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INDMM: Intelligent Numerical Duval Modification Model for Identifying Transformer Fault

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***Abstract*—** Oil-paper insulation is considered the most popular method for insulating the windings within power transformers because of its ability to withstand high electrical and thermal stress. During the life time of power transformers, oil-paper insulation is aged, and hydrocarbon gases are released. Dissolved gas analysis (DGA) is globally recommended as a reliable diagnostic technique used to identify the fault inside these transformers. Several methods have been previously presented to recognize these faults depending on the data obtained from DGA. This paper proposes a new model that converts Duval pentagon diagnostic graph that defines fault zones using a set of linear inequalities to a numerical table, enabling a fully numerical, automated, and simplified fault identification with 100 % accuracy of traditional Duval pentagon 1, 2 and combined. A comprehensive dataset was generated using the proposed model, covering a wide range of possible gas concentration scenarios. Based on this dataset, a smart diagnostic model employing a Gaussian Support Vector Machine (SVM) was developed to predict transformer faults directly from dissolved gas ratios without the need for manual centroid calculations with up to 98.1 % accuracy of Duval Pentagon according to 20 % test dataset. The proposed model is validated through real case studies, achieving identical results of Duval Pentagon. Comparative analysis against conventional DGA methods and other AI-based techniques demonstrates the superior performance of the presented model in terms of accuracy, simplicity, and practicality.

***Keywords*—** Dissolved gas analysis (DGA), Duval pentagon modification, Gaussian support vector machine (SVM), Machine learning algorithms (MLA), Smart diagnostic.

1. INTRODUCTION

Power transformers are among the most vital and expensive components in modern Power transformers are among the most vital and expensive components in modern power systems [1-3]. Consequently, the condition of the insulation system inside these transformers must be periodically assessed to ensure operational reliability and to prevent catastrophic failures. Many transformers currently in operation have exceeded their originally designed service life [4-5]. However, they have not been replaced due to the high cost of replacement, and to avoid service interruption [6]. Usage of oil-paper insulation has expanded in the last decades as a result of not only the benefit of low cost, but also the acceptable mechanical and electrical characteristics in case of thermal and electrical aging conditions [7-9]. Paper insulation is a composite material that consists mainly of cellulose, hemicellulose, and lignin, with cellulose accounting for approximately 90% of its chemical structure [10-11]. When it is

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subjected to either thermal or electrical stresses, cellulose material and insulating oil decomposes, releasing various hydrocarbon gases, carbon oxides, and furan compounds that dissolve into the transformer oil at different concentrations [12-13]. Methane (CH4), acetylene (C2H2), ethylene (C2H4), ethane (C2H6), hydrogen (H2), carbon dioxide (CO2), and carbon monoxide (CO) are the main recorded dissolved gases associated with the aging of transformer insulation systems [14-17]. The concentration of these dissolved gases and furan compounds varies depending on the fault that initiates the aging process of the insulating material inside the transformer. As a result of the urgent necessity to identify the types of faults inside the in-service power transformers, many diagnostic techniques have been presented. Dornenburg's ratio method, Rogers's method, and IEC standard 60559 can be classified as the main techniques which can distinguish the fault nature inside the transformers depending on dissolved gas ratios. Meanwhile, Duval's triangle and pentagon methods can be identified as more accurate graphical techniques, depending on gas concentration patterns for fault identification [18-22].

Many works have been released relying on Duval’s work in order to improve the obtained results. Consequently, this paper proposed a modification of Duval pentagon by converting the traditional pentagon into a numerical method as assigning different linear inequalities for each fault type in order to simplify the process of fault interpretation depending on DGA results. When these inequalities are satisfied the fault is detected. Furthermore, support vector machines (SVM) with Gaussian Kernel function was chosen to build an intelligent model in order to simplify and speed up the fault identification process. The diagnosis of the transformer fault using the resulted smart model has achieved an average accuracy level of up to 98.1% of the investigated cases.

The novelty and contribution of this research lie in modifying Duval pentagon diagnostic graph by generating a table which has some inequalities that should be satisfied if there is (are) fault (s) in the transformer. The type of the fault is determined from that table. A large dataset is generated from the previous table by MATLAB program. Next, the dataset is used to train the SVM machine language algorithm (MLA) to build the smart model. The aim of the model is the ability to predict the transformer fault automatically without going through the previous steps. The intelligent model was proved to predict the fault efficiently. Finally, a comparison was held between the proposed model, other conventional and intelligent works to test its functionality. Moreover, the accuracy of this modification has been assessed by using five different case studies which have been published in previous researches. The results of the proposed model outperform the others. The paper is organized as follows: Section 2 reviews a number of related work to the presented research. Section 3 introduces Duval pentagon (DGA) diagnostic graph method. Section 4 presents the proposed numerical modification of Duval pentagon diagnostic graph. Section 5 presents the methodology of the proposed intelligent model and the results of applying it. Also, it compares the results obtained from the proposed model and existing works to prove its validation. Section 6 shows five case studies by basic oil tests, furan and DGA. Finally, Section 7 concludes the work.

2. RELATED WORK

Dornenburg in [23] introduce the use of four gas ratios (C_2H_2/C_2H_4, C_2H_4/C_2H_6, C_2H_2/CH_4 and CH_4/H_2) in 1974. However, these ratios must exceed a certain level in order to be applicable for usage. The main drawback in Dornenburg's technique is that it cannot determine the fault inside the transformers in many cases due to incomplete ratio ranges. Later, Roger introduced a technique based on three codes according to IEC requirements (C_2H_4/C_2H_6, CH_4/H_2, and C_2H_2/C_2H_4). Due to shortage of accuracy, Rogers four ratios method (CEGB) code has been proposed by adding (C_2H_6/CH_4) ratio to the previously mentioned three ratios. Despite successive improvements, gas ratio-based techniques have continued to exhibit limitations in accurately diagnosing fault types in certain operational scenarios [24-26].

In [27]. Duval introduced an empirical graphical diagnostic method known as the Duval Triangle in 1970s, designed to classify faults inside power transformers based on the concentration of three key dissolved gases: CH_4, C_2H_2, and C_2H_4. The concentrations of these gases are first measured and summed, and then the percentage contribution of each gas to the total was calculated. Finally, these percentages were plotted on triangle map, where the fault type can be identified based on the location of the resulting point. This method, later adopted in IEC 60559, is known for its relatively high accuracy compared to other traditional diagnostic approaches. However, its reliance on only three gases presents a major drawback and may result in uncertainty in certain fault identification cases, in low energy faults and normal insulation aging leads to an error it need to triangles 4, 5 for more information.

Later in [28], Duval introduced a new graphical technique, which incorporates the concentration of five hydrocarbon gases. The inclusion of C_2H_6 and H_2, key indicators for low-temperature overheating and partial discharge faults, respectively, enhanced diagnostic capability compared to the original triangle method. Despite better accuracy in comparison with the Duval triangle technique, Duval pentagon is more complicated, and more time is consumed in determining the centroid of the gases in the pentagon and locating the fault in the graphical map. Thus, previous studies have investigated different methodologies aiming to simplify the technique of DGA fault interpretation [29]. On the other hand, there are many works that have been used for DGA diagnostic using Artificial Intelligence (AI) methods.

Masoud Noori et al. [30] introduced an intelligent method that depends on a fuzzy logic interface system (FIS) to define the fault nature inside power transformers, depending on gas chromatography results. The DGA data, which was collected from the 185 faulty and healthy transformers, have been recalculated by the proposed FIS in order to assess its accuracy. The proposed system has classified the faults correctly in 91.2 % of the investigated DGA results.

S. M. Ghoneim et al [31] proposed a smart fault diagnostic approach (SFDA) that utilizes Artificial Neural Networks (ANNs) to compare the performance of five conventional interpretation methods: the Dornenburg method, IEC code, Central Electricity Generating Code (CEGC) based on Roger’s four-ratio method, Roger’s three-ratio method, and the Duval Triangle. The worst obtained results have been recorded in cases of Dornenbug method and Roger's three ratios code, the Duval triangle provides an accurate interpretation in most cases; however, it could not be reliable in cases of no fault. The accuracy of the proposed SFDA reached 87.8% of the studied cases when combining results from the Duval triangle, Roger's four ratios, and the IEC code. Despite the progress made using fuzzy logic and neural networks, the full potential of Machine Learning (ML) for DGA-based fault diagnosis has not been thoroughly explored until recently.

In [32], six Optimized Machine Learning (OML) methods are used for transformer fault diagnosis: decision tree, discriminant analysis, Naïve Bayes, support vector machines, K-nearest neighboring, and ensemble classification methods. They were implemented using MATLAB Software, based on 542 dataset samples collected from laboratories and literature. The transformer fault diagnosis based on the OML methods has proven its superior predictive accuracy compared to conventional and artificial intelligence methods. Further supporting this trend, [33] confirmed that ML-based methods significantly improve the reliability and effectiveness of transformer fault classification, making them ideal for integration into intelligent monitoring systems.

In [34], a hybrid diagnostic model combining SVM with Bat Algorithm (SVM-BA) and Gaussian Classifiers was proposed. This model used the concentrations of five combustible gases. This model used the concentrations of the five combustible gases as input features to diagnose six major electrical and thermal faults in transformers. Trained and tested on a dataset of 481 records, the hybrid model demonstrated enhanced diagnostic performance compared to traditional methods. Conventional diagnostic methods for power transformers, while simple and easy to implement, often suffer from limited accuracy in identifying specific fault types. In contrast, AI-based techniques have demonstrated higher predictive accuracy; however, their effectiveness typically depends on access to large datasets. Recently, ML approaches have emerged as promising solutions for enhancing DGA-based transformer fault diagnostics [32].

As such, there is a growing need to develop new methods or improve existing ones to achieve both simplicity and diagnostic reliability. Consequently, Intelligent Numerical Duval Modification Model (*INDMM*) is proposed to Identify Transformer Faults which depends on Duval Pentagon Diagnostic Graphical Technique.

3. DUVAL PENTAGON DIAGNOSTIC GRAPHICAL TECHNIQUE

Duval introduced graphical techniques which are used to identify the fault depending on DGA to overcome the limitations of the conventional traditional methods. Firstly, a triangle has been introduced to predict the faults as a result to the concentration of three hydrocarbon gases. Later a pentagon diagnostic graphical method which analyzes the fault inside the power transformer depending on the concentration of five hydrocarbon gases instead of three has been presented. CH_4, C_2H_2, C_2H_4, C_2H_6, and H_2 are the five gases that represent the bases of Duval's pentagon.

3.1. Centroid Calculation

An example of Duval's pentagon is illustrated in Fig. 1 Each summit of the pentagon corresponds to one of the gases. The relative percentage of each gas is calculated as a percentage of the sum of the five gases. For example, the relative percentage of hydrogen is calculated as in Eq. (1).

$$H_2\ \% = (H_2) / (H_2 + C_2H_6 + CH_4 + C_2H_4 + C_2H_2) \quad (1)$$

The concentration of each gas is measured in parts per million (ppm). The previously calculated relative percentage is plotted on the axis between the center of the pentagon, representing the origin point of each gas (zero ppm), and the pentagon summit, which represents 100% of the gas concentration. For example, if C_2H_4 = 40 ppm, C_2H_2 = 0 ppm, C_2H_6 = 100 ppm, CH_4 = 20 ppm, and H_2 = 240 ppm. The relative percentage of each gas is 10%, 0 %, 25%, 5% and 60% respectively. These relative percentages are plotted on the corresponding gas access, providing five different points represented as the blue shape in Fig .1. Then, the cartesian coordinates (xi, yi) of each gas line are calculated from Eq. (2).

$$xi = Pi * \cos \alpha_i \ , \quad yi = Pi * \sin \alpha_i \quad (2)$$

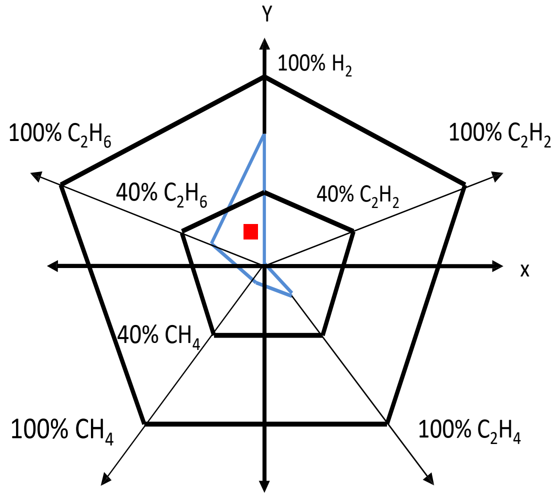

Fig. 1. Example of duval pentagon representation.

where i = (1,2,3,4,5) and Pi is the relative percentage of each gas where p1 is H_2 (%), P2= C_2H_6 (%), CH_4 (%) = P3, C_2H_4 (%) = P4, C_2H_2 (%) = P5 and ∝1 = π /2, ∝2 = 0.9 π, ∝3 = 1.3 π, ∝4 = 1.7 π and ∝5 = 0.1 π [36]. For example, the angle between C_2H_6 and x-axis is {90-(360/5)} = 18°, thus the (x2, y2) coordinates of the C_2H_6 gas can be calculated as x_2 % = -25 cos (18°) = -23.75, and y_2 % = 25 sin (18°) = 7.75. The (xi, yi) coordinates of the other gases are calculated with the same manner. It has been calculated that, the coordinates of H_2, CH_4, C_2H_2, C_2H_4 gases are (0, 60), (2.95, 4.05), (0, 0), and (5.9, 1.8) respectively, finally, the overall cartesian centroid coordinates (Cx, Cy) of this example is calculated by the following Eqs. (3) - (5).

$$C_x = \frac{1}{6A}\sum_{i=0}^{n-1}(x_i + x_{i+1})(x_i y_{i+1} - x_{i+1} y_i) \tag{3}$$

$$C_y = \frac{1}{6A}\sum_{i=0}^{n-1}(y_i + y_{i+1})(x_i y_{i+1} - x_{i+1} y_i) \tag{4}$$

$$A = \frac{1}{2}\sum_{i=0}^{n-1}(x_i y_{i+1} - x_{i+1} y_i) \tag{5}$$

3.2. Duval Pentagon Fault Zones

In order to identify the fault zones inside Duval pentagon, 180 DGA results have been studied. Depending on these results, the area inside the pentagon has been divided between six main basic faults and four advanced thermal sub-types faults. Corona partial discharge (PD), low energy discharge (D1), and high energy discharge (D2) represent the three basic electrical faults. However, thermal faults (T1) occurs when the temperature < 300 °C, (T2) occurs when 300 °C ≤ the temperature ≤ 700 °C and (T3) occurs when the temperature > 700 °C which represent the main three basic thermal faults. These six basic faults are mentioned in IEC, IEEE, and Duval triangle [35, 36]. As it is clear in Fig. 2, Duval pentagon provides a representation of additionally advanced thermal sub-types fault which have not been mentioned either in Duval triangle or in IEC 60559. (T3-H) represents thermal faults in oil insulation system. Presence of carbonized term (C) with red dash line area inside the zones of the three thermal faults indicates. that the insulating paper has been carbonized during the thermal fault [27]. T1- O fault zone indicates overheating inside the power transformer ≤ 250 °C. Finally, (S) stray gassing of mineral oil at 120 and 200 °C in the laboratory. Note that the percentage centroid coordinates are less than 40% if any percentage gas reached 100% so the pentagon summits are limited to 40 %.

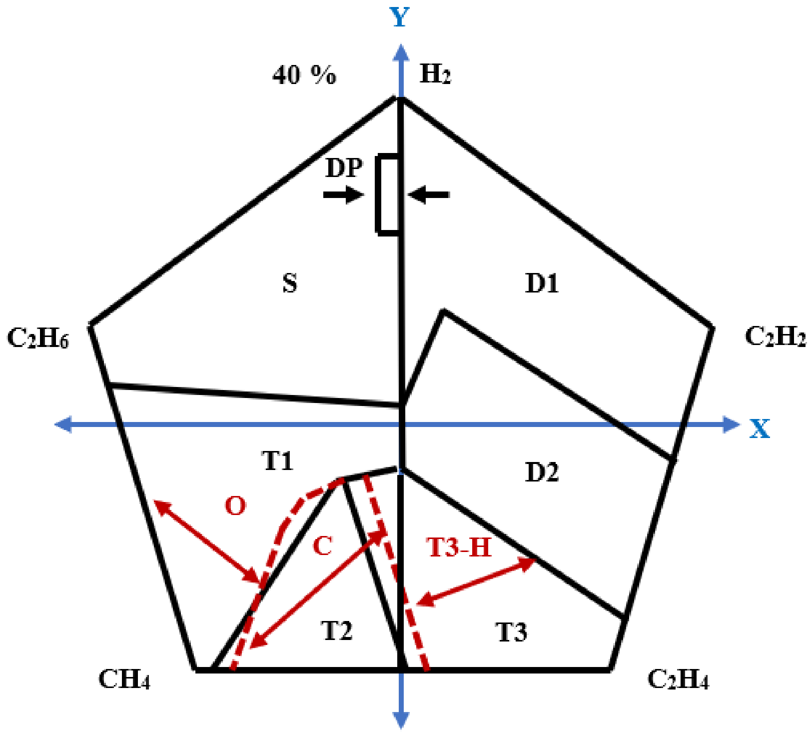

Fig. 2. Duval Pentagon for Basic and Sub-Types of Faults

4. THE PROPOSED MODIFICATION OF DUVAL PENTAGON DIAGNOSTIC GRAPHICAL TECHNIQUE TO NUMERICAL TECHNIQUE

Although Duval Pentagon is used as a complementary tool and introduces almost accurate fault interpretation depending on DGA results, many drawbacks have been noticed during its usage; after calculating of the overall final centroid, the user has to locate this centroid graphically on the pentagon in order to identify the fault nature. As a result, long time is required to identify the fault and the user has to locate the centroid sharply to avoid the inaccurate fault diagnostic. The main aim of this paper is to facilitate the process of fault interpretation depending on Duval pentagon modification. In this paper, a numerical technique is proposed. This numerical technique is based on converting fault zones inside the pentagon to different linear inequalities and using A MATLAB code to speed up the overall centroid and the fault interpretation.

4.1. The Proposed Table

The proposed table depends on converting the faults zones inside the pentagon to different group of linear inequalities as it is clear in Table 1. PD, D2, T2, T3, C and T3-H which are the basic fault and sub-fault zones have been converted to one group of linear inequalities, D1 and T1 basic fault zones have been converted to two groups of linear inequalities, the last sub-fault zones (S) and (O) have been converted to three groups of linear inequalities. A MATLAB code is responsible for generating large dataset where its input is different ratios of the five gases from 0 to 1 with step 0.01. Then the rules of Duval pentagon are applied to find the fault zone and determine the fault type by calculating the relative percentages of the five hydrocarbon gases and then find the cartesian coordinates of each gas (xi, yi), and consequently the centroid coordinates of the investigated case (Cx, Cy) is calculated mathematically using Eqs. (3-5). Next, the proposed MATLAB code is applied in order to identity the fault. The inequalities are generated with coefficients obtained by finding the relation between the inputs and the output of the previous dataset. Finally, Table 1 is generated.

Table 1. Duval pentagon modification to a numerical model.

Basic Faults	K_1	+ / -	K_2	Sub Faults	K_1	+ / -	K_2
PD	0.000	+	33.00	T3-H	1.111	+	-3.000
	0.000	-	-24.5		-0.142	+	-3.000
	1.000		0.000		-4.816	-	20.358
	-1.000		1.000	C	4.816	+	-20.358
D1	-0.789	-	-19.157		-0.800	+	-0.800
	-1.000				-2.323		
			0.000		-0.200	+	17.561
	3.625	-	-1.500			+	-2.800
	-1.000		0.000	O	0.0457	+	1.500
D2	0.789	+	19.157		1.0000		0.000
	-3.620	+	1.500		0.1667	-	3.000
	-1.000		0.000		0.0457	+	1.500
	-1.111	-	3.000		1.0000		0.000
T1	0.045	+	1.500		0.0457	+	1.500
	1.721	-	- 6.327		1.0000		0.000
	0.045	+	1.500		2.3238	-	-17.562
	1.000		0.000	S	-0.0457	-	-1.500
	0.166	-	3.000		1.0000		-1.000
T2	4.057	+	-28.34		-0.0457	-	-1.500
	-1.721	+	6.327		1.000		0.000
T3	1.111	+	-3.000		0.000	+	24.50
	-0.166	+	-3.000		1.000		0.000
	-4.057	-	28.342		0.000	-	-33.00

4.2. Methodology of the Proposed Technique

To use the proposed technique, first of all, the relative percentages of the five hydrocarbon gases are calculated as in Eq. (1). Then, the coordinates of each gas are calculated (xi, yi) as in Eq. (2) and consequently, the overall centroid of the investigated case (Cx, Cy) is calculated mathematically as in previous Eqs. (3)-(5). At last, (Cx, Cy) is used in order to identity the fault. The pentagon has deferent fault zones and boundaries, such as for PD fault zone are (0, 24.5), (0, 33), (−1, 24.5) and (−1, 33), and for D1 fault zone are (0, 40), (38, 12.4), (32, −6.1), (4, 16) and (0, 1.5), etc. [29]. From these fault zones and cartesian coordinate's points location, the linear inequities fault constrains are obtained. For example, PD fault constrains are $Cy \leq 33$, $-Cy \leq -24.5$, $Cx \leq 0$ and $-Cx \leq 1$, where (Cx, Cy) are centroid coordinates inside the fault zone, if these linear inequities are satisfied for Cx and Cy, PD fault is identified. Also D1 fault constrains are $3.625 * Cx - Cy \leq -1.5$, $- 0.7893 * Cx - Cy \leq -19.1571$ and $- Cx \leq 0$. For other fault zones, these linear inequalities can be in the form ($K_1 * Cx \pm Cy \leq K_2$).

Note that the outer lines of pentagon are not be considered because the centroid coordinates cannot be exceeded these lines. Arrangement the linear inequalities parameters K_1 and K_2 for all basic and sub to automate the MATLAB program. To use the table, the coefficient (k_1) is multiplied by (Cx), then the resultant added or subtracted to (Cy), according to the sign in Table 1 and compared to the constant parameter (k_2) as shown in Inequality (6). If all inequalities inside only one of any group are satisfied, the fault is identified. As shown in Table 1, each fault is represented by coefficient (k_1) and constant parameter (k_2). If the point of centroid coordinates fault inside the pentagon lies on the line between two fault zones, < is used instead of ≤ in inequality (6).

$$K_1 * Cx \pm Cy \leq K_2 \tag{6}$$

For example if H2 = 24 ppm, C2H6 = 17 ppm, CH4 = 40 ppm, C2H6 = 21 ppm, C2H2= 1 ppm, using Eqs. (1) and (2) to calculate gas ratios and cartesian coordinates of these ratios (xi, yi), then using Eqs. (3)-(5), to get the cartesian centroid coordinates (Cx = -7.0869, Cy = -8.0203), when we using Table 1 and inequality (6), it's satisfied for two inequalities group of T2 fault only where K1 * (-7.0869) + (-8.0203) ≤ K2 i.e. (4.057) * (-7.0869) + (-8.0203) ≤ -28.34 and (-1.72) * (-7.0869) + (-8.0203) ≤ 6.327.

5. THE PROPOSED INTELLIGENT MODEL (INDMM)

ML algorithms use computational methods to "learn" information directly from data without relying on predetermined equations. A brief summary of the most popular ML algorithms for classification learner toolbox is presented in [32]. In this section, a Support Vector Machine (SVM) algorithm is applied to the data set produced from the proposed model to have a learned intelligent model able to predict the fault in transformers fast and accurate. Support Vector Machines (SVMs) use various kernel functions to handle data. Kernel function maps data into a higher-dimensional feature space, making it easier to find an optimal linear decision boundary (hyperplane) in that transformed space, which corresponds to a non-linear boundary in the original space. The choice of kernel function depends heavily on the nature of the data and the problem. Fine-tuned Gaussian SVM is a high-precision supervised machine learning classification method that uses a Gaussian radial basis function (RBF) kernel with a very small kernel scale. This configuration enables it to create complex, tight decision boundaries around data points, making it highly effective for detailed fault detection and classification tasks.

5.1. The Proposed INDMM

SVM is chosen to teach the proposed model as it is simple, accurate and relatively fast comparing to other ML algorithms where choosing the right algorithm requires trading off benefits against others, including model speed, accuracy, and complexity. The proposed *INDMM* is carried out and implemented based on 47755 dataset samples which are collected from applying the transformation Table 1. Training a SVM model is a part of the proposed model which depends on the dataset generated from applying the new technique. Before applying the smart model, a comparison is held between the new idea of numerical Duval modification with previous works and the results show the superior performance of the presented model in terms of accuracy, simplicity, and practicality. A comprehensive dataset was generated using the proposed model, covering a wide range of possible gas concentration scenarios. The dataset is divided into 80% training set and 20% testing set. The training process is initiated to build the intelligent model which can be exported to be ready to predict the fault faster and easier than applying the technique from the beginning. Simply, Fine-tuned Gaussian SVM is chosen to export its model and apply to new measurements to predict the fault type.

5.2. Results and Discussion

The Confusion matrix is a matrix that shows True Positive Rates (TPR) and False Negative Rates (FNR). TPR is the proportion of correctly classified observations per true class, however, FNR is the proportion of incorrectly classified observations per true class. The matrix in Fig. 3 shows the percentage of each fault's accuracy when using different ML algorithms proving the high accuracy of Fine-tuned Gaussian SVM. The flow chart of the proposed *INDMM* for Recognizing Transformer Faults using Fine-tuned Gaussian SVM is shown in Fig. 4, where n is the number of the dataset, and i is the number of gases (1 to 5).

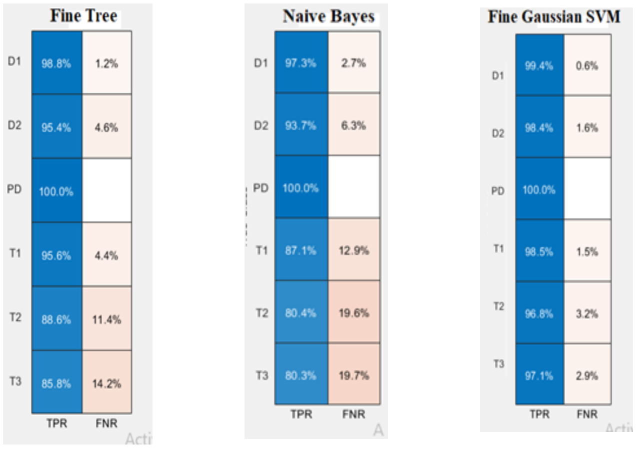

Fig. 3. The confusion matrices of sample of different MLAs.

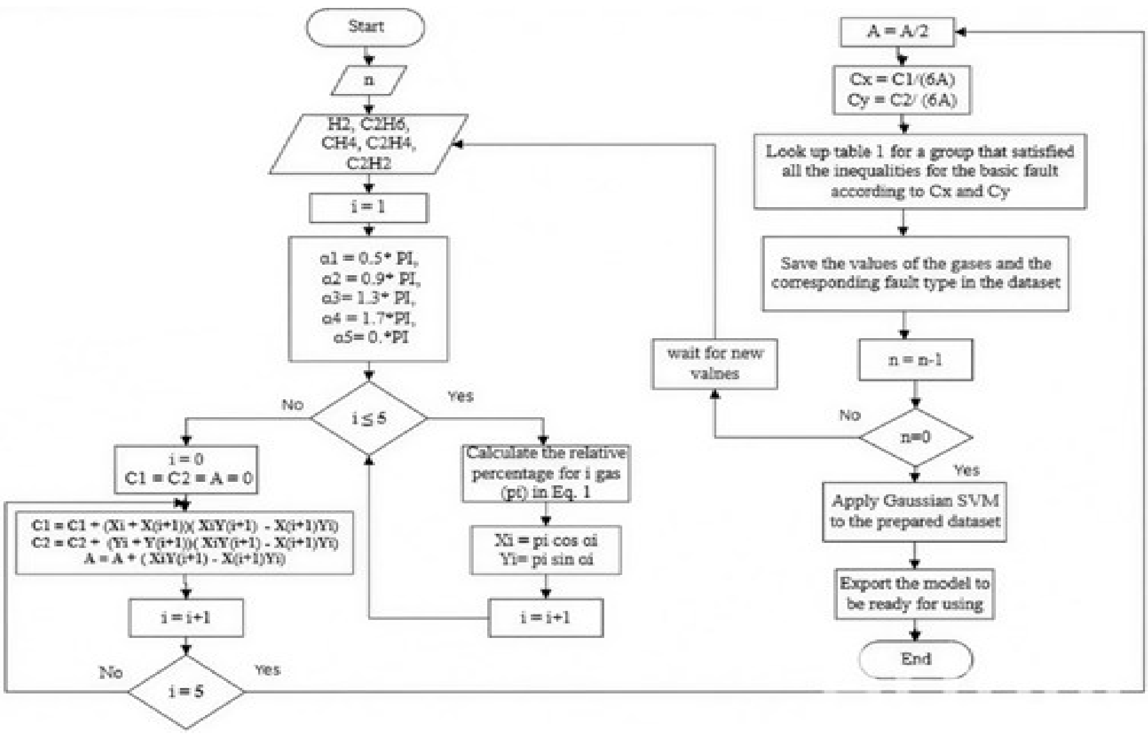

Fig. 4. The proposed INDMM diagnostic model for identifying transformer fault.

Using the angle of each gas from drawing (α i) is measured in radian, pi is the relative percentage of each gas where p1 is H_2 (%), P2 = C_2H_6 (%), P3 = CH_4 (%), P4 = C_2H_4 (%) and P5 = C_2H_2 (%). First of all, the proposed *INDMM* is built as follows: the five gasses ratios measurements (Pi) are used to measure α then the centroid is calculated following Eqs. (1)-(5), then look up the Table 1 for one group of inequalities to be satisfied, the corresponding type of fault is determined and the data is saved for further training and testing. If the number of dataset (n) that is decided at the beginning, is not reached yet, wait for updating and new readings, then go through the previous steps to find the fault type if found. After the number of the dataset (n) is reached, Fine-tuned Gaussian SVM is applied to the previous prepared dataset and the model is extracted. Finally, the resulted model is ready to be used with any new measurement to detect the fault type without going through the previous steps. A comparison is held between the results obtained after applying the proposed *INDMM* on sample of real measurements and other existing works as shown in Table 2. [31] Suggested using EN OML after applying other MLAs to predict the transformer faults. The conventional methods used for comparisons are Rogers' four ratio, and Duval triangle, while the Artificial Intelligent methods are Rogers modified four-ratio (Mod-Rog) [39], and the neural pattern recognition approach (NPR) [40]. The comparison proves the superiority of the proposed *INDMM.*

Table 2. A comparison between the proposed INDMM with the existing works.

Reference #	Method of predicting the faults	Accuracy of Fault Type						Total Accuracy [%]
		D1	**D2**	**PD**	**T1**	**T2**	**T3**	
The proposed *INDMM*	Fine-tuned Gaussian SVM to the modification of Duval Pentagon	99.4	98.4	100	98.5	96.8	97.1	98.1
[30]	Rogers' four ratio	0	62.22	45	74.29	33.33	67.65	50.83
[31]	EN Algorithm to (DGA)	65.52	93.33	95	97.14	94.44	97.06	90.61
[38]	Mod Rog	75.86	82.22	95	77.14	100	94.12	85.64
[39]	NPR	82.76	88.89	95	85.71	94.44	97.06	90.06
[40]	Duval Triangle	79.31	75.56	50	57.14	55.56	100	72.38

6. VALIDATION OF THE PROPOSED INDMM

In order to validate the proposed *INDMM,* five real case studies have been examined. The faults in each case study have been identified using not only INDMM but also the traditional Duval pentagon in order to assess the accuracy of the proposed numerical modification.

6.1. Case Study I

An auxiliary transformer, which operates in one of steam power plant in Egypt since 1983, has been monitored, furan components to evaluate Degree of Polymerization (DP) of this 16 MVA 15/6.3/6.3 kV a three-phase power transformer has been investigated in [4]. It has been recorded that furan compounds level increased tremendously from 2003 to 2009, which reflected a serious problem affecting the strength of the insulating paper (DP). To identify the main reason of DP reduction not only Furan analysis has tested, but also DGA has been implemented. A significant increase has been recorded in O_2, CO_2/CO ratio and N_2 in the time interval between 2003 and 2009 in comparison with the history of DGA as shown in Figs. 5-7. After investigation, it was found that the main reason of this deterioration in the insulating system was an atmospheric air leakage (oil/air interface) detected in the cover of the transformer surface as shown in Fig. 8. From transformer DGA results history we detected that this defect starts at 2003 where high increase in Oxygen (O2) gas levels as shown in the Fig. 5, in the time interval between 2003 and 2009. The leakage was repaired as a part of the transformer overall maintenance. This can help clarify the primary cause of the decrease in dissolved gases and improve CO_2/CO gases ratio and N_2 gas levels as shown in Figs. 6, 7.

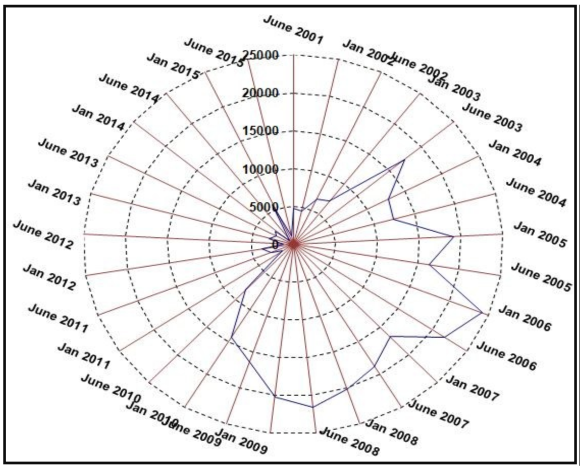

Fig. 5. Dissolved O_2 in (ppm) between 2001 to 2015.

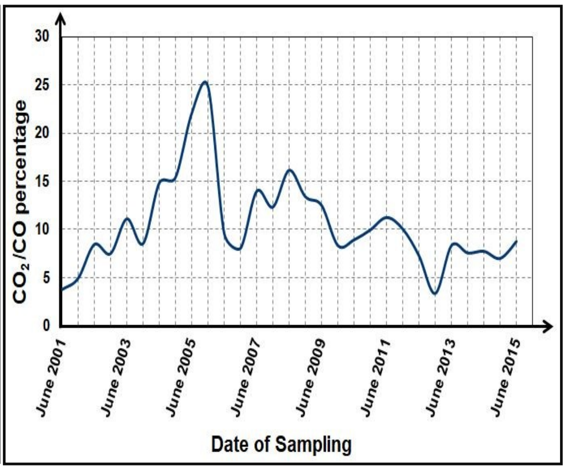

Fig. 6. CO_2/ CO ratio variation between 2001 to 2015.

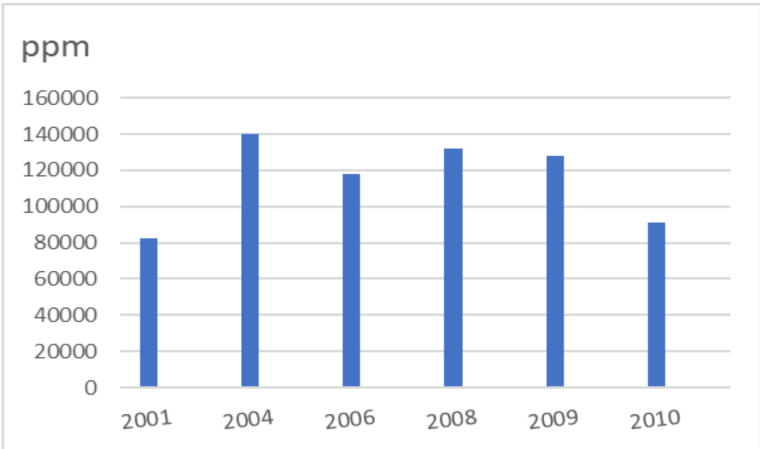

Fig. 7. Dissolved nitrogen (N2) in (ppm) between the period 2001 until 2010.

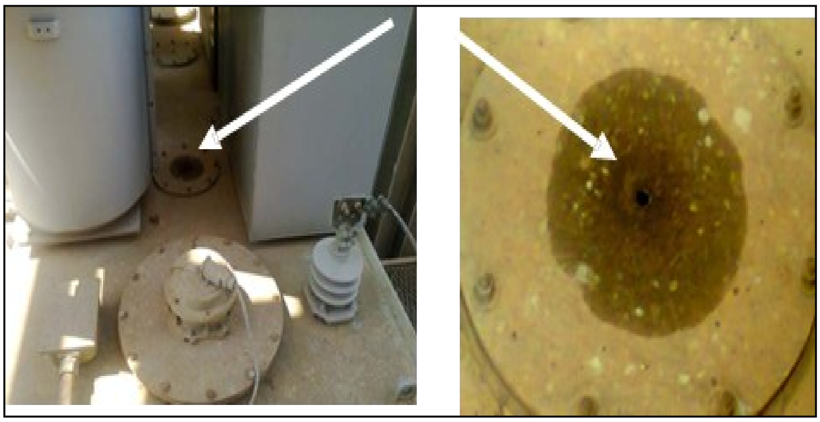

Fig. 8. Atmospheric air leakage in the under-study Transformer [4].

In order to check the accuracy of the proposed *INDMM*, the measurements of the main five hydrocarbon gases were extracted from DGA during the period between 1999 and 2013 in order to identify the centroid and the fault inside the transformer. The results indicated that the transformer was in normal operation during the time interval between 1999 and 2000. Later the defect of atmospheric air leakage took place as mentioned in Fig. 6. Consequently, this oil/air interface provided oil contamination layer with dust and moisture. As a result, the dielectric strength decreased and contradictorily, the power angle loss increased. This increase in the power losses appeared in the form of temperature rise (T2) in the period between 2003 to 2004. The power losses continued its significant increase due to insulating oil oxidation in presence of moisture and in turn the temperature inside the transformer also rose. During this increase in the temperature the oil insulation decomposed into different gases, air bubbles appeared in the surface of the oil. These bubbles discharged inside the whole insulating material and PD sound has been detected during 6/2004 where oil Purification was done and transformer load was lighted. Thus, the majority of the load of this transformer has been removed by the substation operating team. Consequently, the temperature inside the transformer decreased and the centroid of the five gases has been shifted to be located in (T1) fault zone, in 2008 transformer load was completely removed and transformer was still in service so the transformer temperature was decreased to sub fault (S).

After the air leakage defect in 2009, complete maintenance was implemented, the insulating oil was purified, and the defect of leakage air was treated, while the transformer temperature was still at sub fault (S) with transformer full load. Table 3 shows the proposed INDMM in the five-time intervals, IEC 60599 diagnostic method results achieved ≈ 91% of all results of the proposed *INDMM* in this case study since Duval pentagon is more accurate.

6.2. Case Study II

Main, start-up and auxiliary transformers in some power plants were removed from service and visually inspected by experienced maintenance engineers and the fault clearly identified. DGA in oil results were available in all these cases for diagnostic purposes, a comparison between the actual fault by inspection, laboratory diagnostic by various methods, the proposed modified Duval pentagon and *INDMM* shows that all results are identical except the last result as shown in Table 4, the results shows that the accuracy of proposed method reached 88.89 % in this case study.

6.3. Case Study III

Md Farooque etc. al. [37] applied Duval pentagon graphical diagnostic technique on a dataset of actual various faults which have been identified practically, the faulty equipment have been visually investigated by experienced experts and maintenance engineers [37, 38], the accuracy of Duval pentagon graphical technique has been evaluated by comparing the fault identified by DGA with the measured fault practically, the accuracy of Duval pentagon graphical technique has been evaluated by comparing the fault identified by DGA with the measured fault practically. In the current research the type of these faults will be estimated using the proposed modified Duval pentagon and *INDMM*, then the accuracy of the proposed modified techniques are evaluated. Table 5 illustrates the relative percentage of the five gathered hydrocarbon gases in each case, the corresponding centroid coordinates, and the estimated fault type not only by traditional Duval pentagon but also by the proposed modified Duval pentagon and *INDMM* techniques. It is clear that the proposed modified methods accuracy identified the fault in 70 % of the cases studied in Table 5. Although the traditional graphical and the proposed techniques yield identical results except the last result in that table, this is due to errors in calculating the cartesian centroid coordinates using the traditional lengthy and complex method, which consequently shifted the fault diagnostic from high energy discharge (D2) to (T3) high temperature fault ≥ 700 °C also change in the measured accuracy.

Table 3. Diagnostic and evaluation of under study transformer using (DGA) by modified Duval pentagon and INDMM.

Date of (DGA) Test	H_2	C_2H_6	CH_4	C_2H_4	C_2H_2	Diagnostic by Duval Pentagon	Diagnostic by IEC50699	Diagnostic by modified Duval Pentagon using A MATLAB Code		
								Cx	Cy	Diagnostic by *INDMM*
3/1999	78	12	24	16	0	(S)	T < 150°C	-3.1633	9.4923	(S) Normal.
5/2000	78	25	35	30	0			-4.5190	4.8090	
7/2003	27	19	33	24	0	(T2)	T2	-6.1890	-5.4800	(T2) Oil-Air interface.
5/2004	4	43	102	57	0			-9.4090	-16.358	
6/2004	7	24	9	12	0	(T1)	T1	-12.660	0.8030	(T1) Light load, with PD sound inside transformer, oil purification.
1/2006	31	40	40	38	0			-7.5650	-3.8040	
5/2008	27	13	7	14	0	(S)	Normal	-5.500	9.1800	(S) Load removed, but transformer in service.
5/2009	68	11	4	5	0		T3	-3.9070	24.848	
8/2009	71	22	32	11	0	(S)	Normal	-6.0850	8.9720	(S) Purification of insulating oil and prevent atmospheric air leakage, transformer in service full load.
6/2001	26	3	6	2	0		Normal	-3.0490	16.2823	
2/2013	58	20	17	15	0		Normal	-5.5640	11.270	

6.4. Case Study IV

IEC TC 10 [38] introduced database of not only faulty equipment that have been removed from service, but also observation of thousands of operating transformers that operates in more than fifteen individual networks. The faulty equipment has been visually investigated by experienced experts and maintenance engineers in order to identify the faults that cause these equipment urgently to be removed from their electrical grids.

Table 4. Comparison between actual fault, identification results by various methods in the laboratory, visually inspection, proposed modified technique and INDMM.

Actual Fault Type	(DGA) in oil ppm					laboratory diagnostic by various methods	Diagnostic by modified Duval Pentagon using A Matlab code		
	H_2	C_2H_6	CH_4	C_2H_4	C_2H_2		Cx	Cy	Diagnostic by *INDMM*
T1	3	278	157	12	0	T1	-25.4804	-3.15970	T1- O
T2	12	6	41	15	0	T2	-8.27590	-16.6896	T2-C
T1	8	109	121	35	0	T1	-17.4163	-8.97580	T1- O
T1	37	62	82	11	0	T1	-15.0490	-3.75110	T1- O
T1	7	48	76	14	0	T1	-17.4695	-10.9443	T1- O
T1	3	39	45	12	0	T1	-17.6347	-9.19670	T1- O
T3	104.262	125.731	228.428	590.298	0.696	T3	3.58130	-16.4711	T3-H
T3	73.434	86.642	140.729	471.789	0.236	T3	5.28010	-16.9195	T3-H
T1	12.987	2.075	0.380	6.720	0.016	T3	-2.22330	17.4161	S

Table 5. Comparison between fault identification results by Duval traditional graphical technique, proposed modified Duval pentagon and INDMM.

Actual Fault Type	H_2 [%]	C_2H_6 [%]	CH_4 [%]	C_2H_4 [%]	C_2H_2 [%]	Diagnostic by traditional Duval pentagon			Diagnostic by modified Duval Pentagon using A Matlab code		
						Cx	Cy	Diagnostic and notice	Cx	Cy	Diagnostic by *INDMM*
PD	92.8	0.44	6.75	0	0	-0.228	28.76	PD	-0.2292	28.7601	PD
PD	94.96	0.62	4.32	0.02	0.02	-0.235	30.22	PD	-0.2344	30.2627	PD
D1	5.26	0	0	28.2	66.4	26.57	- 0.765	D1	26.6124	-0.7663	D1
D1	47.5	4.5	22.9	9.6	15.3	-0.758	1.175	T1	-0.7308	1.2011	T1-O
D2	37.9	2.16	7.7	18.4	33.7	10.53	-1.04	D2	10.5517	-1.0476	D2
D2	29.1	1.41	11.4	20.34	37.6	11.87	-2.71	D2	11.8882	-2.7189	D2
T1&T2	24	17.28	40.72	21	0.6	-7.54	-8.41	T1&T2	-7.2852	-8.1268	T2-C
T1&T2	92.19	0.19	6.76	0.13	0	-0.38	28.30	PD	-0.2035	27.3681	PD
T3	8.47	8.73	28.22	52.89	1.66	3.11	-18.55	T3	3.1165	-18.5581	T3, T3-H
T3	15.55	7.4	7.4	41.93	6.35	2.14	-14.79	T3	7.4032	-10.8159	D2

Interpretation of (DGA) results of these faulty equipment has been introduced later in IEC60599 [35]. Six main faults have been studied in this publication. PD, D1, D2, T1&T2, and T3, are the main six faults that have been introduced in IEC 60599. The faults inside the investigated faulty equipment's have been classified into these faults. In this paper the faults inside the faulty equipment have been identified by the proposed modified Duval pentagon depending on DGA results. The faults inside the investigated faulty equipment's have been classified into these faults. The whole number of the faulty equipment that have been introduced in IEC TC 10 was 117 equipment [38]. It has been illustrated that nine of these equipment have been removed from the service as a result of (PD) fault, however forty-eight equipment have been removed due to (D2) fault. Sixteen equipment have been removed from their grids due to (T1&T2) faults and eighteen equipment have been removed in consequence of (T3) faults, finally, twenty-six equipment have been removed as a result of (D1) fault. The percentage of the accurate prediction of each fault type is presented in Fig. 9. It is clear that the proposed modified Duval and *INDMM* give high accurate fault interpretation in cases of (D2) and (T3) faults with accuracy level higher than 83 %. However, the accuracy of fault interpretation using of proposed Duval pentagon and *INDMM* decreased to be 78% in case of (PD) fault and 69% in case of (T1&T2) fault. The worst fault identification accuracy has been recorded in (D1) fault with accuracy 23% of the studied cases which represented the original Duval pentagon accuracy for this type of fault in this case study only. This may be due to uncertainty on ppm values coming from laboratories of oil samples, where a typical laboratory accuracy ± 15 %, or inaccuracies in the measurement of the dissolved gases in oil or sample contamination [29] or/and the actual visual inspection of the studied cases due to a mixture (multiple) faults and may be improved for other cases for this fault type in other case studies. The overall fault interpretation accuracy in this case study reached 69.23 % of the whole faulty equipment instead of approximately 87 % as mentioned in ref. [37], this is due to errors in calculating the centroid coordinates in some cases using the traditional lengthy and complex method. However, the proposed modified Duval pentagon identifies the fault more easily and quickly without errors in calculating the centroid coordinates or in determining the fault location in the Duval pentagon map and in a simpler way, due to its reliance on MATLAB software instead of the manual method. It is worth to mention that the dataset has been presented in 1999, however, Duval pentagon was firstly introduced in 2014. Thus, the fault in this case has not identified previously by Duval pentagon. As a result, the identified accuracy represents the accuracy of not only modified Duval pentagon and *INDMM* but also the traditional graphical Duval pentagon itself.

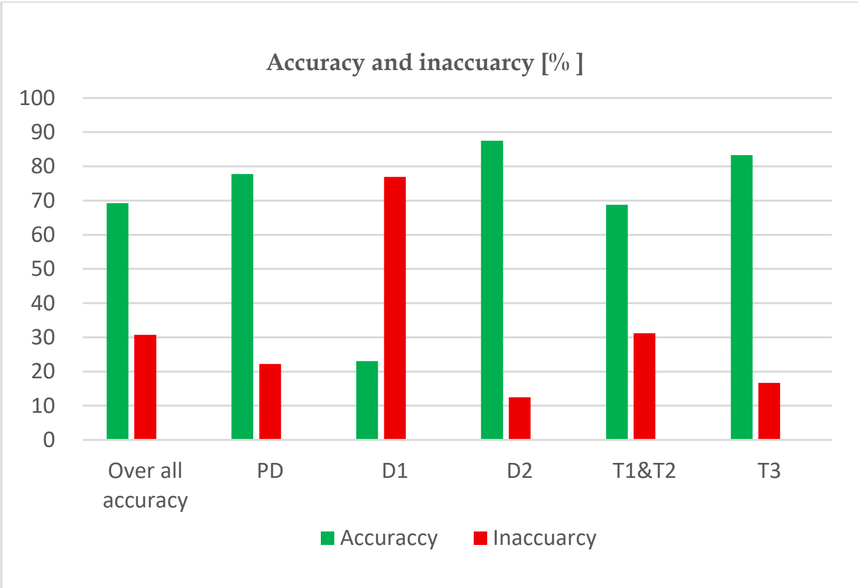

Fig. 9. The percentage of the accurate prediction of the fault.

6.5. Case Study V

A brief description of the selected cases and the summary of the problem found during internal inspection are indicated in Table 6, reference of CIGRE document. diagnostic found by the utilization of both Pentagon 1 and 2, and the Combined Pentagons for basic faults and sub faults [29]. When we using the proposed modified technique and *INDMM*, the results are identical expect the case in raw number 4 in that table, the proposed techniques detect sub-fault T3-C instead of T3-H. This may be due to errors in calculating the centroid coordinates or/and in determining the fault location in Duval pentagon 2, and the Combined Pentagons maps where the centroid coordinates were very close to sub fault (C) zone, so that the proposed modified technique and *INDMM* is correctly diagnose five basic faults and four sub faults achieving 90 % accuracy in this case study.

6.6. The Overall Duval Pentagons Accuracy

When applying the traditional Duval pentagons 1, 2 and combined to real-world cases, to measure the actual overall accuracy of traditional Duval pentagons. For previous case studies. For case 1, diagnosed all faults correctly achieving 100 %. Case 2 indicates that misdiagnosis one state and diagnose the rest correctly achieving accuracy 88.9 %. Case 3 which is a part of case 4 which misdiagnosis thirty-six states and correctly diagnosed the rest of 117 states achieving accuracy of 69.23%.

Table 6. Comparison between actual fault, identification results by reference of CIGRE document [29], proposed modified Duval pentagon and INDMM.

H_2	CH_4	C_2H_2	C_2H_4	C_2H_6	Pentagon			Internal Inspections	Diagnostic by modified Duval Pentagon using A Matlab code		
					1	2	compound		Cx	Cy	*INDMM*
29	204	0	17	264	T1	O	T1-O	Overheated iron sheets	-22.2390	-4.2597	T1-O
555	1050	29	3520	489	T3	T3-H	T3-H	Burned selector in oil	6.3132	-18.2016	T3-H
754	2647	6	2590	1127	T2	C	T2-C	Carbonized leads	-3.9147	-14.6399	T2-C
2070	31879	55	38192	1127	T3	C	T3-C	Carbonized paper	1.3917	-25.2960	T3-H
6	46	0	9	12	T1	C	T1-C	Carbonized winding turns	-13.6591	-15.9323	T1-C

For the last case study, one wrong diagnosis is detected achieving accuracy (5+4)/10 = 90 % for basic fault and sub fault. Therefore, the overall accuracy of traditional Duval pentagons reaches 109/147 ≈ 74.15 % in this case studies, also the results of modified technique and *INDMM* are identical. Duval Pentagon geometry is taken as the idle common technique used in to identify the fault inside transformers and the result of comparing the proposed numerical modified technique reaches 100 % accuracy of traditional Duval pentagon. However, when training SVM with a large dataset which contains 47755 samples, the smart model reduces the accuracy to reach 98.1% because of false prediction.

7. CONCLUSIONS

Although power transformers must be properly maintained to have optimal performance, the cost of maintained these expensive electrical components has made it necessary to seek for alternatives. Consequently, *INDMM* is presented in this paper. A dataset is generated by applying the methodology which involves calculating the gas concentration ratios, determining centroid coordinates using a mathematical model, and applying predefined inequalities to classify faults. The dataset is then used to build the smart model with help with the Fine-tuned Gaussian SVM. *INDMM* is then used directly to identify the transformer fault in seconds after measuring the five gas ratios. The results confirm that the proposed method provides an effective, reliable, and scalable solution for transformer condition monitoring and early fault detection achieving Duval pentagon accuracy after testing it against five case studies. In real-world, oil samples of periodically maintained or faulted transformers in electrical stations and power plants can be sent to central laboratories, to be analyzed and diagnose the faults. Each transformer in a network is given a comprehensive record, which is saved on the cloud for online monitoring. This allows specialists to use the proposed *INDMM* to identify the faults that the transformer in the electrical power system has been exposed to and view the transformer's history via the internet of things (IOT), online monitoring systems, or portable field devices.

FUTURE WORK

Since the chosen smart algorithm is not the main backbone of the work, the simplest comparable algorithm – SVM – is chosen. Deep Learning Algorithms are recommended to implement the proposed Numerical Duval Modification Model and test it against the current INDMM which used SVM to enhance the results.

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