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Hybrid Condition Monitoring System for Power Transformer Fault Diagnosis

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Abstract: The important parts of a transformer, such as the core, windings, and insulation materials, are in the oil-filled tank. It is difficult to detect faults in these materials in a closed area. Dissolved Gas Analysis (DGA)-based fault diagnosis methods predict a fault that may occur in the transformer and take the necessary precautions before the fault grows. Although these fault diagnosis methods have an accuracy of over 95%, their validity is controversial since limited data are used in the studies. The success rates and reliability of fault diagnosis methods in transformers, one of the most important pieces of power systems equipment, should be increased. In this study, a hybrid fault diagnosis system is designed using DGA-based methods and Fuzzy Logic. A mathematical approach and support vector machines (SVMs) were used as decision-making methods in the hybrid fault diagnosis systems. The results of tests performed with 317 real fault data sets relating to transformers showed accuracy of 95.58% using a mathematical approach and 96.23% using SVMs.

Keywords: transformers; dissolved gas analysis; fuzzy logic; support vector machine; hybrid

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1. Introduction

According to research conducted by the Conseil International des Grands Réseaux Electriques (CIGRE), the annual failure rate of power transformers is 0.53% [1]. Failure to provide electrical energy as a result of transformers being out of service due to faults will lead to great economic losses [2]. For this reason, the uninterrupted operation of power transformers is vital for energy continuity [3]. In the case of faults in transformers, some gases occur due to electrical and thermal effects. DGA-based methods detect the fault by analyzing these gases [3–5]. Kalinda et al. [5] used the Rogers Ratio Method (RRM), International Electrotechnical Commission (IEC) Ratio Method (IRM), and Duval Triangle Method (DTM) together with Artificial Neural Networks (ANN) in their studies. They obtained high accuracy with the model supported by ANN. An interface was also developed in the Matlab environment in this study. Lin et al. [6] developed a combined model using the RRM, IRM, Doernenburg Ratio Method (DRM), and Key Gas Method (KGM). The model was tested with 101 data sets and reached 93.8% accuracy. Ghoneim et al. [7] proposed a prediction model based on gas concentrations using 386 data sets. The proposed model predicted failures with an accuracy of 71.5%. In the analysis of Siada et al. [8], the success rates of the KGM, DRM, RRM, IRM, and DTM were 86.7%, 57%, 50%, 51.7%, and 88%, respectively. Using these methods with Fuzzy Logic (FL), they then predicted eight faults correctly. Guardado et al. [9] obtained success rates ranging from 87% to 100% using ANN for five fault diagnosis methods with 33 data sets. Apte et al. [10] increased the success rates of the RRM and IRM methods by using these methods together with FL. Ghoneim et al. [11] proposed a fault prediction model by combining the DTM, RRM, and IRM methods with a mathematical approach. The model predicted faults with 85.2% accuracy in 386 data sets. Ibrahim et al. used the neural pattern-recognition technique on 446 data set samples to diagnose transformer fault types and obtained 92.8% accuracy [12]. Xing et al. used a deep learning neural network (DLNN) to detect the health status of power transformers. A total of 335 case data sets from 12 transformers located in a substation in Wuhan, China, and 42 case data sets collected from reference sources were used. An accuracy of 95.18 $\pm$ 0.81 was obtained when the DLNN method was used in the determination of transformer health status [13]. Li et al. proposed a fault diagnosis model for transformers that contains adaptive synthetic oversampling, the reconstructed data method, and an improved deep coupled dense convolutional neural network. The IEC TC 10 data and collected data were used as the test data. The accuracy of the proposed fault diagnosis model reached 94.05% [14]. Ricardo Manuel Arias Velasquez was able to detect partial discharge with 97.55% accuracy, thermal error with 93.10% accuracy, and remaining life of the transformer with 85.88% accuracy through his method that used soft techniques such as a support vector machine (SVM) and tree models (TM) [15]. Hua et al. set up three error diagnostic models based on multiclass relationship vector machines (MRVMs), multiclass support vector machines (MSVMs), and Back Propagation Neural Networks (BPNN). They also used Particle Swarm Optimization (PSO) to increase the accuracy of these models. They achieved 88.60% diagnostic accuracy with the created algorithm [16].

Although high success rates have been achieved in most of the studies in the literature, these studies were carried out with a small data set. In studies with large data sets, predictions could not be made with high accuracy. In this study, the KGM, Simplified IEC Method (SIM), and DTM methods were preferred and combined with FL instead of the DRM, RRM, and IRM methods that have achieved low success rates. Fuzzy-based fault diagnosis models were tested with 317 data sets from IEC TC 10 Data Base, TEIAS (Turkish Electricity Transmission Corporation), references [7,8]. The proposed hybrid system processes the results of the FL-based KGM, DTM, and SIM methods with a mathematical approach or SVMs and is able to achieve fault prediction with higher accuracy. In Section 2, the DGA fault diagnosis methods are explained. The application of FL to prediction methods is represented in Section 3. Section 4 clarifies the details of the fault diagnosis methods used in the hybrid system. The test results of the proposed hybrid systems are given in Section 5. Section 6 summarizes and discusses the findings.

2. DGA-Based Fault Diagnosis Methods

Electrical and thermal faults cause the release of hydrogen (H_2), methane (CH_4), ethane (C_2H_6), ethylene (C_2H_4), acetylene (C_2H_2), carbon monoxide (CO), and carbon dioxide (CO_2) gases in transformer oil. The amounts of these gases released through the deterioration of transformer oil or cellulose paper are expressed as PPM (Part Per Million) [2,7]. The IEEE C57.104-2019 [17] and IEC 60599:2015 [18] standards are used to analyze gases occurring in electrical and thermal faults in transformers. These standards explain fault types and DGA fault diagnosis methods in detail.

2.1. KGM—Key Gas Method

The KGM uses the individual concentrations of the six fault gases (H_2, CH_4, C_2H_6, C_2H_4, C_2H_2, CO) to detect transformer faults. These six gases, referred to as Total Combustible Gas (TCG), occur if there is a fault in the transformer's oil. Additionally, the KGM is one of the best methods for determining the normal situation of a transformer through DGA using the absolute amount of TCG. Table 1 shows the relationship between the amount of gas produced and the fault [18].

Table 1. Key Gas Method [17].

Key Gas	Fault Type	Typical Proportions of Generated TCG
(C_2H_4)	Thermal mineral oil	Predominantly C_2H_4 with smaller proportions of C_2H_6, CH_4, and H_2. Traces of C_2H_2 at very high fault temperatures.
(CO)	Thermal mineral oil and cellulose	Predominantly CO with much smaller quantities of H_2 Gases. Predominantly C_2H_4 with smaller proportions of C_2H_6, CH_4, and H_2.
(H_2)	(PD)	Predominantly H2 with small quantities of CH_4 and traces of C_2H_4 and C_2H_6.
(H_2, C_2H_2)	(Arcing)	Predominantly H_2 and C_2H_2 with minor traces of CH_4, C_2H_4, and C_2H_6. CO is also present if cellulose is involved.

Table 2 shows the typical gas concentration values observed in power transformers [18].

Table 2. Typical gas concentration values [18].

Key Gas	[PPM]
Hydrogen (H_2)	50–150
Methane (CH_4)	30–130
Carbon monoxide (CO)	400–600
Acetylene (C_2H_2)	
Ethylene (C_2H_4)	60–280
Ethane (C_2H_6)	20–90
Carbon dioxide (CO_2)	3800−14,000

2.2. DTM—Duval Triangles Method

This method predicts DGA data through a graphical representation. Duval's triangle has seven fault zones, as shown in Figure 1. It uses the concentrations of relative % values of CH_4, C_2H_2, and C_2H_4 at the sides of the triangle. The triangle's coordinates can be calculated using Equations (1)–(3) [19].

$$\%C_2H_2 = 100 \cdot x/(x+y+z) \tag{1}$$

$$\%C_2H_4 = 100 \cdot y/(x+y+z) \tag{2}$$

$$\%CH_4 = 100 \cdot z/(x+y+z) \tag{3}$$

x = (C_2H_2), y = (C_2H_4), and z = (CH_4) in ppm.

These relative % values are the coordinates of the DGA point in the Duval triangle [17–19].

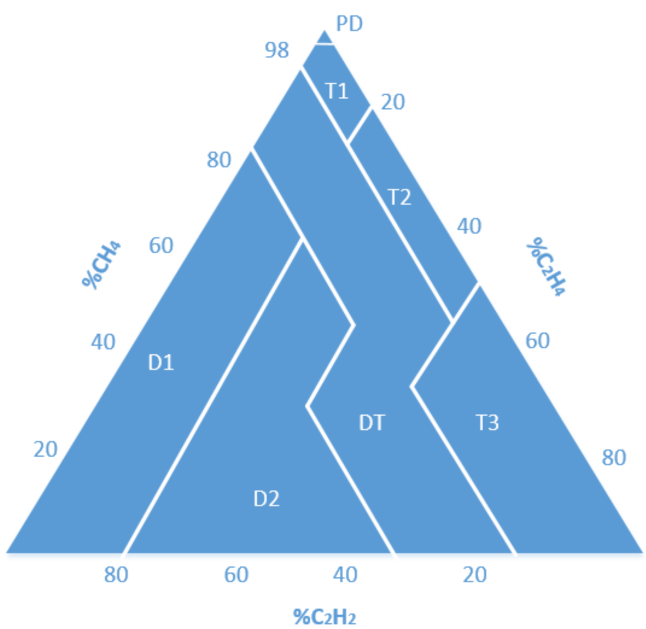

Figure 1. Coordinates and fault zones of the triangle.

D1 and D2, shown in Figure 1, represent high and low energy arcs, partial discharge (PD), T1, T2, and T3 thermal faults at various temperatures, and DT, a mixture of arc and thermal faults [19]. According to the relative percentages of the gases, lines are drawn from all three sides of the triangle parallel to the side reference lines. The region where the intersection of these lines is located is the fault prediction of the DTM [20].

2.3. SIM—Simplified IEC Method

This method interprets faults using the ratios of gases to each other [21,22]. The rules for this method are given in Table 3 and are defined in IEC-60599-2015 [18]. According to Table 3, if the CH_4/H_2 ratio is less than 0.2, the fault is PD. If another C_2H_2/C_2H_4 ratio is higher than 0.2, the fault is an arc; otherwise, it is a thermal fault.

Table 3. Simplified scheme of interpretation [18].

Case	C_2H_2/C_2H_4	CH_4/H_2
PD		<0.2
Arc	>0.2	
Thermal	<0.2	

3. Application of Fuzzy Logic to Fault Diagnosis Methods

Fault diagnosis methods give unclear or inaccurate results in some cases. For this reason, FL has been applied to fault diagnosis methods. The application of FL to the KGM, SIM, and DTM diagnosis methods was performed using LabVIEW Fuzzy System Designer (LFSD) tools. Figure 2 shows the Fuzzy Logic structure used in the study.

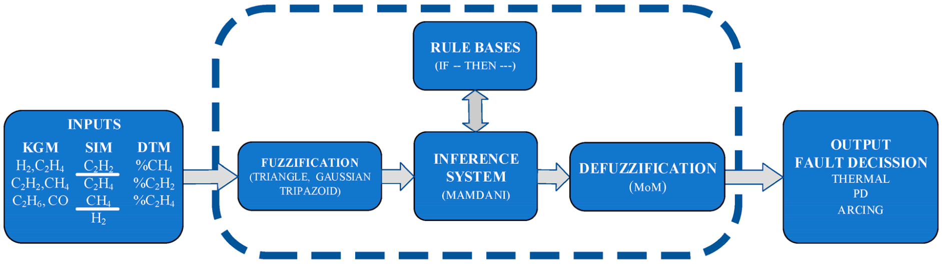

Figure 2. Fuzzy Logic flow chart.

The amount of gases, the ratio of the amounts to each other, and the percentages of the relative ratios were used as input information (C_2H_2/C_2H_4 and CH_4/H_2 gas amounts for the SIM; H_2, CH_4, C_2H_2, C_2H_4, C_2H_6, and CO gas amounts and their relative percentages for the KGM; and $\%CH_4$, $\%C_2H_4$, and $\%C_2H_2$ for the DTM). The triangle, gaussian, and trapezoid functions are determined by a trial-and-error method and used as membership functions. The limits of the input membership functions are determined according to the limit values of the diagnostic methods. Since the limits of the input values are not case parameters, they can be applied to all cases regardless of transformer values. As can be seen in Figure 3, the output membership function is formed to represent the thermal fault, partial discharge, arc fault, and out of code states. The rule base was created according to the rules of the DGA-based fault diagnosis methods used. Mamdani was chosen as the inference method, and Mean of Max was chosen as the defuzzification method.

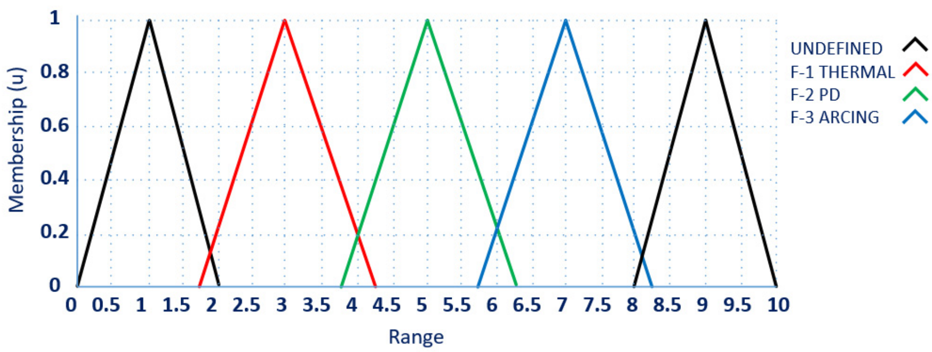

Figure 3. Output membership functions.

The Fuzzy Logic-based SIM (FSIM), Fuzzy Logic-based KGM (FKGM), and Fuzzy Logic-based DTM (FDTM) methods were checked with 317 data sets, and accuracy rates of 92.11%, 88.64%, and 94.64%, respectively, were obtained. According to Table 4, the FDTM created with the DTM gave the most accurate results by making 98.675% and 92.308% accurate predictions for thermal faults and arc faults, respectively, while the FKGM is shown to be superior to other models with 95.65% accuracy for PD faults. While the FSIM obtained successful results for thermal and arc faults, it showed the lowest performance in PD faults. In Table 4, "AI" indicates the 'Accuracy Index' parameter of each method according to the fault.

Table 4. Accuracy index values.

	Thermal			PD			Arc		
Method	**Accu. Cases**	**Inaccu. Cases**	**AITH**	**Accu. Cases**	**Inaccu. Cases**	**AIPD**	**Accu. Cases**	**Inaccu. Cases**	**AIARC**
FKGM	138	13	91.391%	22	1	95.65%	121	22	84.615%
FSIM	147	4	97.351%	18	5	78.26%	127	16	88.811%
FDTM	149	2	98.675%	19	4	82.61%	132	11	92.308%

4. Hybrid Condition Monitoring System (HCMS)

In this study, two different Hybrid Condition Monitoring Systems (HCMSs) are proposed that use an FL-based mathematical approach and SVM to make predictions with high accuracy. Both hybrid systems have advantages over each other. The hybrid system, which classifies with a mathematical approach, was designed only in the LabVIEW environment. On the other hand, the system that classifies with an SVM provided higher accuracy after being designed in the LabVIEW and Matlab environments.

4.1. The HCMS with a Mathematical Approach

The proposed HCMS is a hybrid system that uses the combination of FL and a mathematical approach to predict with high accuracy. This system analyzes the results of the FL-based FKGM, FSIM, and FDTM fault diagnosis models with a mathematical approach and makes fault predictions. Figure 4 shows a flow chart of the system.

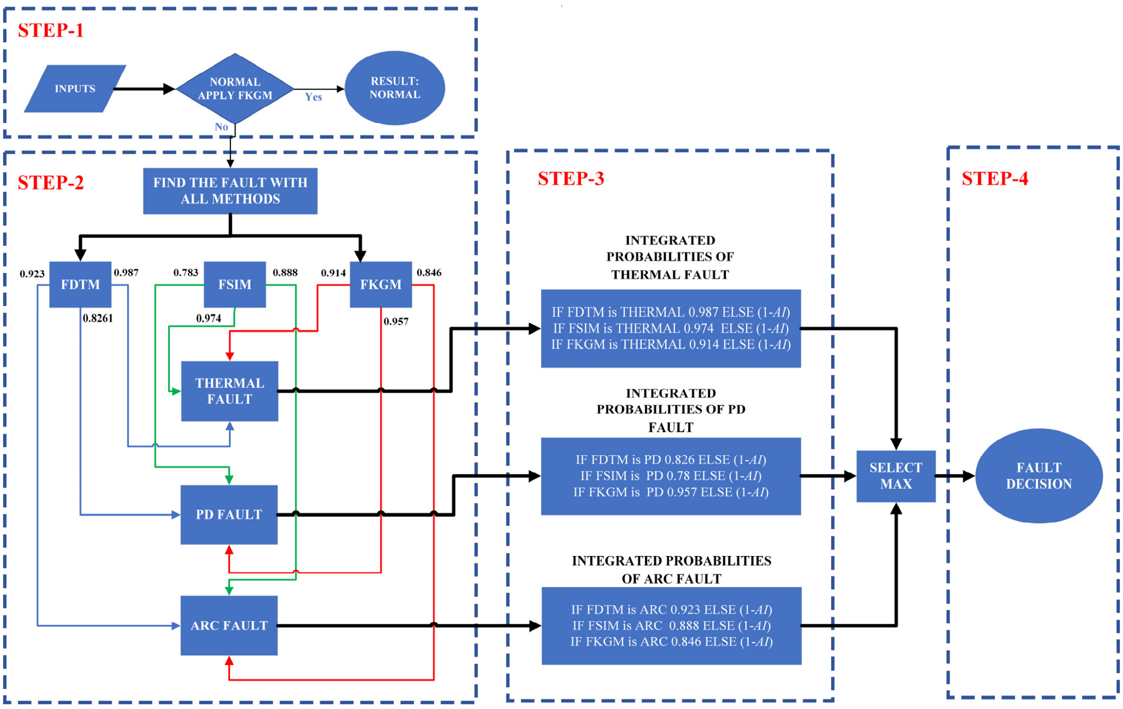

Figure 4. HCMS flow diagram.

The operation of the three-step model, whose flow diagram is given in Figure 4, starts with the user entering the gas quantities. In Step 1 specified in the diagram, whether or not there is a fault in the transformer is determined using the FKGM. If there is no fault, the next sections are not passed and the normal operational information of the transformer is given as output. If there is a fault, it is passed to Step 2, where the FKGM, FSIM, and FDTM methods are used for analysis. The probability of each fault according to the relevant method is known as 'discrete error probability' and is calculated by Equation (4)–(12) [23]. 'AI' values are given in Table 4. The 'x' value is the fault output of the FL-based models in the LabVIEW program. Step 3 aims to find error probabilities and choose the largest one. After calculating the discrete error probabilities, the 'integrated probabilities' of each fault are calculated in Step 3 according to Equations (13)–(15) [23]. The most probable fault as a result of the calculation will be the output of the hybrid model.

$$f_{KGM}^{th}(x) = \begin{cases} AI_{Th}, x = Thermal \\ 1 - AI_{PD}, x = PD \\ 1 - AI_{Arc}, x = Arc \end{cases} \tag{4}$$

$$f_{SIM}^{th}(x) = \begin{cases} AI_{Th}, x = Thermal \\ 1 - AI_{PD}, x = PD \\ 1 - AI_{Arc}, x = Arc \end{cases} \tag{5}$$

$$f_{DTM}^{th}(x) = \begin{cases} AI_{Th}, x = Thermal \\ 1 - AI_{PD}, x = PD \\ 1 - AI_{Arc}, x = Arc \end{cases} \tag{6}$$

$$f_{KGM}^{pd}(x) = \begin{cases} 1 - AI_{Th}, x = Thermal \\ AI_{PD}, x = PD \\ 1 - AI_{Arc}, x = Arc \end{cases} \tag{7}$$

$$f_{SIM}^{pd}(x) = \begin{cases} 1 - AI_{Th}, x = Thermal \\ AI_{PD}, x = PD \\ 1 - AI_{Arc}, x = Arc \end{cases} \tag{8}$$

$$f_{DTM}^{pd}(x) = \begin{cases} 1 - AI_{Th}, x = Thermal \\ AI_{PD}, x = PD \\ 1 - AI_{Arc}, x = Arc \end{cases} \tag{9}$$

$$f_{KGM}^{arc}(x) = \begin{cases} 1 - AI_{Th}, x = Thermal \\ 1 - AI_{PD}, x = PD \\ AI_{Arc}, x = Arc \end{cases} \tag{10}$$

$$f_{SIM}^{arc}(x) = \begin{cases} 1 - AI_{Th}, x = Thermal \\ 1 - AI_{PD}, x = PD \\ AI_{Arc}, x = Arc \end{cases} \tag{11}$$

$$f_{SIM}^{arc}(x) = \begin{cases} 1 - AI_{Th}, x = Thermal \\ 1 - AI_{PD}, x = PD \\ AI_{Arc}, x = Arc \end{cases} \tag{12}$$

$$f_{Thermal} = f_{KGM}^{th}(x) \cdot f_{SIM}^{th}(x) \cdot f_{DTM}^{th}(x) \tag{13}$$

$$f_{PD} = f_{KGM}^{pd}(x) \cdot f_{SIM}^{pd}(x) \cdot f_{DTM}^{pd}(x) \tag{14}$$

$$f_{Arc} = f_{KGM}^{arc}(x) \cdot f_{SIM}^{arc}(x) \cdot f_{DTM}^{arc}(x) \tag{15}$$

The hybrid system in which the mathematical approach was used was developed in LabVIEW, and the GUI shown in Figure 5 was created for user convenience.

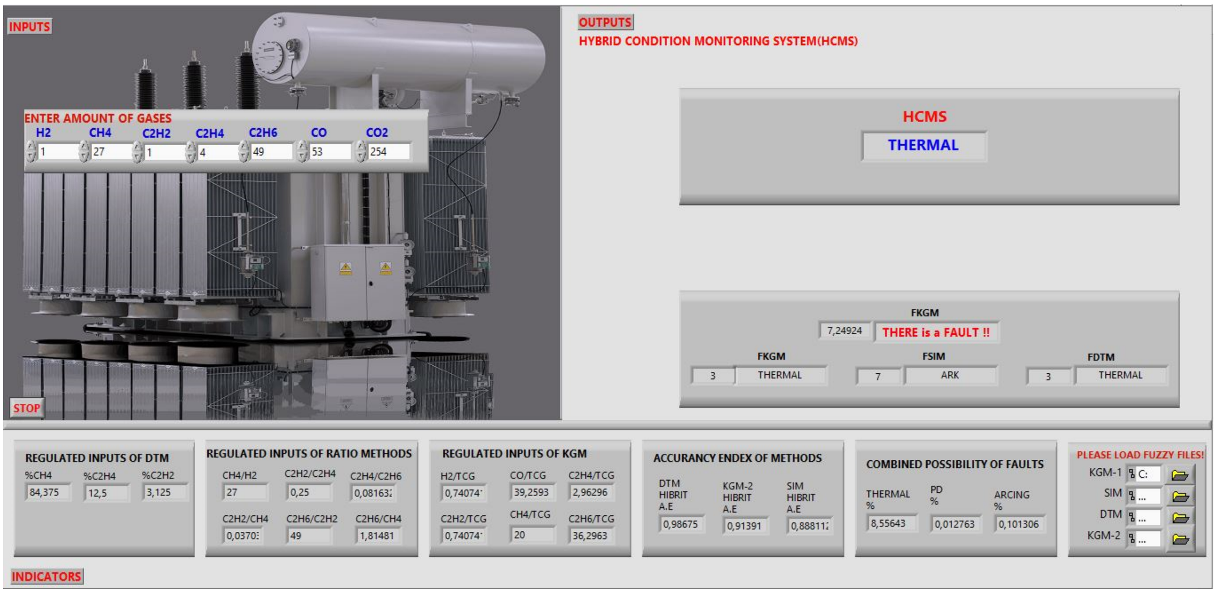

Figure 5. LabVIEW front panel.

4.2. HCMS with an SVM

The other recommended HCMS is a hybrid system that combines FL and SVMs. The system classifies the results of the Fuzzy Logic-based FKGM, FSIM, and FDTM fault diagnosis models with an SVM and makes fault predictions.

$$\begin{cases} w^T x_i + b \geq 1 - \xi_i, y_i = 1 \\ w^T x_i + b \geq -1 + \xi_i, y_i = -1 \\ \xi_i \geq 0, \forall_i \end{cases} \tag{16}$$

$$\begin{cases} \min \frac{\|w\|^2}{2} + C \sum\limits_{i=1}^{n} \xi_i \\ y_i(w^T x + b) \geq 1 - \xi_i \\ \xi_i \geq 0 \end{cases} \tag{17}$$

For data that cannot be classified linearly using a SVM, the extreme plane should satisfy the inequalities in Equation (16), and the best extreme plane is found with the inequalities in Equation (17). The ξ_i slack variable shows examples of misclassification. C is the penalty parameter, which is a positive number. Classification performance depends on how the penalty parameter is set.

In addition, for data that cannot be classified linearly, the kernel function is used to move the data to the high-dimensional feature space, and the best extreme plane here is determined by Equation (18). The radial basis kernel (Equation (19)) is one of the most commonly used kernel approaches in SVMs. With the width of the σ expression, the best value is selected in all iterations [24,25].

$$f(x) = \text{sgn}(\sum_{i=1}^{m} \alpha_i y_i K(x_i, x_j) + b) \tag{18}$$

$$K(x_i, x_j) = \exp(-\frac{\|x - y\|^2}{2\sigma^2}) \tag{19}$$

STPRtool (statistical pattern recognition toolbox), developed in the Matlab environment by Franc and Hlavac [26], was used to develop SVM for the classification of FKGM, FSIM, and FDTM fault diagnosis results. A one-versus-one approach was used in this study for the multi-classification application of SVMs, which is a binary classifier. Half of the 317 data sets were used as training data, and the other half were used as test data.

5. Results

A hybrid system was designed by using the KGM, SIM, and DTM, which are basic Dissolved Gas Analysis methods that were developed to diagnose the condition of oil-type transformers. The performance of the system was tested with 317 data sets from IEC TC 10 Data Base, TEIAS [7,8]. Table 5 shows the data of some faulty transformers and the results obtained from the mathematical approach we designed.

Table 5. Output examples of the HCMS with a mathematical approach *.

	Data from Faulty Transformers								HCMS Results			
	Real Fault	**H_2**	**CH_4**	**C_2H_2**	**C_2H_4**	**C_2H_6**	**CO**	**CO_2**	**FSIM**	**FDTM**	**FKGM**	**OUTPUT**
1	Thermal	1	27	1	4	49	53	254	ARC	Thermal	Thermal	Thermal
2	Thermal	48	610	-	10	29	1900	970	Thermal	PD	Thermal	Thermal
3	Thermal	40,000	400	6	600	70	800	218	Thermal	Thermal	PD	Thermal
4	Thermal	150	22	11	60	9	-	-	Thermal	Thermal	ARC	Thermal
5	PD	9340	995	7	6	60	60	620	ARC	PD	PD	PD
6	PD	40,280	1069	1	1	1060	1	-	PD	PD	PD	PD
7	PD	26,788	18,342	-	27	2111	704	-	Thermal	PD	PD	PD
8	PD	106	4	0	1	2	-	-	PD	Thermal	PD	PD
9	Arc	2510	202	1730	208	139	-	-	PD	Arc	Arc	Arc
10	Arc	169	38	5.8	6.5	48.5	-	-	Arc	Arc	PD	Arc
11	Arc	17	42	20	12	192	-	-	Arc	Arc	Thermal	Arc
12	Arc	522	50	27	23	8	672	2294	PD	Arc	Thermal	Arc

* Inaccurate predictions are shown in red and accurate predictions are shown in green.

Table 6 shows the prediction accuracy of the HCMS with a mathematical approach. The HCMS showed high performance, with 303 accurate fault predictions out of 317 total faults.

Table 6. Performance of the system with a mathematical approach *.

	Thermal			PD			Arc			
Method	**True**	**False**	**Accu.**	**True**	**False**	**Accu.**	**True**	**False**	**Accu.**	**Total Accuracy**
FKGM	138	13	91.39%	22	1	95.65%	121	22	84.62%	88.64%
FSIM	147	4	97.35%	18	5	78.26%	127	16	88.81%	92.11%
FDTM	149	2	98.68%	19	4	82.61%	132	11	92.31%	94.64%
HCMS	150	1	99.34%	21	2	91.30%	132	11	92.31%	95.58%

* The final output performances of the HCMS with mathematical approach are given in green.

The HCMS with an SVM showed a performance level of 96.23%. Table 7 shows the prediction accuracy of the HCMS with an SVM.

Table 7. Performance of the system with an SVM *.

	Thermal	**PD**	**Arc**	**Total Accuracy**
Thermal	76	0	0	
PD	1	10	0	
Arc	1	4	67	
Accuracy	97.44%	71.43%	100%	96.23%

* The green cells show the number of accurate predictions. The cells highlighted in red show in which class the error was mistakenly predicted.

6. Conclusions

DGA is used to detect incipient faults in power transformers. Many DGA-based applications have been made for the diagnosis of faults. In the literature, there are two different methods: classical fault diagnosis methods and intelligent fault diagnosis models. Classical fault diagnosis methods are the methods in which gases dissolved in transformer oil are used as direct input and are specified by the relevant standards. The diagnostic accuracy of these methods is low. Today, there is no method that has been made with sufficient and reliable data sets and so has reached very high accuracy. The innovation in the proposed hybrid approach aims to achieve high accuracy in transformer fault estimation while overcoming the challenge of developing a comprehensive framework. In this study, a hybrid fault diagnosis system was designed using DGA-based methods and Fuzzy Logic. To operate independent of case values, the inputs of Fuzzy Logic are the outputs of basic DGA methods. A mathematical approach and support vector machines (SVMs) were used as decision-making methods in the hybrid fault diagnosis systems. The effectiveness of the proposed method was tested with 317 data sets obtained from the IEC TC 10 database provided by TEIAS. The results of tests performed with 317 real fault data sets from transformers indicate that the mathematical approach attained 95.58% accuracy and the system with an SVM attained 96.23% accuracy. The method we propose in this study increased the reliability and accuracy of fault diagnosis. In addition, this paper provides detailed information for future research on transformer fault analysis. It may act as a reference or guide when performing detailed diagnosis associated with a particular type of transformer fault.

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Abbreviations

$f_{KGM}^{th}(x)$	Discrete probability of a thermal fault with the FKGM model
$f_{SIM}^{th}(x)$	Discrete probability of a thermal fault with the FSIM model
$f_{DTM}^{th}(x)$	Discrete probability of a thermal fault with the FDTM model
$f_{KGM}^{pd}(x)$	Discrete probability of a PD fault with the FKGM model
$f_{SIM}^{pd}(x)$	Discrete probability of a PD fault with the FSIM model
$f_{DTM}^{pd}(x)$	Discrete probability of a PD fault with the FDTM model
$f_{KGM}^{arc}(x)$	Discrete probability of an arc fault with the FKGM model
$f_{SIM}^{arc}(x)$	Discrete probability of an arc fault with the FSIM model
$f_{DTM}^{arc}(x)$	Discrete probability of an arc fault with the FDTM model
AI_{Th}	Accuracy Index of thermal faults
AI_{PD}	Accuracy Index of PD faults
AI_{Ar}	Accuracy Index of arcing faults
$f_{Thermal}$	Integrated probability of a thermal fault (13)
f_{PD}	Integrated probability of a PD fault (14)
f_{Arcing}	Integrated probability of an arcing fault (15)
KGM	Key Gas Method
SIM	Simplified IEC Method
DTM	Duval Triangle Method
FKGM	Fuzzy Logic-based KGM
FSIM	Fuzzy Logic-based SIM
FDTM	Fuzzy Logic-based DTM
FL	Fuzzy Logic

HCMS	Hybrid Condition Monitoring System
LFSD	LabVIEW Fuzzy System Designer
T1	Thermal fault in mineral oil and/or paper below 300 °C
T2	Thermal fault in mineral oil and/or paper above 300 °C
T3	Thermal fault above 700 °C
PD	Partial discharge of the cold plasma (corona) type
D1	Low-energy discharges
D2	High-energy discharges

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