions of some techniques such as Heptagon graph, TRT ratio, and CTT triangle have close accuracy percentages of 99.75%, 99.01%, and 98.52%, respectively 734 cases. In comparison, the Duval triangle technique has a maximum accuracy of 91.39%. While techniques that use direct diagnosis (did not consider the marginal value of normal condition) of fault gases based on each value of fault gases are less accurate.

However, based on the total number of cases, the accuracy shows a different trend due to the high value of cases with no prediction. So, the accuracy drops significantly less than 70% for Rogers and IEC Techniques. Noteworthy, the Doernenburg ratio technique does not determine the degrees of severity of the incipient faults. According to Table 4, it is clear that the Heptagon graph, CTT triangle, and TRT ratio techniques can effectively diagnose thermal decomposition faults, partial discharge, and electrical arcing. In contrast, Rogers and IEC ratio techniques are weak in diagnosing. In contrast, the Doernenburg ratio and Duval triangle can have the best performance for conventional techniques but are not as powerful as the TRT ratio, CTT triangle, and Heptagon techniques. Heptagon graph technique has considerably better performance than other techniques for detecting the incipient fault conditions, including the concentration of cellulose degradation and their severity, classified within thermal decomposition faults (T1 and T2) in the other techniques.

The diagnosis of cellulose degradation can be more precisely evaluated by furans formation, but it is costly. Therefore, the Furan test [37] should be performed in the case of HCCD degradation. So, the main merit of the heptagon technique over all the other conventional DGA techniques is distinguishing between the thermal decomposition faults in the T1 and T2 zones and concentration of cellulose degradation in the HCCD, MCCD, and LCCD.

V. CONCLUSION

Several DGA techniques were implemented in this work. These techniques were Conventional DGA, Fuzzy logic, Artificial Neural Network models based DGA ratio, Heptagon graph, three ratios using five diagnosis gases (TRT), and modified Duval triangle (CTT). The results of these techniques were investigated using a statistical study of the various faults. The accuracy of these techniques is analyzed based on their output results of 734 samples that have been collected from different transformers of different ratings and different life spans reported by IEC TC 10, Egyptian Electricity Holding Company, and related databases. Furthermore, it systematically discusses the accuracy based on the individual fault type and main fault types of these DGA techniques.

The overall percentages of successful predictions of the Heptagon graph, TRT ratio, and CTT triangle techniques as compared with the other methods based on main faults; have close accuracy percentages of 99.75%, 99.01%, and 98.52%, respectively for the 734 cases under investigation, while Duval triangle technique reaches to 91.39%. Dornenburg, Rogers, and IEC conventional techniques have the accuracy of 76.76%, 49.40%, and 53.34%, respectively. Their accuracy is improved by using the Fuzzy logic algorithm to be 89.02% for Doernenburg, 64.82% for Rogers, and 69.25% for IEC technique. The Neural Network algorithm also improved the above techniques but with fewer values.

This article can help experts evaluate the condition of transformers and their most critical components for having a clear perspective on the application and accuracy of the conventional and artificial intelligence techniques for the incipient fault detection in transformers. In addition, the accuracy of detecting each fault type using the investigated techniques is presented.

The authors believe that the hybrid artificial intelligence methods may be more accurate, but it may be difficult for experts to detect faults in electrical transformers, and in any case, such these methods will be considered in future studies.

For future research, the authors prepare a proposed plan to enhance the diagnostic accuracy of the transformer faults based on machine and deep learning tools.

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