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Towards Identification of Transformer Oil Faults via Novel Combined DGA Approach

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ABSTRACT
Transformers are expensive but essential pieces of machinery in electric power systems. As a result, the electrical network suffers large financial losses when transformers fail. Therefore, early identification of likely transformer problems has a favorable impact on the dependability and continued functioning of electrical grids. One common chemical test for identifying potential problems with power transformers is the dissolved gas analysis. Conventional DGA approaches include the Rogers ratio, key gas ratio, Dornenburg ratio technique, Duval, and IEC gas ratio procedures. Unconventional DGA techniques include, among others, conditional probability, clustering, Rogers Refined, and IEC Refined. This work offers a novel method for accurately interpreting transformer faults in this regard. The proposed methodology is built around a blend of traditional and non-traditional methods with innovative processes. The Egyptian Electricity Transmission Company (EETC) provided 386 datasets with known defects, which are used to demonstrate the beneficial aspects of the suggested approach. In order to verify the enhanced accuracy of the proposed DGA technique, it is then compared with more contemporary DGA techniques utilizing the same concentration of sample gases. The developed strategy came to the conclusion that the overall accuracy of fault detection is improved by integrating several DGA techniques with varying fault accuracy. Furthermore, a case study on aged transformers with a rating of 66/11Kv has been provided to examine how aging affects dissolved gases.

Keywords: *(Power transformers, Condition monitoring, Dissolved gas analysis (DGA), ANN, Conditional probability technique.*

1. Introduction

Dissolved gas analysis (DGA) is an effective diagnostic technique for the early detection of transformer faults. The DGA, in particular, is one of the most important tests for insulating fluid materials in electrical components with various intelligent sensors. In addition, power transformers are thought to be the most important equipment in electric power substations. Practically, a sample of oil from a transformer can be periodically examined from any electrical device at any moment without having to switch it off. The following gases are important for understanding how oil and paper insulation degrades: ethylene (C_2H_4), carbon dioxide (CO_2), methane (CH_4), hydrogen (H_2), acetylene (C_2H_2), ethane (C_2H_6), and carbon monoxide (CO). Several fault types are diagnosed based on these dissolved gases as thermal fault with various levels, arcing fault with low and high level in addition to partial discharge. Traditional DGA diagnostic methods frequently produce inaccurate analyses while skipping significant incipient defects, which results in the "no decision" problem. Numerous artificial intelligence approaches were used to achieve high accuracy, sufficient diagnostics, and identification of specific transformer failure types [1-4]. The diagnostic methods based on artificial intelligence, in turn, are a useful tool for planning maintenance on transformers [5-7]. Because of this, graphical DGA techniques are simple to use but still have poor diagnostic accuracy for various transformer defects [7, 8]. The artificial neural network (ANN) is now thought to be the technique that has been employed the most frequently in the literature for DGA as well as a variety of practical applications [9-11]. In [12], a hybrid grey wolf optimizer that combines a fuzzy logic system with a metaheuristic approach adjusts DGA while taking uncertainty-resistant diagnostic methods into account. Fuzzy logic, metaheuristics, and ANN have been shown to perform better in general engineering applications [13-17]. In order to depict two graphical shapes and increase the diagnostic efficacy of transformer faults, the DGA technique was used in [18]. A method for enhancing fault diagnostic accuracy has also been described [3, 19], and it is based on the percentage restrictions of new gas concentrations. Convolutional neural network (CNN) models have been developed to reliably identify different fault types when measurement noise levels vary [20]. Extreme machine learning-based DGA has also been suggested [21]. A novel reliability and cost assessment-based decision-making method has been proposed for power transformers [22].There has been an introduction of support vector machine (SVM) optimization for transformer flaw diagnostic accuracy [23]. 360 datasets collected from the literature and a central laboratory were utilized in a novel DGA strategy that was described in [24] and produced accuracy of 93%. This new DGA strategy depends on the combining of the findings of five DGA methods. According to the literature cited above, the majority of DGA approaches now in use can have subpar diagnostic accuracy [17] and may be unable to identify oil problems in transformers. This study attempts to address the problem by enhancing the diagnostic precision of transformer defects. This challenging effort is completed by integrating various methodologies into a single framework, maximizing the diagnostic accuracy in comparison to individual approaches. The first portion, in particular, discusses the innovative approach that was created and is based on the combination of the outputs of clustering, conditional probability, the Duval triangle, artificial neural networks (ANN), and Roger's modified. 386 datasets from the substation of the Egyptian Electricity Transmission Company (EETC) were used to evaluate the proposed technique. Finally, this study summarizes the examination of the concentration of dissolved gases in parts per million (ppm) for samples obtained of an old transformer with a rating of (66/11 kV) and oil type Diala B that is present in EETC networks.

2. The Types of Transformer Faults

2.1. Partial Discharge

PDs are brief pulses that usually coincide with the emission of light, heat, sound, and chemical reactions. Air bubbles and water droplets are examples of floating items that might induce partial discharges in liquid insulation. After initializing, a partial discharge might propagate with increasing intensity until it dismisses as an arc discharge [4].

2.2. Arcing Discharge Fault

Arcing discharges result in extremely high temperatures and a significant concentration of gases, mostly C_2H_3 and H_3. This kind of problem is quite risky and, if ignored, might result in a possibly lethal explosion and high pressure inside the transformer tank [4, 16].

2.3. Thermal Fault

Eddy current heat, loose connections, and insufficient cooling cause thermal transformer faults. Low-temperature faults are those that occur at temperatures below 150 ºC, medium-to-high faults are those that occur at temperatures between 300 ºC and 700, and high-temperature faults are those that occur at temperatures over 700 ºC [5, 17].

3. Conventional and Unconventional DGA Techniques

To determine the fault type that occurred in the transformer oil, many DGA approaches are utilized. These techniques are divided into conventional techniques and unconventional techniques, and are briefly discussed below.

3.1. Duval Technique

The foundation of this method is the awareness of the three dissolved gases C_2H_2, C_2H_4 and CH_4. and Partial discharge (PD), thermal fault T1 (at T less than 300 ºC), thermal fault T2 (at T between 300 ºC and 700 ºC), thermal fault T3 (at T greater than 700 ºC), low energy discharge (D1), high energy discharge (D2) arching, and partial discharge (PD) faults are the seven zones that are typically classified in the Duval triangle according to Equations (1), (2) and (3) as showing in Table 1 [2].

$$R_1 = \frac{CH_4}{CH_4 + C_2H_4 + C_2H_2} \quad (1)$$

$$R_2 = \frac{C_2H_4}{CH_4 + C_2H_4 + C_2H_2}\% \quad (2)$$

$$R_3 = \frac{C_2H_2}{CH_4 + C_2H_4 + C_2H_2}\% \quad (3)$$

3.2. Rogers Refined Technique

By modifying the ratio limits and their relationships, one can achieve the connection between the updated fault type and the actual fault, increasing the correctness of Rogers' four ratio approaches. CH_4/H_2, C_2H_6/CH_4, C_2H_4/C_2H_6, and C_2H_2/C_2H_4 are the four gas ratios in this technique [24].

3.3. Conditional Probability Technique

Based on the percentage of the main 5 gases concerning their whole amounts, this method is utilized to diagnose transformer fault kinds. In this method, the probabilities of each fault type occurrence and non-occurrence are determined. According to the ratio the probability of occurrence for each fault category to the probability of non-occurrence, the function of conditional probability (CPF) is computed. Then, the transformer oil fault categories as partial discharge (PD), arcing (AR), or thermal (TH), is satisfied. Therefore, for each fault category, the conditional probability function is calculated to determine each of fault type as showing in Fig 1[4, 24].

3.4. Clustering Technique

This technique depends on the major 5 dissolved gases; H_2, C_2H_2, C_2H_6, C_2H_4, and CH_4 percentage with respect to their summation. The fault type is diagnosed according to Table 2. [25]

3.5. Artificial Neural Network (ANN) Techniques

The application of ANNs as mathematical models for composite structural modeling is thought to be possible. In particular, ANNs have three layers: the input layer, the hidden layer, and the output layer. While the third layer models the outputs, the first layer characterizes the inputs. The nodes in the hidden layer try to functionally map the model inputs as they are optimized in relation to the model outputs [26]. Three DGA techniques are merged using the ANN methodology. These techniques are Duval, IEC, and Rogers. Each technique uses a four-layer network (1 input layer, 2 hidden layers, and 1 output layer). According to each approach, the input patterns are the gas ratios. Adopted weights represent the relationship to the input, and the strength of it is determined by the product of the weight and the input. Multiple inputs from several sources are delivered to a particular neuron. The six primary fault types (PD, D1, D2, T1, T2, and T3) are regarded as the output patterns according to Fig. 2.

Table. 1 Fault Type Diagnostic Using Duval Technique

Fault type	PD	D1	D2	T1	T2	T3
R1	≥98	-	-	76≤ R1 ≤ 98	46≤ R1 ≤80	≤50
R2	≤ 2	≤23	≤ 77	≤20	20≤ R2 ≤ 50	≥50
R3	≤ 3	≥0	13≤R3≤79	≤4	≤4	≤ 15

Table 2. Fault Type Diagnosis Using Clustering Technique

Fault type	PD	D1	D2	T1	T2	T3
(H_2 / TDCG) %	30 -90	10-96	≤ 61	≤ 50	≤ 25	≤ 35
(CH_4/ TDCG) %	≤ 18	≤14.5	≤ 40	≤80	≤ 83	≤ 50
(C_2H_6/ TDCG) %	≤ 66	≤ 42	≤70	≤100	4- 90	≤ 20

(C_2H_4/ TDCG) %	≤ 13	≤ 5	≤ 35	≤ 40	10-70	30 -100
(C_2H_2/ TDCG) %	≤ 2.5	≤ 40	≤ 80	≤ 4	≤ 2	≤ 12

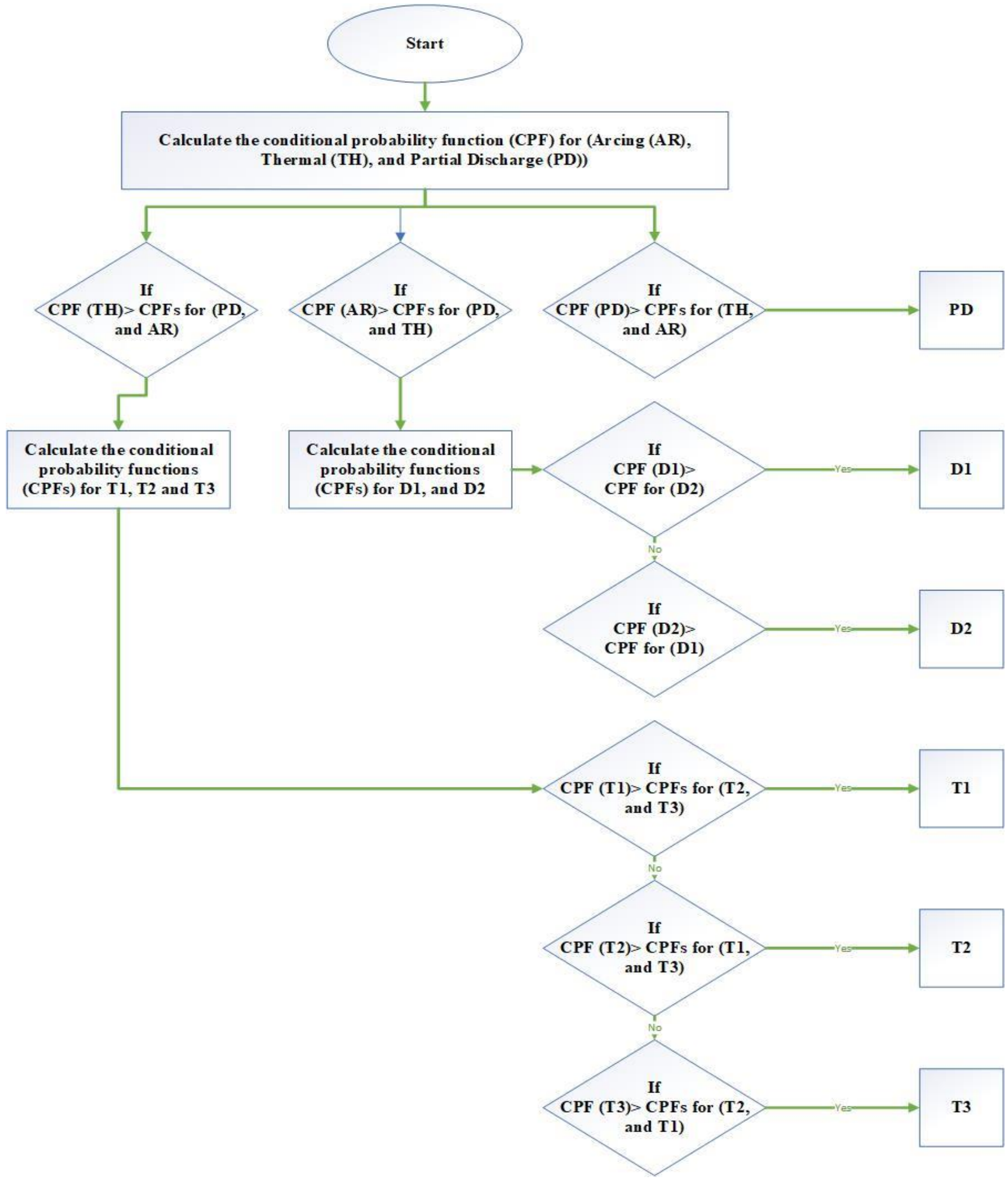

Fig. 1. Flowchart of the conditional probability technique.

4. The Proposed Techniques

This technique depends on the integration among the results of conventional technique as Duval technique and unconventional (DGA) techniques as conditional probability, Clustering, Rogers refined and ANN techniques as showing in Fig. 3. The procedures of this technique using (switch-case) expression in M- file in MATLAB are as following: -

Switch: Insert the results of DGA techniques (Clustering (dig1), Conditional probability (dig 2) and Duval (dig3)).

- **Case1:** the output (Out1) is partial discharge fault type (PD), if any two of dig1, dig2 and dig3 are detected partial discharge.
- **Case2:** the output (Out1) is low energy discharge fault type (D1), if any two of dig1, dig2 and dig3 are detected low energy discharge.

- **Case3:** the output (Out1) is high discharge energy fault type (D2), if any two of dig1, dig2 and dig3 are detected (D2).
- **Case4:** the output (Out1) is thermal fault of low level (<150 ºC) (T1), if any two of dig1, dig2 and dig3 are detected (T1).
- **Case5:** the output (Out1) is thermal fault of medium level (between 150 ºC and 300 ºC) (T2), if any two of dig1, dig2 and dig3 are detected (T2).
- **Case6:** the output (Out1) is thermal fault of high level (>300 ºC) (T3), if any two of dig1, dig2 and dig3 are detected (T3).
- **Otherwise:** the output (Out1) is identical to dig2.

Switch: Insert the results of DGA techniques (Rogers refined (dig4) and ANN (dig5)).

- **Case1:** the output (Out2) is partial discharge fault type (PD), if dig4 and dig5 detected (PD) or only dig5 detected PD and dig4 aren't detected low or high thermal fault.
- **Case2:** the output (Out2) is low discharge energy fault type (D1), if dig4 and dig5 detected (D1) or only dig5 detected (D1).
- **Case3:** the output (Out2) is high discharge energy fault type (D2), if dig4 and dig5 detected (D2) or only dig5 detected (D2).
- **Case4:** the output (Out2) is low thermal fault type (T1), if dig4 and dig5 detected (T1) or only dig4 detected (T1).
- **Case5:** the output (Out2) is medium thermal fault type (T2), if dig4 and dig5 detected (T2) or only dig5 detected (T2).
- **Case6:** the output (Out2) is high thermal fault type (T3), if dig4 and dig5 detected (T3) or only dig4 detected (T3).
- **Otherwise:** the output (Out2) is identical to dig5.

Switch: Insert the DGA results (Out1 and Out2)

- **Case:** the fault type diagnosis is identical to (Out2), if Out2diagnosed T1 or T3 and Out1 diagnosis isn't T2).
- **Otherwise:** the fault type diagnosis is identical to (Out1).

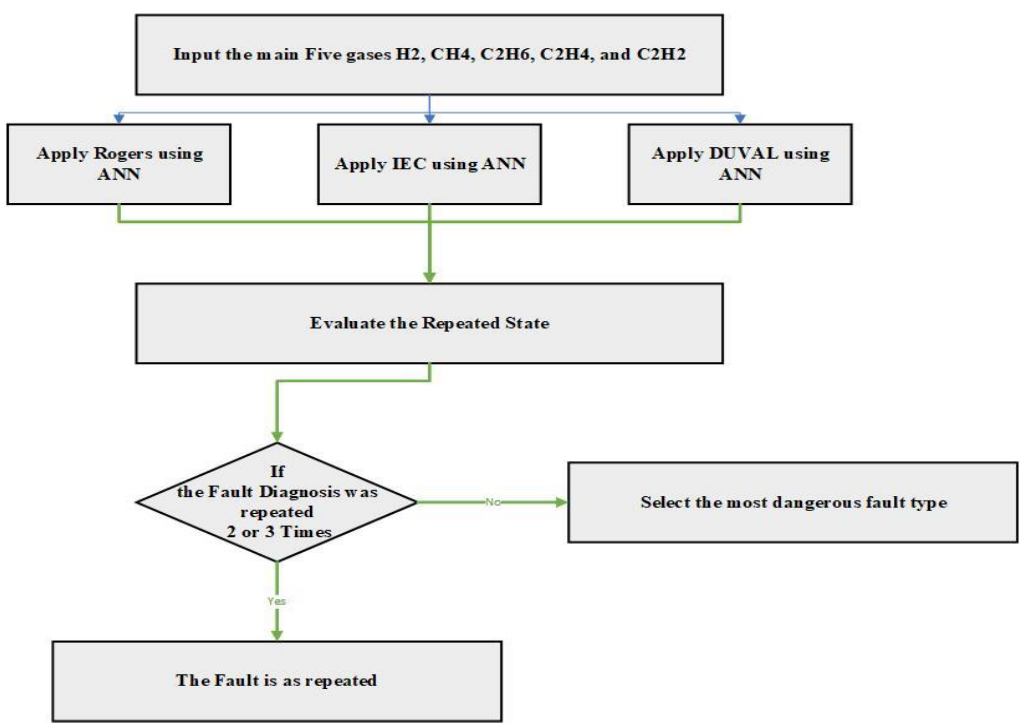

Fig. 2. The Procedures of ANN Technique

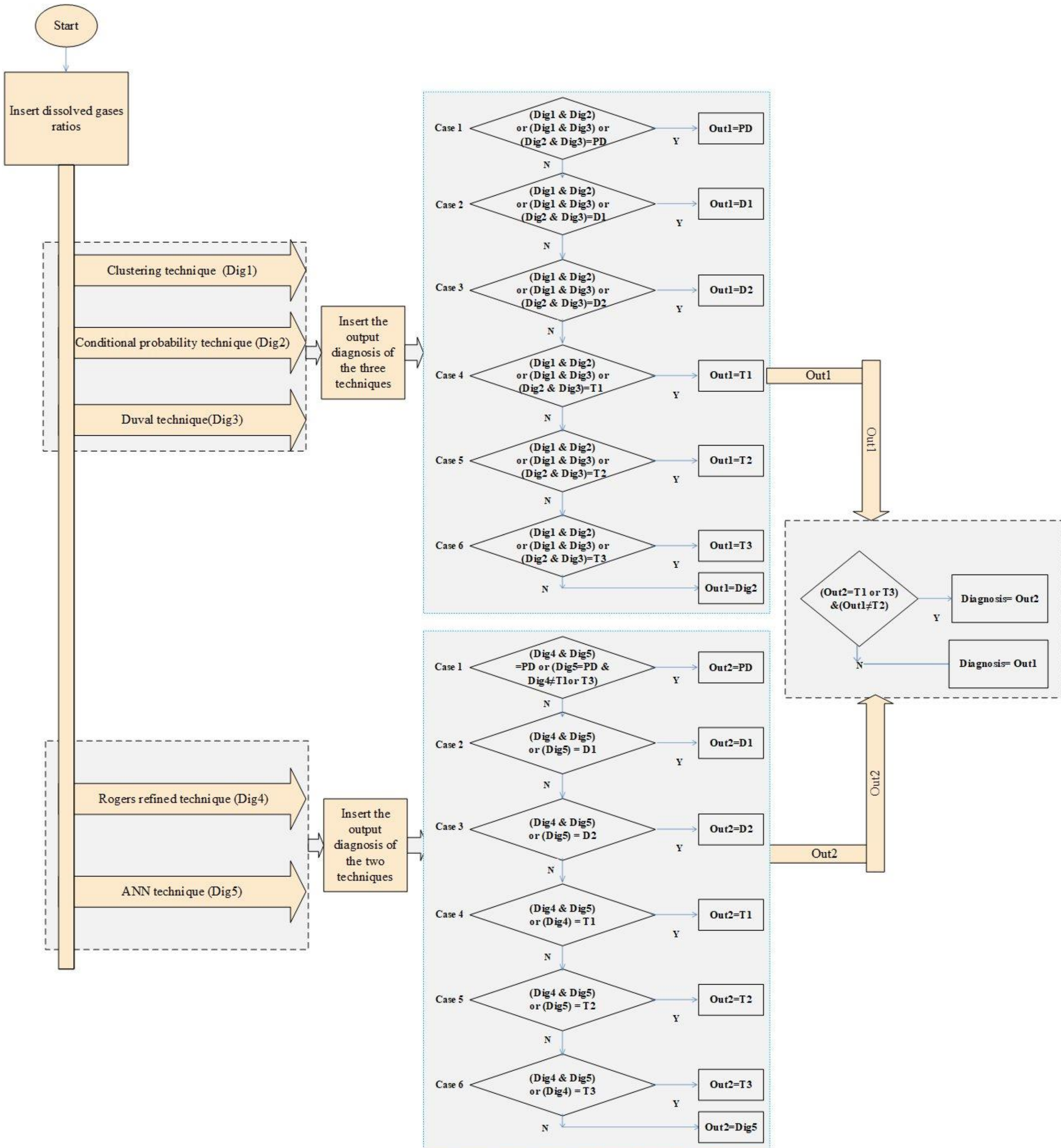

Fig. 3. Flowchart of the Novel Approach.

5. Evaluation The Proposed DGA Technique

The training Egyptian ministry data set used was 386 samples collected from the literature researches using different transformers rating with various aging durations. Table 3 shows the number of samples for each fault type. The performance of the proposed technique is evaluated by using MATLAB software using (switch-case) expression. In comparison to the five strategies (Duval, Conditional probability, ANN, Roger's 4 ratios revised, and Clustering) that were used to create this methodology, the total accuracy % of the novel approach is improved. This technique has an overall accuracy % of 87.82, while the five other methods (Duval, Conditional Probability, ANN, Roger's 4 ratios refined, and Clustering) have total accuracy percentages of 60.88, 85.75, 83.16, 60.62, and 63.47, respectively (see Table 4 and Figure 4).

Table 3. The number of samples for each fault type.

Fault Type	PD	D1	D2	T1	T2	T3	All
Sample	43	69	115	81	24	54	386

Table 4. Accuracies percentage of the Novel, Duval, Conditional probability, ANN, Roger's 4 ratios refined and Clustering techniques.

	Duval	Cond- prob	ANN	Rogers Refined	Clustering	Novel
PD	48.83	90.69	88.37	27.91	95.39	88.37
D1	72.46	68.11	62.31	11.59	40.58	66.66
D2	59.13	93.91	89.56	69.56	94.78	94.78
T1	48.14	85.18	91.35	91.35	29.63	95.06
T2	29.16	91.66	66.66	37.5	58.33	87.5
T3	92.59	85.18	87.03	94.44	53.70	88.89
All	60.88	85.75	83.16	60.62	63.47	87.82

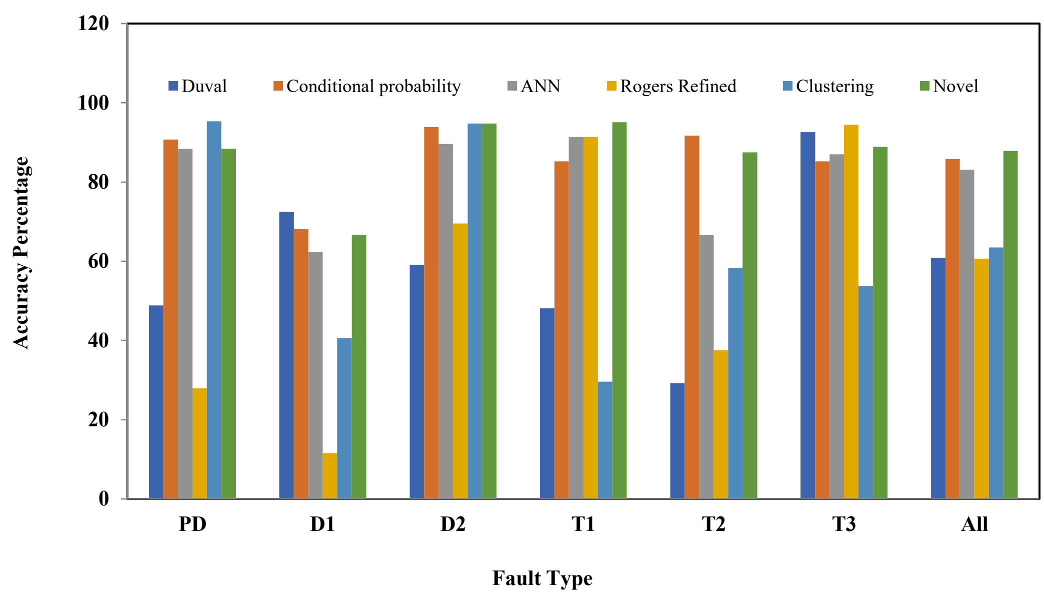

Fig. 4. Accuracies percentage of the Novel, Duval, Conditional probability, ANN, Roger's 4 ratios refined and Clustering techniques.

6. Transformer Case Study

In this section, an aging transformer of rating 66/11 kV of (Diala B) oil type and 15 years has been studied for 7 consecutive years. The dissolved gases in the immersed oil were analyzed to know the most effective gases and its effect on the detecting fault type during this duration. The part per million (ppm) of the extracting gases CO_2, CO, H_2, C_2H_6, CH_4, C_2H_4, and C_2H_2 in addition to the actual fault type according to Central Laboratory of the Egyptian Ministry of Electricity were given for samples numbers as shown in Table 5. After any oil fault diagnosis, the oil was treated and returned to the service

By studying the concentration of the main five gases H_2. CH_4, C_2H_6, C_2H_4, and C_2H_2 during the studying duration, it appeared that the dominant gases after 15, 16 and 17 years of aging were H_2, C_2H_4 and CH_4. Hence, these dissolved gases represented the key gases in thermal fault type of low level according to Fig 5. In addition, after 18 and 21 years of aging, the dominant dissolved gases C_2H_6 and CH_4. Hence, these dissolved gases are the key gases in medium thermal fault type. After 19 years of aging of high thermal fault type, the main dissolved gases were CH_4 and H_2 in addition CO_2 appeared with high concentration level which reflected the paper degradation and its effect on increasing the level of thermal fault in transformer oil. Generally, the main fault type appeared through transformer of (Diala B) oil type was thermal fault. Therefore, this type of fault needs researches to reduce it, and thus increase the life of the transformer of (Diala B) oil type.

Table 5. The DGA history of the case study

Aging Years	ppm	CO_2	H_2	C_2H_6	C_2H_2	CH_4	CO	C_2H_4	Fault type
15	381	2330	12	1	0	5	355	4	T1
16	401	4539	12	2	0	3	369	4	T1
17	319	2043	10	2	0	2	265	3	T1
18	817	2088	9	149	0	113	412	16	T2
19	337	5159	9	1	0	14	291	2	T3
20	160	1324	2	2	0	2	144	2	normal
21	341	3352	17	93	0	74	149	8	T2

Conclusion

This study suggested a method for interpreting transformer oil defects that is more precise. This suggested method depends on the integration between recently techniques in addition to unconventional techniques. Using MATLAB, the evaluation results were obtained. The total accuracy was improved when compared to the conventional and unconventional techniques as Duval, and Clustering, Rogers refined, conditional probability and ANN approaches, respectively. The Egyptian Electricity Transmission Company's 386 datasets with known faults are used to illustrate the suggested approach's favorable aspects (EETC). The accuracy of fault diagnosis using the suggested method was 87.7%, compared to 63.47% for Clustering, 60.88 % for Duval, 60.62% for Rogers refined, 85.75% for the conditional probability and 83.16% for ANN approaches. While seven samples during seven consecutive years are used to assess the case study of transformer (66-11kV) of (Diala B) oil type. H_2, C_2H_4 and CH_4 gases represented the key gases in thermal fault type of low level. The dominant dissolved gases C_2H_6 and CH_4 are in medium thermal fault type. The main dissolved gases were CH_4 and H_2 in addition CO_2 appeared with high concentration level which reflected the paper degradation and its effect on increasing the level of thermal fault in transformer oil. Generally, the main fault type appeared through transformer of (Diala B) oil type was thermal fault. Therefore, the main Fault in this case study is the thermal fault of the oil, which will affect the life of the oil. Therefore, this study recommends continuous thermally maintenance of the oil for this transformer

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