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Identification of Transformer Oil incipient Faults Based on the Integration between Different DGA Techniques

Sayed A. Ward [1,2*], Shimaa A. Ibrahim[1], Adel EL-Faraskoury[3], Diaa-Eldin A. Mansour[4,5], Mohamed Badawi[1]

[1] Department of Electrical Engineering, Faculty of Engineering at Shoubra, Benha University, Cairo, Egypt
[2]Faculty of Engineering, Delta University for Science and Technology, Gamasa, Egypt
[3] Extra High Voltage Research Centre, Egyptian Electricity Holding Company, Egypt
[4]Electrical Power Engineering Department, School of Electronics, Communications and Computer Engineering, Egypt-Japan University of Science and Technology, Alexandria, Egypt
[5]Electrical Power and Machines Engineering Department, Faculty of Engineering, Tanta University, Tanta, Egypt

* **Correspondence:** Faculty of Engineering, Delta University for Science and Technology, Gamasa, Egypt.
E-mail address: drsayedw@yahoo.com

ABSTRACT
Premature diagnosis of transformer oil faults enables the operator for diagnosing the transformer condition and hence operating the transformer continuously without outage. DGA is one of the most popular chemical tests used for fault diagnosis and there are many techniques which have been developed in this regard. This paper presents a proposed DGA technique for transformer oil fault identification based on the results of the recently published techniques. The proposed technique has been constructed based on the integration between the outputs of two recently established DGA techniques; Conditional probability and artificial neural network. A total of 532 datasets, obtained from the Egyptian Electricity Transmission Company (EETC) with known faults, have been used for designing and testing the proposed technique. The proposed fault diagnostic technique's accuracy attained 86.6 %, which is higher than the results of the combined techniques; 81.7% for ANN and 82.8% for conditional probability technique. The proposed developed technique came to the conclusion that integrating several DGA techniques, with higher accuracy, enhances fault detection's overall accuracy.

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

1. Introduction

In the electrical power system grid, transformers are crucial and very expensive component. A significant financial cost impact for the electrical network happens due to transformer downtime or increased maintenance expenses (X. Shen, 2022, J. Liang, 2022, S. S. M. Ghoneim, 2021, E. Bezerra, 2020). Mineral oil is utilized as a heat-transfer and insulating medium in power transformers. Thermal and electrical stresses may cause the oil insulating medium degradation and aging, and hence, occurrences of electrical and thermal faults. The oil common incipient electrical faults are Partial discharge (PD), and arcing discharge of high and low energy (D2 and D1). While the thermal types of faults as high, medium and low (T3, T2, and T1) are types of thermal faults (S. S. M. Ghoneim, 2021, E. Bezerra, 2020, H. Salem, 2022, S. A.Ward, 2019, H. C. Chen, 2022). Hence, for improving the power system reliability and lowering the risk of transformer failure, it is crucial to identify the oil insulation levels with regular proactive and predicative maintenance program. Several electrical, chemical, and physical tests are used for detecting the transformer oil insulation level and hence, the maintenance program. One of the most used chemical tests used for oil fault identification is the dissolved gas analysis (DGA) (H. Salem, 2022, S. A.Ward, 2019, H. C. Chen, 2022). Where, low-concentrated gases are produced during ordinary operation; such as methane (CH_4), carbon monoxide (CO), hydrogen (H_2), ethylene (C_2H_4), carbon dioxide (CO_2), ethane (C_2H_6) and acetylene (C_2H_2). These low concentrated gases are generated with higher concentrations, when the faults occur in transformer. The determination of the generated gases concentrations, when there are electrical and thermal defects, is the basis of the DGA technique (S. A. Wani, 2021, X. Liu, 2022).

For the transformer failures interpretation based on analysis of dissolved gas tool, various conventional methods were developed and used, including Rogers' ratio, key gas ratio (IEEE Std, 2008), Dornenburg ratio technique, Duval and IEC gas ratio Techniques (IEEE Std, 2008, IEC Std, 2007, M. Duval, 2012). Conventional approaches frequently result in erroneous analysis while missing significant emerging faults, which leads to the "no decision" problem (O. Laayati, 2022). The bulk of current DGA methods lacks enough diagnostic precision and may be unable to identify problems with transformer oil (S. Ghoneim, 2019). More studies have been published to improve the conventional interpretation methods employing artificial intelligence (AI) and novel strategies (N. Poonnoy,2022, G.S. Naganathan, 2021, A. Samy, 2015). Contrarily, the majority of AI techniques are intricate and challenging to implement in real-world settings (S. A. Wani, 2021). This research area is therefore still pertinent for improving the accuracy of diagnosing transformer failure. Alternative methods that can integrate and combine the results of various diagnostic methods have recently been created. Several approaches were offered: approach (1) was built using the results of three techniques, Duval, Roger's four ratios refined, and IEC refined procedures; approach (2) was built using the results of three (DGA) techniques (clustering, Duval triangle, and conditional probability). The result of Roger's refined and artificial neural network (ANN) techniques were used to determine the preceding approach (3). The combined outputs of procedures (2) and (3) were the base for the final approach (4). These techniques enhanced overall detection accuracy of 69.96%, 84.96%, 83.27%, and 85.3 percent (S.A. Ward, 2021) based on 532 datasets. The DGA technique has been utilized in (M.M. Emara, 2021) to illustrate two graphical shapes and improve the diagnostic effectiveness of transformer failures. Additionally, a technique for improving fault diagnostic accuracy has been published (S. S. M. Ghoneim, 2021), and it is based on the percentage limitations of new gas concentrations. Convolutional neural network (CNN) model has been presented for accurately detecting the fault kinds under different levels of measurement noise (I. B. M. Taha, 2021). Another DGA approach has been proposed based on extreme machine learning (J. Li, 2021). For power transformers, a unique reliability and cost assessment-based decision-making technique has been put forth (M. Dong, 2019). Support vector machine (SVM) optimization for transformer defects diagnostic accuracy has been introduced (Y. Benmahamed, 2021). A new DGA strategy that depends on the combination of the five DGA methods was presented in (M. Badawi, 2022) and used 360 datasets gathered from the literature and a central laboratory to achieve an accuracy of 93%.

2. Research Significance

In light of the necessity for greater accuracy in order to present reliable transformer fault detection, DGA is still an open issue for study and development. This research aims to enhance the diagnosis accuracy of the transformer oil type using analysis of the dissolved gases tool, which appears with high concentrations during oil faults. For this purpose, this work offers a proposed technique, more accurately for interpreting transformer oil faults. This offered approach is built using the outputs of two recently DGA techniques; conditional probability (I. B. M. Taha, 2017) and artificial neural network with a modified scenario (Sherif S. M. Ghoneim, 2016). The comparing of the suggested DGA approach with the ANN and conditional probability DGA techniques is presented using 532 datasets of identified fault types selected from the Egyptian Electricity Transmission Company (EETC) in addition the literatures. Additionally, this proposed approach was compared with recently four DGA techniques, which also based on the integration between different DGA methods. In addition, 50 samples have been used for validation check of the suggested approach compared with previously published methods; clustering, ANN, condition probability, IEC refined, Rogers refined, in addition to four recently published techniques.

3. Proposed Oil Fault Interpretation Detection Technique

New proposed techniques are needed to address the shortcomings of current DGA procedures. Because of the interaction between electrical and thermal faults, the accuracy limit of standard DGA approaches is still a serious problem for recognizing transformer failures. Hence, a proposed one is developed and presented that combines the findings of Conditional Probability and Artificial Neural Network (ANN) (I. B. M. Taha,2017, Sherif

S. M. Ghoneim, 2016) approaches. The descriptions of the two techniques as well as the proposed technique are as follows:

3.1 Artificial Neural Network (ANN) Techniques

ANN, as an oil fault detection technique, is built based on inputs extracted from traditional techniques; IEC 60599, Duval and Roger's technique. ANN for each of these techniques consists of four layers. The first layer in the input layer, that consists of the dissolved gas ratios according to the considered technique. The second layer is the output layer which exhibits the fault types. The remaining layers are two hidden layers whose weights are adjusted based on the training dataset. ANN is regarded as one DGA approach that produced greater accuracy than traditional techniques. Hence, it shall be used in the building of the suggested approach. The descriptions of the traditional techniques used in ANN are as follows:

IEC ratio method: IEC analysis is based on three ratios (C_2H_4/C_2H_6, C_2H_2/C_2H_4 and CH_4/H_2). Table 1 shows the fault detection using the ratios of IEC 60599 method.

Duval triangle: This method is based on three gasses; CH_4, C_2H_4 and C_2H_2. This technique depends on certain gas percentages (R_1, R_2, and R_3) as follows (IEEE Std, 2008, IEC Std, 2007, M. Duval, 2012):

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

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

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

Table 2 shows the faults diagnosis using Duval technique.

Table 1 IEC 60559 DGAtechnique

Fault type	**C_2H_4/C_2H_6**	**C_2H_2/C_2H_4**	**CH_4/H_2**
PD	<0.2	Not significant	<0.1
D1	>1	>1	0.1-0.5
D2	>2	0.6-2.5	0.1-1
T1	<1	Not significant	>1
T2	1-4	<0.1	>1
T3	>4	<0.2	>1

TABLE 2 DUVAL TRIANGLE DGATECHNIQUE

Fault Type	**The ratios**
PD	R_1>=98, R_2<=2 and R_3<=2
D1	R_2<=23 and R_3>=0
D2	(R_2<=77 and 13=<R_3<=79) or (R_2<=85 and 4=< R_3<=29)
T1	98=> R_1>=76, R_2<=20 and R_3<=4
T2	80=> R_1>=46, 50=>R_2>=20 and R_3<=4
T3	R_1<=50, R_2>=50 and R_3<=15

Roger's ratio method: It utilizes the main five gases for detecting the fault type. This strategy depends on four gas ration, which are C_2H_6/ CH_4, C_2H_4/ C_2H_6, CH_4/H_2, and C_2H_2/C_2H_4 for diagnosis (IEEE Std, 2008).

3.2 The Conditional Probability Technique

The conditional probability technique is DGA tool based on that for each fault type, the probability of occurrence and non-occurrence are calculated. The probability indicator of each fault occurrence can therefore be provided in accordance with the conditional probability of a specific fault occurrence. The categorization of fault types is divided into thermal, arcing, and partial discharge (TH), (AR) and (PD). It is possible to identify the type of fault that depends on the occurrence conditional probability. This approach is based on the ratio of the major five gases to their sum ([26] I. B. M. Taha, 2017):

$$GCP_{H_2} = \frac{H_2}{H_2 + CH_4 + C_2H_4 + C_2H_6 + C_2H_2}\% \quad (4)$$

$$GCP_{CH_4} = \frac{CH_4}{H_2 + CH_4 + C_2H_4 + C_2H_6 + C_2H_2}\% \qquad (5)$$

$$GCP_{C_2H_6} = \frac{C_2H_6}{H_2 + CH_4 + C_2H_4 + C_2H_6 + C_2H_2}\% \qquad (6)$$

$$GCP_{C_2H_4} = \frac{C_2H_4}{H_2 + CH_4 + C_2H_4 + C_2H_6 + C_2H_2}\% \qquad (7)$$

$$GCP_{C_2H_2} = \frac{C_2H_2}{H_2 + CH_4 + C_2H_4 + C_2H_6 + C_2H_2}\% \qquad (8)$$

3.3 Proposed DGA Technique for Fault Detection

The suggested fault diagnosis technique is based on integrating the outputs of the conditional probability and ANN techniques with novel procedures and steps. As listed in Table 3, 532 oil samples of known fault types obtained from the Egyptian Electricity laboratory and literature will be utilized to design and evaluate the proposed DGA technique.

TABLE 3. Samples number for each type of fault (S. A. Ward, 2021)

Samples No.	**PD**	**D1**	**D2**	**T1**	**T2**	**T3**
532	59	96	175	92	30	80

According to IEEE Std. C57.104-2008, the utilized samples have been analyzed Fig.1 presents the gas concentration percentage (GCP) for each type of transformer faults. According to Fig. 1(a), the PD fault type causes production of hydrogen (H_2) as it is the key gas in partial discharge fault. In case of low arcing discharge, H2 and C2H2 are the dominant key gases, Fig. 1(b).

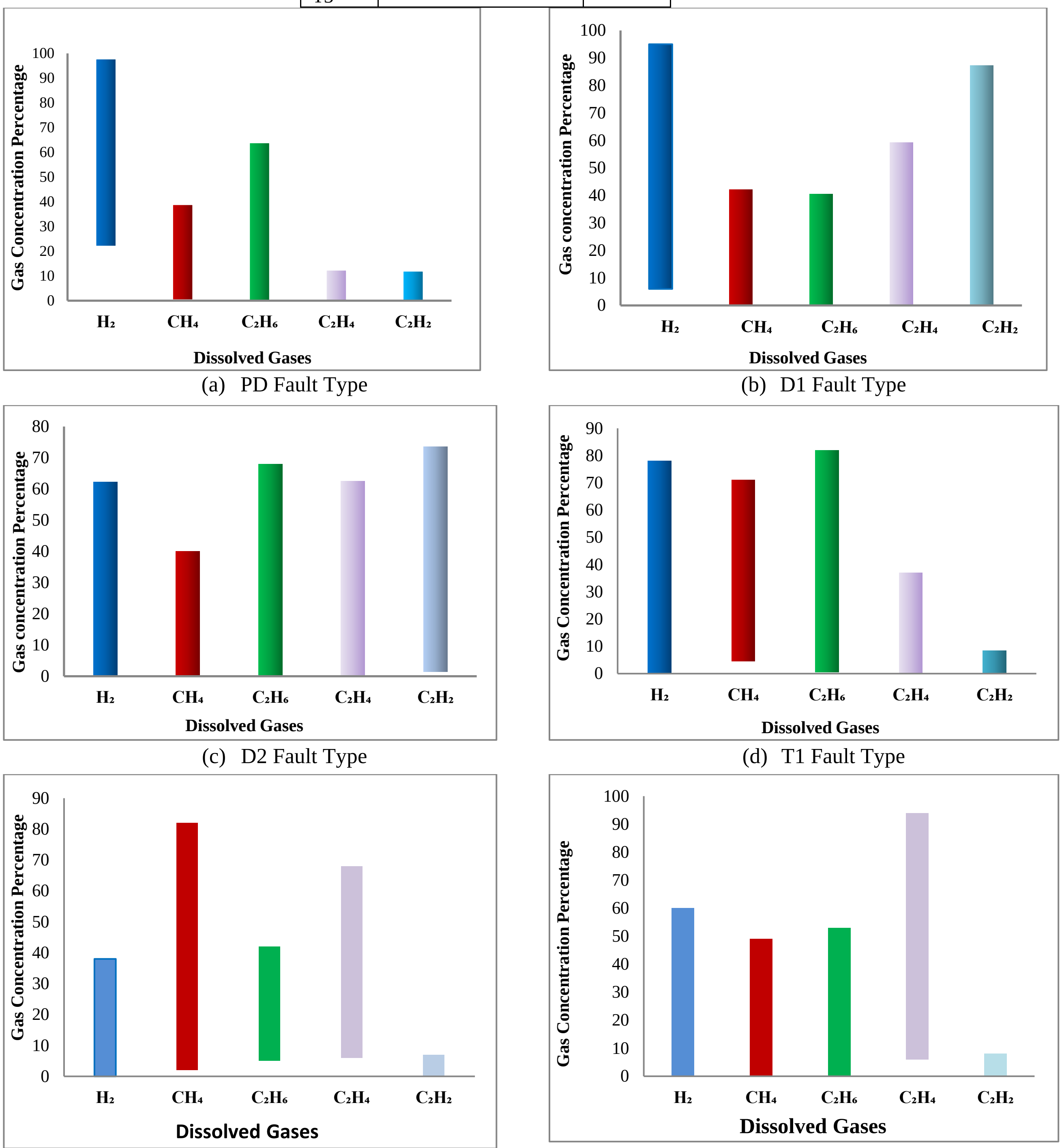
C2H2 is the dominant gas with a higher contribution of C2H6 and H2 in the case of D2, Fig. 1(c). In the case of T1, C2H6 is the dominant gas with a higher contribution of CH4 and H2, Fig. 1(d). CH4 is the dominant gas with a higher contribution of C2H4 in the case of T2, Fig. 1(e). C2H4 is the main gas in case of thermal fault of high level, Fig. 1(f). Laboratory measurements show that the key gas for each fault produced complies with IEEE Std. C57.104-2008. Thus, the 532 dataset's accuracy and dependability are validated.

The two techniques (ANN and Condition probability) have been applied for the 532 sample dataset of know fault. Table 4 presents the method which is more effective for each fault type detection and diagnosis. The ANN technique is better in detection of low and high thermal faults, while, the conditional probability technique is more accurate for diagnosing the other fault types. Hence, the proposed technique strategy is built using the most accurate method for each fault type. Fig. 2 presents the flowchart illustrating how the construction of the proposed technique. MATLAB software uses switch, case, and otherwise statements to process it. The following actions in this situation are based on the results of the two DGA techniques:

- Switch: Insert the diagnosis results of conditional probability techniques and ANN, Dig1 and Dig2 respectively.
- Case 1: The type of fault is detected as low discharge (D1), if the diagnosis of ANN and conditional probability techniques or only ANN diagnosis is low discharge (D1).
- Case 2: The type of fault is detected as low discharge (D2), if the diagnosis of ANN and conditional probability techniques or only ANN diagnosis is low discharge (D2).
- Case 3: If the diagnosis of ANN and conditional probability techniques or only conditional probability diagnosis is the thermal fault of low level (T1), The type of fault is detected as low thermal (T1).
- Case 4: If the diagnosis of ANN and conditional probability techniques is partial discharge or conditional probability diagnosis is partial discharge and ANN diagnosis is not the thermal fault of low and high level, the fault type is diagnosed partial discharge (PD).
- Case 5: when the diagnosis of ANN and conditional probability techniques or only ANN diagnosis is medium thermal fault (T2), the type of fault is detected as medium thermal (T2).
- Case 6: If the diagnosis of ANN and conditional probability techniques or only ANN diagnosis is high thermal fault (T3), The type of fault is detected as thermal of high level (T3).
- Otherwise: The type of fault is detected as conditional probability diagnosis.

Table 4. Higher Accuracy Techniques For Each Fault Type

	Conditional probability	**ANN**
PD	•	
D1	•	
D2	•	
T1		•
T2	•	
T3		•



(a) PD Fault Type

(b) D1 Fault Type

(c) D2 Fault Type

(d) T1 Fault Type

(e) T2 Fault Type

(f) T3 Fault Type

Fig. 1 Distribution of gases' concentration percentage for each fault type

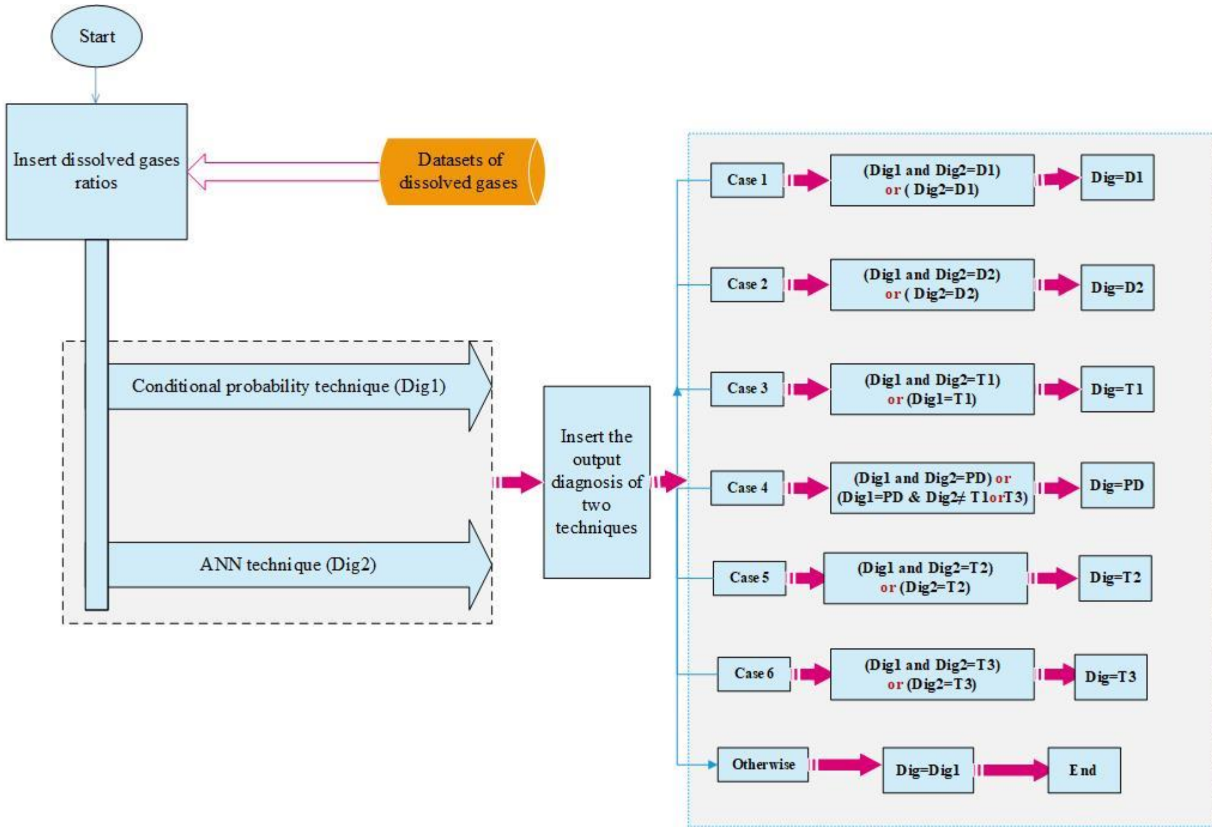


Fig. 2 Flowchart of the proposed DGA technique

4. Results and Discussion

The results were obtained based on the percentage of fault diagnosis using the proposed technique to the central laboratory diagnosis, this for each fault type separately then for the total datasets. The comparison between the proposed approach result, ANN and conditional probability techniques for the 532 samples are presented. Table 5 shows the results of the integrated and proposed techniques. Also, the results are presented in Fig. 3. The suggested technique's overall accuracy is 86.65%, compared with 81.76% for ANN and 82.89% for condition probability, respectively. Its overall accuracy was improved due to its individual accurate detection in low, high discharge energy and high thermal fault type. The result proved that mixing the outputs of different DGA techniques could improve the overall accuracy. In addition, this proposed technique was compared with recently DGA techniques (1, 2, 3 and 4) which also based on the integration between different DGA methods (S.A. Ward, 2021) with the same dataset samples. Its overall accuracy was enhanced with compare to these recently DGA techniques. It achieved an overall accuracy percentage of 86.65%. In contrast, the recent techniques (1, 2, 3 and 4) accuracies were 69.9%, 84.9%, 83.2% and 85.3%, respectively, as shown in Table 6 and Fig. 4. In addition, the proposed technique was compared with Clustering (S. S.M. Ghoneim, 2016), IEC refined and Rogers refined (I. B. M. Taha, 2016) techniques. The proposed technique's overall accuracy proved its higher accuracy of 86.65% compared with these techniques of 81%, 66.9% and 59.9%, respectively, according to Table 7. Fifty-five samples, representing 10% of the total samples gathered from the central laboratory in Egypt, were used as testing samples to validate the proposed DGA technique. The accuracy of the suggested approach was compared with the accuracy of the techniques that were included in its structure using the validation testing samples. It was also compared with recently developed techniques (S. S.M. Ghoneim, 2016, I. B. M. Taha, 2016), as shown in Table 8. The proposed technique's overall accuracy is 78.4% which is higher than the overall accuracy of all used techniques in comparison and validation check, as shown in Table 8. The proposed approach validated that integrating several DGA techniques enhances fault detection's overall accuracy.

TABLE 5. THE ACCURACY IN PERCENTAGE OF THE PROPOSED TECHNEQUE

	ACT	Condition Probability Technique (%)	ANN Technique (%)	Proposed Technique (%)
PD	59	91.52	84.74	91.5
D1	96	61.45	60.41	66.6
D2	175	92.57	90.28	96.5
T1	92	82.6	91.3	82.6
T2	30	86.66	60	86.6
T3	80	80	83.75	90
All	532	82.8	81.76	86.65

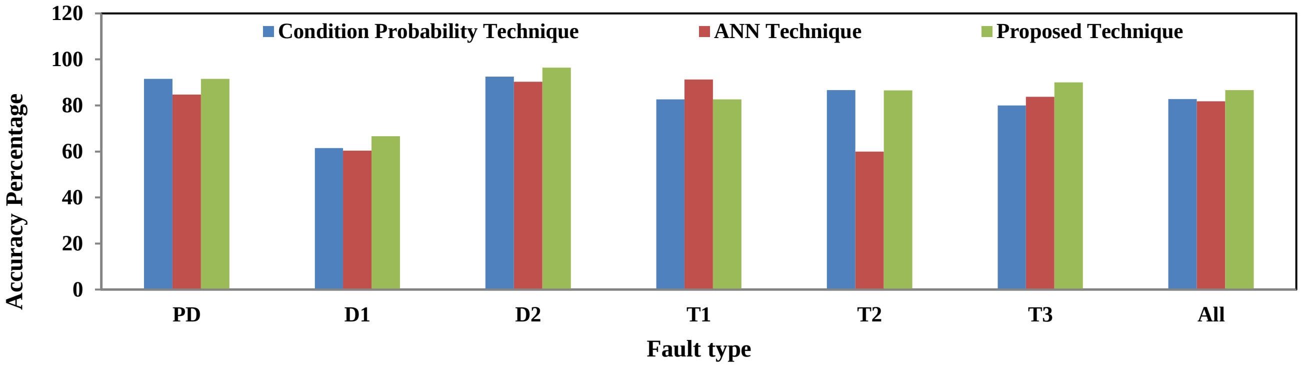


Fig. 3 Flowchart of the proposed technique

Table 6 . THE PROPOSED TECHNEQUE AND PREVIOUS PUBLISHED TECHNIQUES (S.A. Ward, 2021) ACCURACY FOR EACH FAULT TYPE

Fault type	Accuracy percentage				
	No. 1	No. 2	No. 3	No. 4	Proposed Technique
PD	50.84	91.5	84.7	89.8	91.5
D1	31.25	60.4	60.4	60.4	66.6
D2	81.14	96	90.2	94.8	96.5
T1	90.21	83.6	94.5	91.3	82.6
T2	43.33	83.3	60	83.3	86.6
T3	92.5	87.5	90	85	90
ALL	69.92	84.96	83.27	85.3	86.65

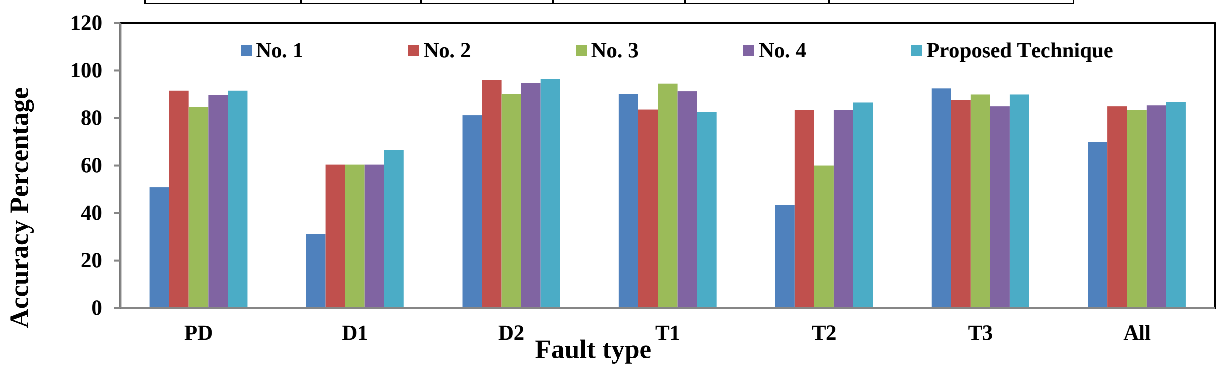


Fig. 4 Accuracy percentage of the Proposed Technique compared with recently published techniques (1, 2, 3 and 4).

Table 7 . The Proposed Techneque And Previous Published Techniques , Clustering, Iec Refined And Rogers Refined Techniques (S. S.M. Ghoneim, 2016, I. B. M. Taha, 2016)

Fault type	Accuracy percentage			
	Clustering	IEC refined	Rogers refined	Proposed Technique
PD	93.2	57.6	32.2	91.5
D1	70.8	29.1	8.3	66.6
D2	82.2	81.7	70.2	96.5
T1	91.3	67.3	88	82.6
T2	53.3	66.6	46.6	86.6
T3	80	86.2	92.5	90
ALL	81.01	66.9	59.9	86.65

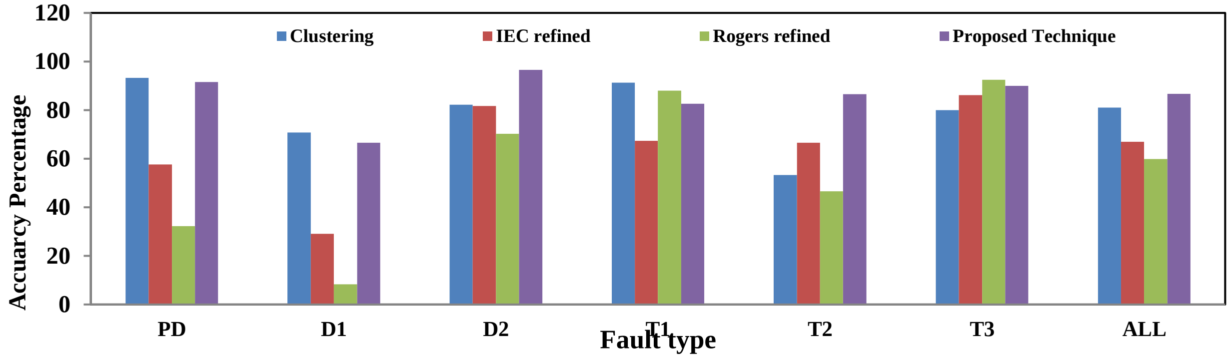


Fig. 5 Accuracy percentage of the Proposed Technique compared with published techniques Clustering, IEC refined and Rogers refined.

TABLE 8 . The Proposed Technique And Previous Published Techniques Using Validation Samples

Fault type	Sample No	Accuracy percentage									
		Clustering [28]	IEC refined[29]	Rogers refined[29]	ANN [27]	Con-prob [26]	No. 1 [18]	No. 2 [18]	No. 3 [18]	No. 4 [18]	Proposed Technique
PD	5	80	60	60	60	80	60	80	60	80	80
D1	5	20	60	0	60	0	20	0	60	0	60
D2	16	75	75	56.2	93.75	93.75	75	87.5	93.75	87.5	93.75
T1	10	90	80	60	90	60	70	60	90	60	60
T2	6	16.6	50	83.3	33.3	66.6	66.6	66.6	33.3	66.6	66.6
T3	13	76.6	84.6	84.6	69.2	92.3	84.6	84.6	84.6	84.6	84.6
ALL	55	67.2	72.7	61.8	74.5	74.5	69.1	70.91	78.1	70.99	78.4

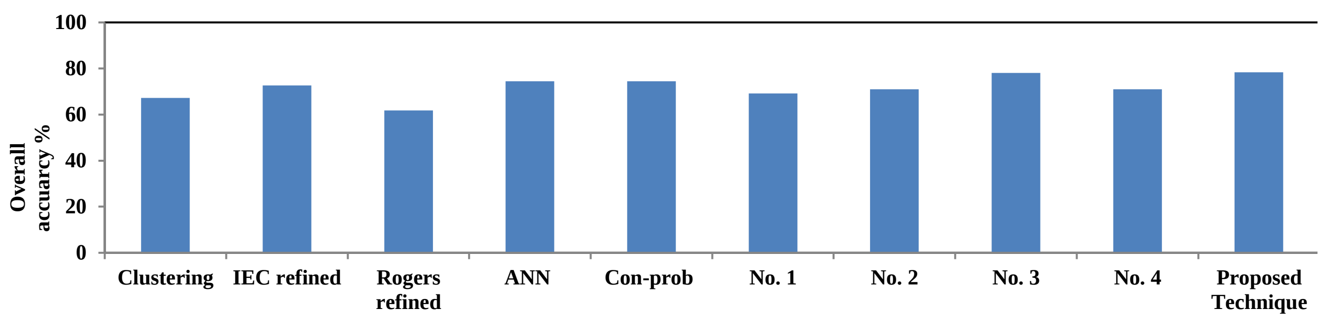


Fig. 6 Accuracy percentage of the Proposed Technique compared with published techniques using validation samples.

5. Conclusion

This work proposed a more accurate technique for interpreting transformer oil faults. This proposed technique was built using the outputs of two DGA techniques that were recently established; conditional probability and artificial neural network. Comparing the proposed technique to the ANN and conditional probability DGA techniques, the overall accuracy was increased. The proposed approach's advantageous features are demonstrated using 532 datasets with known faults received from the Egyptian Electricity Transmission Company (EETC). The proposed approach's fault diagnostic accuracy was 86.6%, compared with 81.7% for ANN and 82.8% for the conditional probability technique. In addition, this proposed approach was compared with recently DGA techniques which also based on the integration between different DGA methods. It achieved an overall accuracy percentage of 86.65%, while these recent techniques (1, 2, 3 and 4) accuracies were 69.9%, 84.9%, 83.2% and 85.3%, respectively. The proposed approach validated that integrating several DGA techniques accuracy enhances fault detection's overall accuracy

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References

A. Samy, S. A. Ward, and M. N. Ali, ‘‘Conventional ratio and artificial intelligence (AI) diagnostic methods for DGA in electrical transformers," International Electrical Engineering Journal (IEEJ), Vol. 6, pp. 2096-2102, 2015.

E. Bezerra, F. Z Garcia, F.A Ikuyo Nabeta, S Martha, G.F Chabu, I.E Santos, J.C Junior, S.N Pereira and F.H , “Wavelet-like transform to optimize the order of an autoregressive neural network model to predict the dissolved gas concentration in power transformer oil from sensor data,” Sensors, 2020,

G.S. Naganathan, M. Senthilkumar, S. Aiswariya, S. Muthulakshmi, G. Santhiya Riyasen, M. Mamtha Priyadharshini, ‘‘Internal fault diagnosis of power transformer using artificial neural network,’’ Materials Today: Proceedings, 2021.

H. C. Chen, Y. Zhang and M. Chen, ‘‘Online DGA sensor calibration using GANN and data augmentation, ’’ IEEE 5th International Electrical and Energy Conference (CIEEC), 2022.

H. Salem, I. M. El-Hasnony, A.E Kabeel, E. M.S. El-Said, O.M. Elzeki, ‘‘Deep learning model and classification explainability of renewable energy-driven membrane desalination system using evaporative cooler, ’’ Alexandria Engineering Journal, vol. 61, 2022.

I. B. M. Taha, D. A. Mansour, S. S. M. Ghoneim and N. I. Elkalashy, ‘‘Conditional probability-based interpretation of dissolved gas analysis for transformer incipient faults,’’ IET Generation, Transmission & Distribution, vol. 11, pp. 943-951, 2017.

I. B. M. Taha, et al. ‘‘Refining DGA methods of IEC Code and Rogers four ratios for transformer fault diagnosis,’’ IEEE Power and Energy Society General Meeting (PESGM), 2016.

I. B. M. Taha, S. Ibrahim and D. E. A. Mansour, ‘‘Power transformer fault diagnosis based on DGA using a convolutional neural network with noise in measurements,’’ IEEE Access, vol. 9, pp. 111162-111170, 2021.

IEC Std. 60599, ‘‘Mineral oil-impregnated electrical equipment in service- Guide to the interpretation of dissolved and free gases analysis,’’ 2007.

IEEE Std. C57.104, ‘‘IEEE Guide for the Interpretation of Gases Generated in Oil-Immersed Transformers,’’ 2008.

J. Li, C. Hai, Z. Feng, and G. Li, ‘‘A transformer fault diagnosis method based on parameters optimization of hybrid kernel extreme learning machine,’’ IEEE Access, vol. 9, pp. 126891-126902, 2021.

J. Liang, S. Chen, Z. Wei, S. Zhao, W. Zhao, ‘‘HAGDetector: Heterogeneous DGA domain name detection model, ’’ Computers & Security, vol. 120, 2022.

M. Badawi, S. A. Ibrahim, D. E. A. Mansour and et al, ‘‘Reliable estimation for health index of transformer oil based on novel combined predictive maintenance techniques,’’ IEEE Access, vol. 10, pp. 25954-25972, 2022.

M. Dong, ‘‘A novel maintenance decision making model of power transformers based on reliability and economy assessment,’’ IEEE Access, vol. 7, pp. 28778-28790, 2019.

M. Duval, ‘‘State of the art of technical diagnosis through interpretation of DGA,’’ in Proceedings of My Transfo Conference. Torino, 2012.

M. M. Emara, G. D. Peppas and I. F. Gonos, ‘‘Two graphical shapes based on DGA for power transformer fault types discrimination,’’ IEEE Transactions on Dielectrics and Electrical Insulation, vol. 28, pp. 981-987, 2021.

N. Poonnoy, C. Suwanasri and T. Suwanasri, ‘‘Neural network approach to dissolved gas analysis for fault analysis in power transformers," International Electrical Engineering Congress (IEECON), 2022.

O. Laayati, H. El Hadraoui, M. Bouzi and A. Chebak, ‘‘Smart energy management system: oil immersed power transformer failure prediction and classification techniques based on DGA data,’’ 2nd International Conference on Innovative Research in Applied Science, Engineering and Technology (IRASET), 2022.

S. A. Wani, A. S. Rana, S. Sohail, O. Rahman, S. Parveen and S. A. Khan, ‘‘Advances in DGA based condition monitoring of transformers: A review,’’ Renewable and Sustainable Energy Reviews, vol.149, 2021.

S. A. Ward, A. ElFaraskoury, M. Badawi, S. A. Ibrahim, K. Mahmoud, M. Lehtonen, and M. M. F. Darwish, ‘‘Towards precise interpretation of oil transformers via novel combined techniques based on DGA and partial discharge sensors,’’ Sensors, vol. 21, 2021.

S. A.Ward, A. ELFaraskoury, M. Badwi and S. A. Ibrahim, ‘‘A modified dissolved gas analysis technique as a diagnostic tool for faults in power transformers, ’’ 21st International Middle East Power Systems Conference (MEPCON), 2019.

S. Ghoneim, D. Mansour and I. Bedir, ‘‘A Decision Transformer Fault Diagnostics System Based on Dissolved Gas Analysis,’’ 21st International Middle East Power Systems Conference (MEPCON), 2019.

S. S. M. Ghoneim, K. Mahmoud, M. Lehtonen and M. M. F. Darwish, ‘‘Enhancing diagnostic accuracy of transformer faults using teaching-learning-based optimization, ’’ IEEE Access, vol. 9, pp. 30817-30832, 2021.

S. S. M. Ghoneim, K. Mahmoud, M. Lehtonen, and M. M. F. Darwish, ‘‘Enhancing diagnostic accuracy of transformer faults using teaching-learning-based optimization,’’ IEEE Access, vol. 9, pp. 30817-30832, 2021.

S. S.M. Ghoneim, I.B.M. Taha, ‘‘A new approach of DGA interpretation technique for transformer fault diagnosis,’’ International Journal of Electrical Power & Energy Systems,vol. 81, 2016.

Sherif S. M. Ghoneim, I. B. M. Taha and N. I. Elkalashy, ‘‘Integrated ANN-based proactive fault diagnostic scheme for power transformers using dissolved gas analysis,’’ IEEE Transactions on Dielectric and Electrical Insulation, 2016.

X. Liu, ‘‘DGA botnet detection method based on capsule network and k-means routing, ’’ Neural Comput & Applic, pp. 8803–8821, 2022.

X. Shen, X. Zhang and Y. Chen, ‘‘Deep learning powered adversarial sample attack approach for security detection of dga domain name in cyber physical systems, ’’ IEEE Wireless Communications, vol.. 29, pp. 16-21, 2022.

Y. Benmahamed, ‘‘Accuracy improvement of transformer faults diagnostic based on DGA data using SVM-BA classifier,’’ Energies, 2021.