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A Fuzzy Logic Model for Power Transformer Faults' Severity Determination Based on Gas Level, Gas Rate, and Dissolved Gas Analysis Interpretation

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Abstract: In determining the severity of power transformer faults, several approaches have been previously proposed; however, most published studies do not accommodate gas level, gas rate, and Dissolved Gas Analysis (DGA) interpretation in a single approach. To increase the reliability of the faults' severity assessment of power transformers, a novel approach in the form of fuzzy logic has been proposed as a new solution to determine faults' severity using the combination of gas level, gas rate, and DGA interpretation from the Duval Pentagon Method (DPM). A four-level typical concentration and rate were established based on the local population. To simplify the assessment of hundreds of power transformer data, a Support Vector Machine (SVM)-based DPM with high agreements to the graphical DPM has been developed. The proposed approach has been implemented to 448 power transformers and further implementation was done to evaluate faults' severity of power transformers from historical DGA data. This new approach yields in high agreement with the previous methods, but with better sensitivity due to the incorporation of gas level, gas rate, and DGA interpretation results in one approach.

Keywords: dissolved gas analysis; fuzzy logic; health index; power transformer; support vector machine

1. Introduction

A high-voltage power transformer is one of the most vital pieces of equipment in the electric power system. Utilities often assess the severity of transformers and rank them to determine maintenance schedules. To define the overall condition of a transformer, various observations and measurements are carried out. Those observations and measurements data could be included in a power transformer composite index for overall condition determination, which is often introduced as Transformer Health Index, or in the most recent brochure [1], called Transformer Assessment Indices. Numerous aspects are considered in power transformer Health Index determination, in which faults' severity is one of the most important due to the threat it brings toward a power transformer.

A typical power transformer insulation system consists of cellulose insulation immersed in mineral oil. When in service, power transformers are subjected to stresses. Due to the thermal and electrical stresses that the insulation experiences, paper and oil decomposition can occur, reducing its insulation integrity and generating gases that dissolve in the oil [2,3]. An electrical fault is defined as disruptive discharge through the insulation. It can be caused by electrical stresses from both inside and outside of the power transformer. Partial discharge, an electric discharge that only partially bridges the insulation, or more significant discharge, such as arcing, can happen inside the transformer. Lightning and switching overvoltage are one of the main factors of failures in electric power systems [4]. If the discharge current that passes through the transformer is high enough, it can result in stress and ageing of the insulation, and possible failure [5–7]. Meanwhile, a thermal fault is an excessive temperature rise in the insulation. It can be caused by insufficient cooling, excessive current circulation in the metal parts or the insulation, overheating of the winding, or overloading [8].

The most convenient and frequent method to assess faults in a power transformer is by dissolved gas in oil measurements and interpretations. The traditional process for faults' severity based on Dissolved Gas Analysis (DGA) uses the amount of each gas compared to the scoring table and is then weighted to find the DGA factor [9–11]. This process only uses the value of each gas, not utilizing widely used DGA interpretation methods and generation rate of each gas.

The success of DGA interpretation methods in preventing catastrophic failures of power transformers has been recognized worldwide [1]. Various interpretation methods have been proposed, and the discrepancy of the results from different DGA methods has become an issue. Most previous studies have proposed methods to improve consistency in interpreting DGA. A study in Reference [12] used a fuzzy logic approach for a consistent interpretation of DGA. This study compared and then combined several methods such as roger ratio, IEC (International Electrotechnical Commission) ratio, doernenburg ratio, duval triangle, and key gas. A study in Reference [13] used a scoring index method to improve the accountability of the DGA interpretation process. While solving the consistency of DGA interpretation, these studies have not proposed faults' severity of a transformer due to DGA.

Several studies have initiated to propose faults' severity assessment of power transformers. A study in Reference [14] uses fuzzy logic to identify the severity of the transformer based on DGA data. This paper divided the criticalities into four, namely: oil thermal, paper thermal, Partial Discharge (PD) electrical, and arcing electrical. The severity output is 0 to 1, with 1 being very high severity. A study in Reference [15] proposed a flowchart of a DGA interpretation norm. This norm divides the interpretation results of duval triangle into three conditions. A study in Reference [16] used gene expression programming to identify power transformer severity and asset management decision based on DGA. This paper divided the fault type of five DGA methods into four categories. The output of this model is four conditions, from no fault or normal operation to extreme caution. This study suggests the asset management decision, such as reducing operation, increasing sampling frequency, and removal consideration. A study in Reference [17] proposed a five-categories condition that divides the interpretation results of a duval triangle. A more recent study [3] developed a fuzzy inference system and neural network model to classify multiple faults in dissolved gas analysis, and Reference [18] presented that using the proposed fuzzy model eases the DGA analysis for the less expert technicians. All of the studies mentioned above have the ability to determine faults' severity of a power transformer, but gas increase rate has not been included in the model. Most only use gas rate as further actions after identifying the severity of the faults of each transformer.

This paper presents a novel approach to incorporate multi-criteria, namely, gas concentration level, gas rate of increase, and DGA interpretation result, to enhance power transformer faults' severity determination. In order to accomplish that, recent DGA data are collected and compared to the history to obtain population-specific gas level and yearly gas rate. Those gas levels and gas rates were compared and evaluated to the available guidelines. Duval Pentagon Method (DPM) will be used as a DGA interpretation method. To simplify the assessment of hundreds of transformer data, a Support Vector Machine (SVM) model based on duval pentagon will also be proposed.

The next step is to develop a norm to assign the duval pentagon interpretation results into four conditions. For the other criteria, another norm is developed using the population-specific gas level and gas rate to assign four conditions. The combination of these multi criteria, such as gas concentration level, gas rate of increase, and DPM interpretation will be implemented in the fuzzy logic model. Fuzzy logic is employed to gain benefits from using a fuzzy rather than a crisp value. The use of fuzzy logic for DGA assessment has also been reported in References [19–25]. The results were evaluated by comparing to two widely used approaches, scoring and weighting of Dissolved Gas Analysis Factor (DGAF) proposed in Reference [9] and total dissolved combustible gas (TDCG), as suggested in Reference [26].

To increase the reliability of the assessment, a novel approach to determine faults' severity of a power transformer based on a combination of duval pentagon DGA interpretation, gas rate, and gas level will be presented in this paper. The proposed approach has been tested on 448 transformers to calculate the faults' severity, and further implementation has been done on historical data of four power transformers.

2. Power Transformer Faults' Severity

The purpose of this study is to develop a method for assessing the severity of a power transformer due to faults. This faults' severity can be implemented on transformers Health Index, or acts itself to assign action based on DGA in oil.

2.1. Health Index Concept

Power transformers are frequently monitored with various parameters. In order to identify the overall condition of a power transformer, a health index is used as a composite of parameters to provide a single value of a power transformer's overall condition. The parameters are compared to the scoring table and then multiplied by its weighting factor. Equation (1) shows the calculation of transformer HI.

$$HI = \sum_{i=1}^{I} W_i S_i \tag{1}$$

where, S_i = Score of each parameter, W_i = Weighting Factor.

In assessing the overall condition of a power transformer, there are many aspects to be considered. Several aspects to be assessed are, for example, paper condition, oil condition, and faults' severity. One of the most important and frequently measured aspects in a power transformer is dissolved gas in oil. This data is measured annually, or even more than once a year for some critical power transformers. Dissolved gas in oil data is a key factor in determining faults' severity of a transformer. This faults severity can be inserted into the Health Index calculation or can act solely as action-based DGA determination.

2.2. Fault Severity Methods

In order to determine faults' severity of a power transformer, DGA data are used. This section discussed some approaches that have been proposed by previous studies.

2.2.1. Scoring and Weighting Methods

The approaches in References [9–11] use the scoring and weighting method to determine the faults' severity of a power transformer. The scoring table used is shown in Table 1. As many as seven dissolved gases: 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), are divided into six scores according to each gas value. This score is then multiplied with its predefined weighting factors to find the DGAF (Dissolved Gas Analysis Factor). After calculating the DGAF, Table 2 is used. The output of this method is a five-categories rating, from A for Good transformer, to E for Very Poor transformer.

Table 1. Scoring and weight factors for gas levels (parts per million/ppm).

Gas	Score						Weight
	1	2	3	4	5	6	
H_2	≤100	100–200	200–300	300–500	500–700	>700	2
CH_4	≤75	75–125	125–200	200–448	448–600	>600	3
C_2H_6	≤65	65–80	80–100	100–120	120–150	>150	3
C_2H_4	≤50	50–80	80–100	100–150	150–200	>120	3
C_2H_2	≤3	3–7	7–35	35–50	50–80	>80	5
CO	≤350	350–700	700–900	900–1100	1100–1448	>1448	1
CO_2	≤2500	2500–3000	3000–4480	4480–5000	5000–7000	>7000	1

Table 2. Transformer rating based on Dissolved Gas Analysis (DGA) factor [10].

Rating Code	Fault Type	DGAF
A	Good	<1.2
B	Acceptable	1.2–1.5
C	Need Caution	1.5–2
D	Poor	2–3
E	Very Poor	>3

The output of this is five conditions, from A for Good, up to E for Very Poor condition. This approach used only the gas value, not utilizing DGA interpretation methods. Furthermore, in aggregating the severity, gas rate of increase is not incorporated into the algorithm.

2.2.2. Total Dissolved Combustible Gas (TDCG)

An internal fault is suspected to occur when a sudden increase in dissolved gas in power transformer oil happens. A four-level criterion has been developed in Reference [26] to evaluate power transformers using TDCG. Table 3 shows the four-conditions with each recommended action. This method will act as a comparison to the approach this paper has proposed.

Table 3. Actions based on Total Dissolved Combustible Gas (TDCG) [26].

	TDCG Levels (ppm)	TDCG Rate (ppm/day)	Sampling Interval	Operating Procedures
Condition 4	>4630	>30	Daily	Consider removal from service. Advise manufacturer.
		10 to 30	Daily	
		<10	Weekly	Exercise extreme caution. Analyze for individual gases. Plan outage. Advise manufacturer.
Condition 3	1921 to 4630	>30	Weekly	Exercise extreme caution. Analyze for individual gases. Plan outage. Advise manufacturer.
		10 to 30	Weekly	
		<10	Monthly	
Condition 2	721 to 1920	>30	Monthly	Exercise caution. Analyze for individual gases. Determine load dependence.
		10 to 30	Monthly	
		<10	Quarterly	
Condition 1	≤720	>30	Monthly	Continue normal operation.
		10 to 30	Quarterly	
		<10	Annual	

2.2.3. Duval Pentagon Method (DPM)

Various DGA interpretation methods have been introduced, from ratio methods to graphical methods. Some examples of ratio methods are Roger's Ratio, IEC Ratio, Doernenburg Ratio, or more recent studies proposing ratio methods, such as in Reference [27]. Some examples of graphical methods are the Duval Triangle Method [28] and the more recent Duval Pentagon Method that uses five gas ratios [29].

DPM is one of the well-known graphical DGA interpretation methods and has been used in several studies [13,30–33]. DPM has considerably better performance in detecting faults in power transformers compared to other methods discussed in Reference [34]. This study uses DPM 2 as a DGA interpretation method, using five gas inputs to find the incipient faults within power transformers. DPM defines seven zones, as shown in Figure 1. Those zones are as follows.

- PD: Corona partial discharges
- D1: Low-energy discharges
- D2: High-energy discharges
- T3-H: Thermal faults in oil above 700 °C
- C: Thermal faults above 300 °C and below 700 °C with carbonization of paper
- O: Overheating below 250 °C
- S: Stray gassing

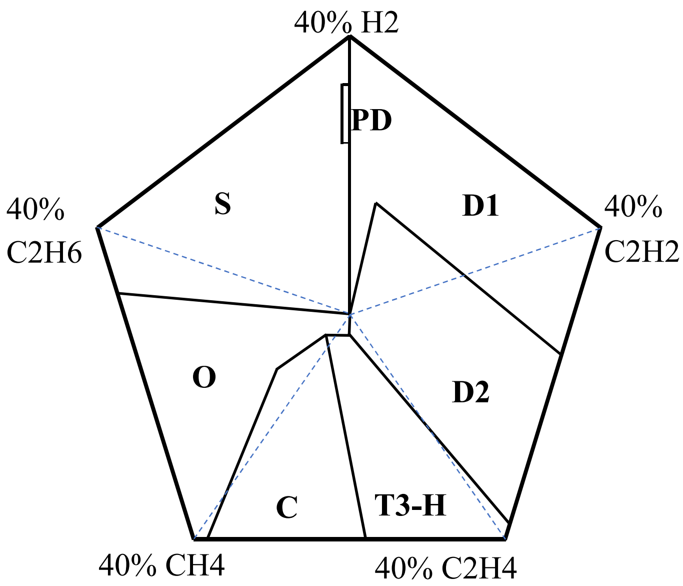

Figure 1. Duval pentagon method (DPM).

3. Methodology

This study started with collecting the DGA database of power transformers from electrical utility PLN-UITJBTB. The transformers observed consist of 500/150 kV, 150/70 kV, 150/20 kV, and 70/20 kV. The data collected are recent DGA measurements and historical DGA data.

Guidelines in References [8,35] recommend that utilities propose typical concentration values and typical gas increase rates for the utility itself in order to assess the transformer based on its own transformer population. After generating typical values, different DGA interpretation methods will be compared, and suitable methods will be selected. A model to score fault severity based on DGA will be developed with the consideration of previous analysis. Figure 2 shows the methodology of this research.

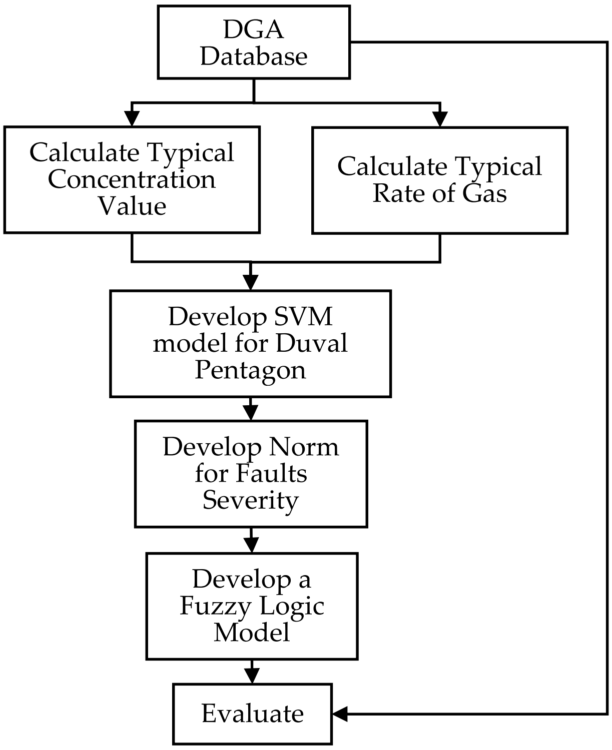

Figure 2. Methodology of the research.

3.1. Typical Gas Concentration Value

IEC 60599-2015 and IEEE (Institute of Electrical and Electronics Engineers) C57.104-2019 propose utilities to specify its typical gas concentration values, to adjust, or to confirm the selected norms based on specific transformer populations. In order to accomplish this, DGA results of 448 units of power transformers were collected, as in References [30,36]. The 90th percentile is used as a boundary to define normal and abnormal dissolved gases' concentration value.

Table 4 is the comparison of typical normal concentration values of dissolved gases from IEEE C57.104-2019, IEC 60599-2015, and the proposed normal threshold from Indonesian utility (PLN-UITJBT). The normal concentration value from IEC 60599-2015 is specified in the form of a range, derived from 90% typical gas concentration values observed in power transformers. Most of the gases show a similar limit to the other guidelines, except for C_2H_6, where PLN-UITJBT data has a higher value of 300 ppm.

Table 4. Comparison of typical normal concentration values of dissolved gases (ppm).

	H2	CH_4	C_2H_2	C_2H_4	C_2H_6	CO	CO_2
IEEE C57.104-2019	80	90	1	50	90	900	9000
IEC 60599-2015	50–150	30–130		60–280	20–90	400–600	3800–14,000
PLN-UITJBT [30]	85	180	3	45	300	900	6500

This approach acts as initial guidelines for action based on DGA. Only when the value of at least one gas concentration is more than this threshold, a fault is possibly detected.

The next step is to apply the 95th percentile to the second boundary, and the 97.5th percentile to the third boundary. These values can be used to classify each gas into four levels of classification as shown in Table 5, namely L1 to L4. Utilities can use these values as a comparison of their transformer population to the larger ones that are represented with typical values from guidelines. Furthermore, such analysis can be used to decide whether to confirm or to adjust the selected classifications provided by the guidelines.

Table 5. Gas concentration, four-levels classification.

	H2	CH_4	C_2H_2	C_2H_4	C_2H_6	CO	CO_2
L1	<85	<180	<3	<45	<300	<900	<6500
L2	85–130	180–240	3–8	45–85	300–425	900–1090	6500–8000
L3	130–225	240–350	8–20	85–390	425–580	1090–1280	8000–9750
L4	>225	>350	>20	>390	>580	>1280	>9750

3.2. *Typical Rate of Gas Increase*

If the rate of gas increase is minimal, even though the level is indicating abnormal DGA data, the faults within the power transformer have probably disappeared. Assessing transformer faults' severity using only gas concentration is inadequate; therefore, the rate of gas increase is needed to consider the significance of gas measured in the sample [35]. Another dataset from the previous year of those 448 units of power transformers was obtained, and the rate of increase was calculated. The same thresholds were applied, with 90 percent of the data considered normal, and another 10 percent considered abnormal. While Reference [8] also proposed the 90th percentile, the newer guideline [35] proposed to use the 95th percentile to reduce false-positive results. Table 6 shows a comparison of the typical yearly rate of gas increase from IEC 60599-2015 [8], IEEE C57.104-2019 [35], and the obtained typical rate of gas value from Reference [36].

Table 6. Comparison of typical rate of gas increase on normal level (ppm/year).

	H2	CH_4	C_2H_2	C_2H_4	C_2H_6	CO	CO_2
IEC 60599–2015	35–132	10–120	0	32–146	5–90	260–1060	1700–10,000
IEEE C57.104–2019	20	10	0	7	9	100	1000
PLN TJBT [36]	20	20	0	7	29	88	766

Table 7 shows the classification of the four-level rate of gas increase. The same 95th and 97.5th percentile were used to develop these levels, namely R1 to R4.

Table 7. Rate of gas increase classification.

	H2	CH_4	C_2H_2	C_2H_4	C_2H_6	CO	CO_2
R1	<20	<20	<0	<7	<29	<88	<766
R2	20–31	20–37	0–1	7–16	29–58	88–200	766–1526
R3	31–59	37–72	1–7	16–48	58–145	200–305	1526–2462
R4	>59	>72	>7	>48	>145	>305	>2462

3.3. *SVM Model for Duval Pentagon 2*

After the threshold and levels classification has been set, the next step is to implement the Duval Pentagon Method (DPM) into the assessment. To simplify the assessment of hundreds of power transformer data, a Machine Learning-based DPM has been developed using the tool provided by MATLAB. The use of machine learning in power transformer assessment has also been reported by several studies [17,37–45].

The development of the model is started by identifying all the coordinates in the DPM graph. According to Reference [29], the coordinates of the boundaries are as follows:

- PD: (0, 24.5), (0, 33), (−1, 24.5), (−1, 33),
- D1: (0, 40), (38, 12), (32, −6), (4, 16), (0, 1.5),
- D2: (4, 16), (32, −6), (24, −30), (−1, −2),
- T3: (24, −30), (−1, −2), (−6, −4), (1, −32),
- T2: (1, −32), (−6, −4), (−22.5, −32),
- T1: (−22.5, −32), (−6, −4), (−1, −2), (0, 1.5), (−35, 3),

- S: (−35, 3), (0, 1.5), (0, 24.5), (0, 33), (−1, 24.5), (−1, 33), (0, 40),
- T3−H: (−24, −30), (−3.5, −3), (2.5, −32),
- C: (2.5, −32), (−3.5, −3), (−11, −8), (−21.5, −32),
- O: (−21.5, −32), (−11, −8), (−3.5, −3), (−1, −2), (0, 1.5), (−35, 3).

After plotting the coordinates and getting the boundaries, the next step is calculating the relative percentage of each of the five gases: H_2, CH_4, C_2H_6, C_2H_4, and C_2H_2. Those values are then plotted into the pentagon, resulting in coordinates of five relative gas percentages. The next step is to find the centroid of the pentagon created by five relative gas percentage coordinates. The area of the pentagon is calculated using Equation (2). The centroid x (Cx) and centroid y (Cy) of a pentagon are calculated using Equations (3) and (4):

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

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

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

The next step is to create a training database, consisting of Cx and Cy as input parameters, and seven faults' identifications as the targets, namely: C, D1, D2, O, PD, S, and T3–H. As many as 961 training data were prepared and then validated using 5-fold cross-validation. Four machine learning models (decision tree, support vector machine, k-nearest neighbor, and random forest) have been trained and tested. The resulting accuracy is shown in Table 8, where the Support Vector Machine (SVM) model got the highest agreement with the direct application of Duval Pentagon, as much as 97.5%. Figure 3 shows a confusion matrix of 961 training data for SVM-based DPM.

Table 8. Performance comparisons of Machine Learning models of DPM.

Model No.	Classifier	Accuracy
1	Decision Tree	71.8%
2	Support Vector Machine	97.5%
3	k-Nearest Neighbor	84.5%
4	Random Forest	95.6%

Target	D1	D2	T3-H	C	O	S	PD
D1	178	5				1	
D2	3	177					
T3-H		2	99	1			
C			1	110	2		
O				3	158		
S	3				1	167	
PD						2	48
	Predicted						
Accuracy	97%	96%	99%	96%	98%	98%	100%

Figure 3. Confusion matrix of 961 data of SVM-based DPM.

The trained SVM-based DPM was then further evaluated using real transformer data. As many as 127 transformers which were classified as abnormal DGA data were collected and used to evaluate the model. Five dissolved gases form those 127 transformers were analyzed using graphical DPM, provided in Reference [29]. Those data were also calculated to find the Cx and Cy using Equations (2) to (4) and then inserted into the SVM-based DPM.

Table 9 shows ten samples out of 127 real transformer DGA data. The prediction using the model developed resulted in 97.62% agreement with the graphical DPM. Figure 4 shows the plotting of 127 faults' identification results into the DPM graph. As we can see, there were only three misclassified cases near the border. It can be concluded that the trained model has a high agreement to the graphical DPM and can be used to simplify the assessment process of hundreds of data in identifying transformer faults' type based on DPM interpretation.

Table 9. 10 Samples of SVM-based DPM prediction.

No	DGA Concentrations (ppm)					SVM-Input		SVM-Based DPM
	H_2	CH_4	C_2H_2	C_2H_4	C_2H_6	C_x	C_y	
1	85	22	0	10	10	−2.96	13.41	S
2	36	5	7	9	10	−3.06	12.67	S
3	185	93	0	112	44	−2.10	−1.24	O
4	39	299	0	173	762	−19.49	−1.10	O
5	358	14	0	1	5	−0.45	30.24	PD
6	106	4	0	2	4	−1.10	29.12	PD
7	3282	154	0	231	7	0.21	9.77	D1
8	9	9	142	42	8	23.44	1.10	D1
9	58	568	0	1440	471	2.32	−16.63	T3−H
10	274	141	0	240	72	4.36	−23.08	T3−H
11	27	0	95	57	25	17.54	−1.80	D2
12	14	0	74	37	16	19.83	−1.20	D2

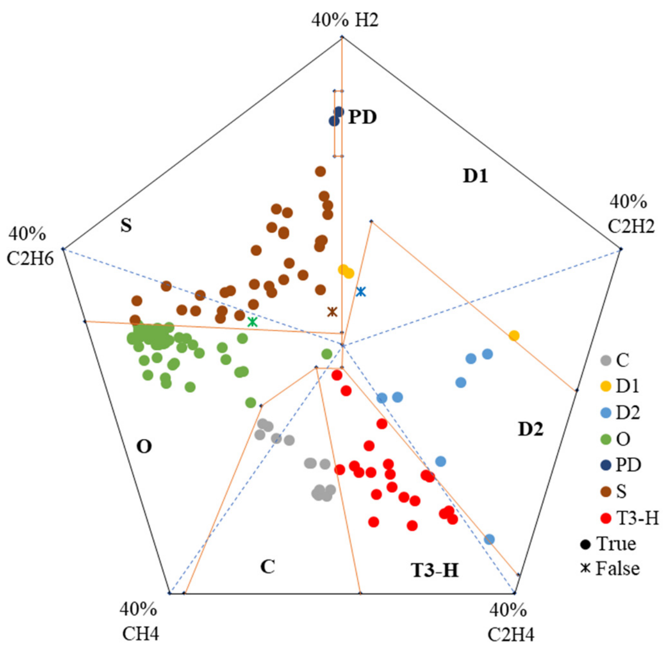

Figure 4. Prediction results of SVM-based DPM.

3.4. Faults' Severity Norm Development

Figure 5 shows the flowchart of the proposed approach. DGA data will be compared to Table 4. If all gas is within normal gas concentrations, then the transformer is reported normal (Condition 1).

If one of the gases is more than the typical normal gas concentration, then apply DPM. Level and gas rate of increase will also be assessed. The results of DPM, gas level, and gas rate will become the input of the judgment process to find faults' severity of a power transformer based on DGA.

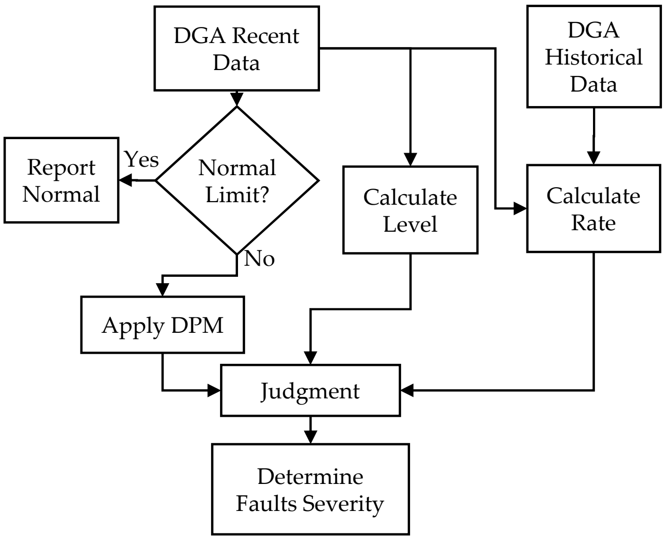

Figure 5. Flowchart of the proposed approach.

The output of the faults' severity model of a power transformer is five-condition categories, A for normal condition, B for acceptable, C for need caution, D for poor, and E for very poor. Table 10 shows these classifications, with its recommended actions.

Table 10. Output of power transformer faults' severity model.

Condition	Interpretation	Recommended Action
A	Normal	- Normal operation - Yearly DGA Measurement
B	Acceptable	- Normal operation - Yearly DGA Measurement - Check generation rate
C	Need Caution	- Caution operation - Half-yearly DGA measurement - Check generation rate
D	Poor	- Extreme caution - Monthly DGA measurement - Check generation rate - Discuss with manufacturer - Check electrical tests to confirm
E	Very Poor	- Weekly DGA measurement - Check generation rate - Consider take out of service and do further investigation

The previous paper has developed a norm in the form of a flowchart to classify DGA interpretation into conditions. This study modifies the flowchart developed by a study in Reference [15], classifying DPM interpretation results into four conditions.

First is to compare each of the five gases (H_2, CH_4, C_2H_6, C_2H_4, and C_2H_2) into typical concentration values in Table 4. Another two gases, CO and CO_2, were not used in this analysis. Those gases are to be used in another study to determine paper condition severity. The example of the use of Figure 6 is as follows. If there is at least one gas more than the normal limit (L1), apply DPM. Otherwise, report normal or Condition 1. If DPM results in S (Stray Gas), check rate. If any yearly gas rate of increase is more than R1, report condition 2, otherwise report normal. The output of the flowchart in Figure 6 is four-conditions classifications, from Condition 1 to Condition 4.

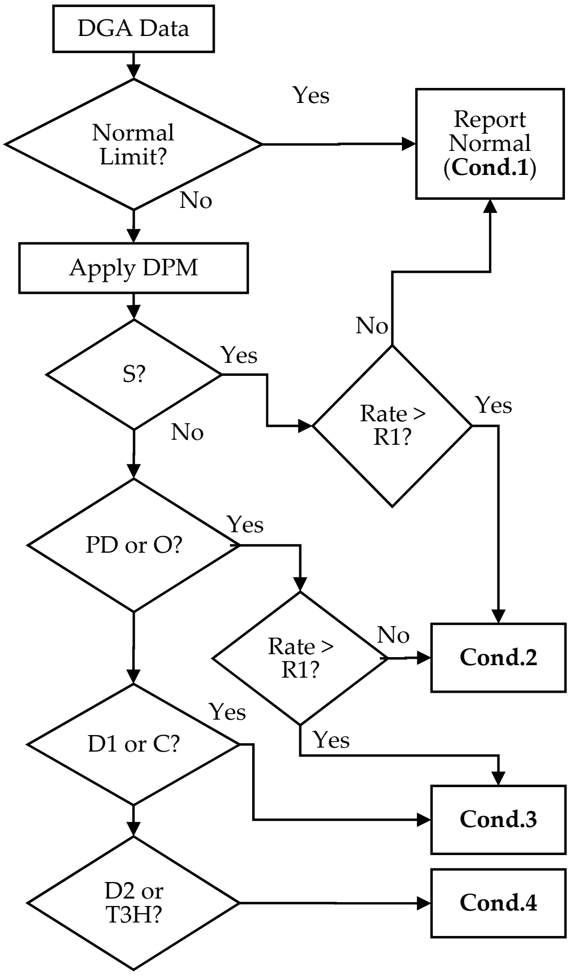

Figure 6. Flowchart of four-conditions classification from DPM results.

After checking the DPM, the next phase is to check the gas level and gas rate. The gas level is based on Table 5, and the gas rate is based on Table 7. Table 11 is applied to the maximum gas rate and gas level. This results in four-conditions classifications. The example of Table 11's use is as follows. When the maximum gas level is L1, then report condition regardless of the rate. If the gas level maximum is 2, and the maximum gas rate is 2 or 3, then report condition 2, and so on.

Table 11. Assigned condition based on gas level and gas rate.

Gas Level (Max)	Gas Rate (Max)	Assigned Condition
1	any	Cond.1
2	1	Cond.1
2	2–3	Cond.2
2	4	Cond.3
3	1	Cond.2
3	2–3	Cond.3
3	4	Cond.4
4	1	Cond.3
4	3–4	Cond.4

So far, two conditions have been assigned based on DPM interpretation, gas rate, and gas level. Table 12 is to combine the conditions based on the flowchart in Figure 6 to the gas level and gas rate in Table 11. The output of Table 12 is five categories of faults' severity, namely A to E, while ND stands for Not Defined. The example of this is as follows. When the DPM flowchart results in C1, then the faults' severity is reported as A. If the DPM flowchart is resulting in C2, and the gas level-rate results in C2, then the faults' severity is B, and so on. The implementation of this norm is then done using Fuzzy Logic and is introduced in the next results section.

Table 12. Norm of faults' severity based on DPM, gas level, and gas rate.

		Gas Level and Gas Rate			
		C.1	**C.2**	**C.3**	**C.4**
DPM	C.1	A	ND	ND	ND
	C.2	ND *	B	B	C
	C.3	ND	C	C	D
	C.4	ND	D	D	E

* ND = Not Defined.

4. Results

DGA data of 448 power transformers were collected and analyzed. Faults' severity were calculated in three approaches, the first calculation was based on References [9–11], the second calculation was TDCG, as described in Reference [26], and the third calculation was using the proposed approach implemented in the fuzzy logic model.

4.1. Fuzzy Logic Model

The approach proposed in this study categorizes power transformers into five-category faults' severity based on DPM interpretation, gas level, and gas rate. The fuzzy logic model was developed and implemented using the tool provided by MATLAB. The faults' severity fuzzy logic model is shown in Figure 7. Five fuzzy logic models were developed, such as gas level fuzzy logic (FL), gas rate FL, gas level and rate FL, DPM FL, and Faults' Severity FL. The hierarchy of this model can be seen in Figure 7.

For the input membership functions of DPM FL, trapezium membership functions were used as seen in Figure 8. Figures 9–13 shows the input membership functions of five gas concentrations in ppm. The values in Table 5 are considered in forming these input membership functions. The advantage of this implementation is the use of fuzzy rather than the traditional crisp values. This allows a gas concentration to be considered in two levels with its own degree of membership.

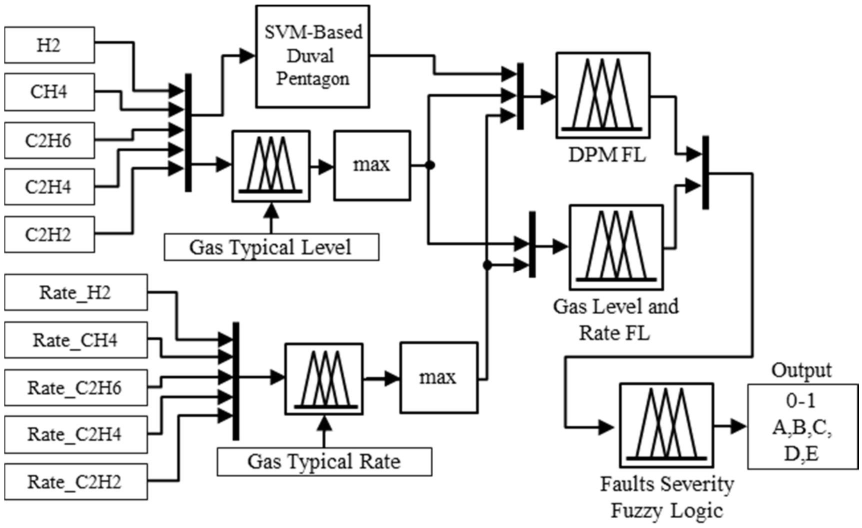

Figure 7. Faults' severity fuzzy logic model.

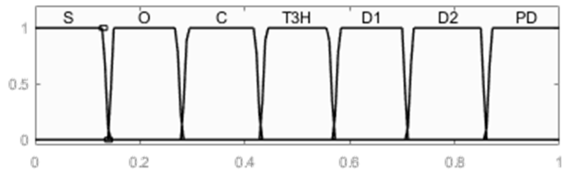

Figure 8. Input membership functions for DPM interpretation results.

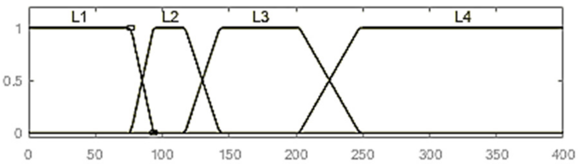

Figure 9. Input membership functions for H_2.

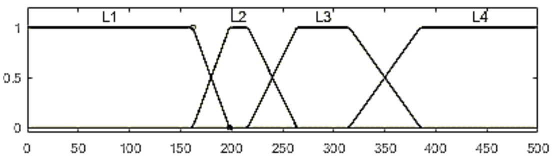

Figure 10. Input membership functions for CH_4.

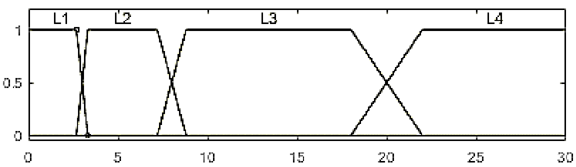

Figure 11. Input membership functions for C_2H_2.

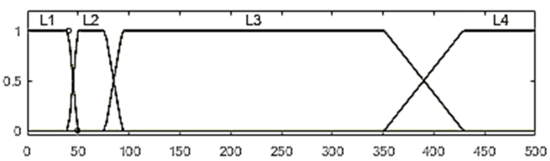

Figure 12. Input membership functions for C_2H_4.

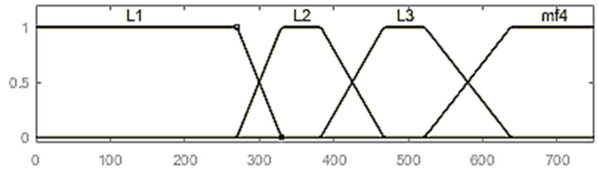

Figure 13. Input membership functions for C_2H_6.

Figure 14 shows the output membership functions of faults' severity. The output of this fuzzy logic model is as much as five categories of faults severity, A to E. The rules are then assigned based on flowcharts in Figure 6, gas level and rate in Table 11, and faults' severity norm in Table 12. Examples of 10 rules for faults severity fuzzy logic as the implementation of Table 12 is shown in Figure 15.

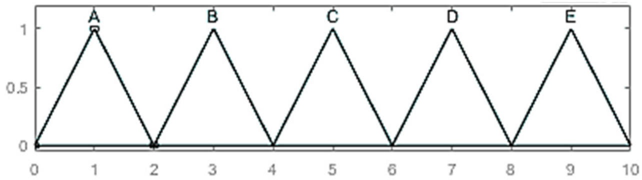

Figure 14. Faults' severity output membership functions.

1. If (DPM is C1) and (GasLVRT is C1) then (FaultsSeverity is A)
2. If (DPM is C2) and (GasLVRT is C2) then (FaultsSeverity is B)
3. If (DPM is C2) and (GasLVRT is C3) then (FaultsSeverity is B)
4. If (DPM is C2) and (GasLVRT is C4) then (FaultsSeverity is C)
5. If (DPM is C3) and (GasLVRT is C2) then (FaultsSeverity is C)
6. If (DPM is C3) and (GasLVRT is C3) then (FaultsSeverity is C)
7. If (DPM is C3) and (GasLVRT is C4) then (FaultsSeverity is D)
8. If (DPM is C4) and (GasLVRT is C2) then (FaultsSeverity is D)
9. If (DPM is C4) and (GasLVRT is C3) then (FaultsSeverity is D)
10. If (DPM is C4) and (GasLVRT is C4) then (FaultsSeverity is E)

Figure 15. Rules for Faults' Severity Fuzzy Logic.

This fuzzy logic implementation is then to be applied to the in-service power transformers DGA data. The results will be presented in the next section.

4.2. Faults' Severity Results

The fuzzy logic implementation of faults' severity based on DPM interpretation, gas rate, and gas level has been developed. This section describes the evaluation of the model proposed. Initially, as many as 448 sets of recent DGA of in-service power transformer data were collected. These power transformers are from the same populations as the ones that were used to form typical values and rates. The faults' severity model will be applied to these transformers to get the severity of this power transformer population due to faults. The results were compared to two other approaches. Further implementation of this fuzzy logic was done to four transformers with historical data, with four years of data to highlight the applicability of the model to assess historical data of power transformer faults' severity.

Figure 16 shows the results of faults' severity of 448 power transformers observed. As many as 324 transformers were in the normal condition (category A), whereas 30 power transformers were in category B, 57 transformers needed caution (category C), 30 transformers were in poor condition (category D), and seven others were in very poor faults' severity (category E). The next section discusses these results and compares them to other previously proposed approaches such as HI_{DGA} in References [9–11] and TDCG in Reference [26].

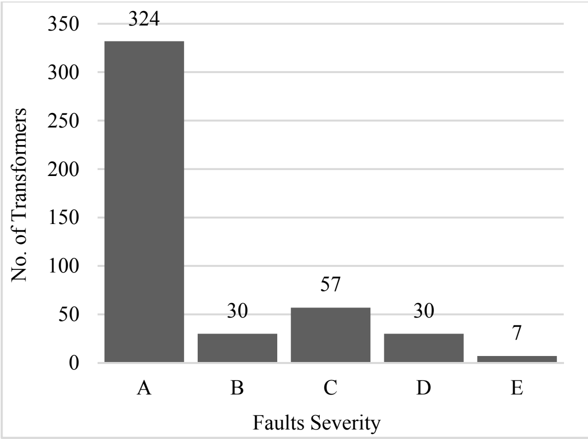

Figure 16. Results of fault severity of 448 power transformers with recent DGA measurements.

5. Discussion

The faults' severity method has been developed, and consists of five fuzzy logic models, such as gas level fuzzy logic (FL), gas rate FL, gas level and rate FL, DPM FL, and Faults Severity FL. The hierarchy of this model can be seen in Figure 7. This section discusses the comparison of the proposed method to the previously published methods, and the implementation of the faults' severity method to the historical data of power transformer.

5.1. Faults' Severity of 448 Power Transformers

The method has been implemented to assess faults' severity of 448 sets of DGA data from the in-service power transformer. To validate the results of the proposed approach, recent DGA data from 448 in-service power transformers were observed and compared to other previously proposed approaches [9–11,26]. The proposed faults' severity fuzzy logic models were applied to five gases (H_2, CH_4, C_2H_6, C_2H_4, and C_2H_2). Another two gases, CO and CO_2, were not used in this analysis, since those gases are to be used in another study to determine paper condition severity.

From the 26 power transformers in Table 13, the faults' severity approach proposed resulted in high agreements with the other approaches. For transformers with normal faults' severity (samples 1–13), most other approach also resulted in condition A. However, some differences can be seen in several other cases. For case 14, DPM interpretation resulted in thermal faults above 300 °C and below 700 °C with carbonization of paper, gas level maximum (max) was 3, and gas rate max was 1. Using the HI_{DGA} approach, case 14 was in the C (Need Caution) condition. This is due to the level of several gases being moderately high, which was shown by a max gas level of 3. Despite the high concentration level of several gases, the rate of increase was minimal. This power transformer in this proposed method will be assigned to condition B. Another similar result can be seen in case 17. This shows that the proposed faults' severity is more sensitive in some cases due to the inclusion of gas rate of increase.

Transformer 26 was in Very Poor faults' severity. The DPM result of transformer 26 shows an indication that high-energy discharge occurs within the transformer. Besides, the high level and rate were also found. Using the recommended action in Table 10, utilities need to check transformer 26 for weekly DGA measurements, check the rate, and to consider taking this transformer out of service to do further investigation.

Table 13. Sample of 26 power transformers' faults' severity results.

No	H_2 (ppm)	CH_4 (ppm)	C_2H_2 (ppm)	C_2H_4 (ppm)	C_2H_6 (ppm)	Rate H_2 (ppm/year)	Rate CH_4 (ppm/year)	Rate C_2H_2 (ppm/year)	Rate C_2H_4 (ppm/year)	Rate C_2H_6 (ppm/year)	Level Max	Rate Max	DPM Interpretation	HI DGA* [2]	TDCG [17]	Faults Severity
1	47	8	0	0	11	Neg	Neg	0	Neg**	Neg	1	1	S	A	A	A
2	0	32	2	0	105	0	3	3	0	17	1	3	O	A	A	A
3	68	0	0	1	3	Neg	0	0	1	4	1	1	PD	A	A	A
4	68	0	0	6	2	Neg	Neg	0	9	3	1	2	PD	A	A	A
5	0	71	0	2	145	0	19	Neg	3	35	1	2	O	A	A	A
6	26	26	0	0	56	Neg	13	Neg	0	16	1	1	S	A	A	A
7	40	73	0	21	83	Neg	Neg	0	Neg	Neg	1	1	O	A	A	A
8	23	9	0	0	0	28	Neg	0	0	Neg	1	2	S	A	B	A
9	0	2	5	0	0	0	Neg	0	0	0	2	1	D2	A	A	A
10	16	46	0	0	98	20	Neg	0	0	Neg	1	1	O	A	A	A
11	25	8	0	0	13	31	7	0	0	16	1	2	S	A	A	A
12	0	0	0	35	0	0	Neg	Neg	Neg	0	1	1	T3-H	A	A	A
13	9	28	0	0	34	Neg	1	0	0	11	1	1	O	A	B	A
14	0	273	0	338	193	Neg	Neg	0	Neg	6	3	1	C	C	B	B
15	34	151	0	6	323	Neg	Neg	0	Neg	30	2	2	O	B	B	B
16	36	168	0	7	354	Neg	17	0	10	69	2	3	O	B	B	B
17	50	180	0	6	368	6	36	Neg	9	Neg	2	2	O	C	B	B
18	100	121	0	7	170	5	Neg	0	2	50	2	2	S	A	B	B
19	46	257	0	10	378	4	19	0	1	47	3	2	O	C	B	C
20	46	229	0	37	690	Neg	Neg	Neg	Neg	Neg	4	1	O	D	B	C
21	109	108	10	29	166	Neg	Neg	7	2	Neg	3	4	S	C	B	D
22	22	247	2	4	881	Neg	Neg	3	Neg	Neg	4	3	O	D	B	D
23	24	302	3	0	917	Neg	Neg	4	Neg	Neg	4	3	O	D	B	D
24	21	237	0	4	926	Neg	Neg	0	Neg	58	4	2	S	D	B	D
25	7	551	0	1083	128	Neg	Neg	0	Neg	Neg	4	1	T3-H	D	C	D
26	36	8	60	51	3	26	3	77	9	4	4	4	D2	C	B	E

* HI DGA = Health Index DGA, ** Neg= Negative.

5.2. Faults Severity of Power Transformers' Historical Data

Further implementations were done with historical data of four power transformers. The dissolved gas in oil of these transformers was measured once a year. Table 14 shows the results of four years of faults' severity of four power transformers.

Table 14. Four years of faults' severity determination of four power transformers.

Transformer No.	Years	H_2	CH_4	C_2H_2	C_2H_4	C_2H_6	Level Max	Rate Max	DPM	FS
1	1	0	35	0	28	23	1	1	C	A
	2	0	27	0	13	0	1	1	C	A
	3	0	27	0	0	0	1	1	O	A
	4	28	28	0	0	18	1	2	S	A
2	1	0	95	0	23	147	1	1	O	A
	2	0	43	0	0	19	1	1	O	A
	3	56	126	0	19	66	1	3	O	A
	4	70	158	0	24	86	1	3	O	A
3	1	0	19	0	0	19	1	1	O	A
	2	0	0	0	0	21	1	1	S	A
	3	0	230	0	49	0	2	4	C	C
	4	0	159	0	67	154	2	4	O	C
4	1	0	343	0	457	239	4	1	C	C
	2	0	414	0	508	276	4	3	C	D
	3	336	1568	2	1728	579	4	4	C	D
	4	582	2398	4	2960	753	4	4	C	D

For transformer number 1, the gas concentration level of five power transformers does not exceed 1, so although the DPM interpretation is C or O, this transformer is assigned normal faults' severity. A similar instance is shown by transformer 2.

For transformer 3 in Table 14, the increase of faults' severity was observed in the second year. The concentration level increased to more than level one and the yearly gas rate of increase accelerated into 4. This leads to 'need caution' faults' severity. For transformer 4, the maximum gas level was level 4, and the DPM interpretation results indicated that within transformer 4 occurs thermal faults above 300 °C and below 700 °C with carbonization of paper. Furthermore, the gas rate of increase of transformer 4 in the second-year forward was high. This results in poor faults' severity of transformer 4. Monthly DGA measurements need to be done, and immediate oil treatment is necessary.

The proposed method resulted in high agreements with other approaches. However, some differences can be seen in several other cases, as highlighted in Section 5.1. The proposed faults' severity is more selective and shows more sensitivity in some cases, due to the inclusion of gas rate of increase. The results also highlight the ability of the proposed method to assess historical data of power transformer DGA data, as discussed in Section 5.2.

6. Conclusions

This paper presented a new approach to determine faults' severity of power transformers based on a combination of gas level, gas rate, and DGA interpretation from the Duval Pentagon Method. The level of gas concentration and rate of increase has been composed of the transformer population itself. In order to simplify the assessments of hundreds of power transformers, an SVM-based DPM was constructed and evaluated. The agreements of the proposed SVM algorithm to graphical-based DPM were evaluated, resulting in 97.5% using 5-fold cross-validation, and 97.62% when validated using 127 real power transformers' abnormal DGA data. The implementation of the proposed approach is in the fuzzy logic model and has been applied to 448 power transformers. The developed faults' severity model was evaluated and resulted in high conformity with other previously proposed approaches. Furthermore, using proposed multi-criteria to aggregate the information is considered as the optimal approach in making detailed interpretations. The use of gas level, gas rate, and DPM interpretation, in combination, yields more reliable assessment so that more accurate decisions can be made. The proposed faults' severity is more selective and shows more sensitivity, in some cases, due to the inclusion of multi-criteria. Further implementations have been done to the historical power transformer DGA data, showing that the model is able to highlight the increase in faults' severity of a power transformer. However, more historical data from more power transformers could be added so that the proposed method can be adjusted to form a more consistent model.

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Conflicts of Interest: The authors declare no conflict of interest.

References

1. WG A2.49. Condition Assessment of Power Transformers. *CIGRE Reference:761*, March 2019.
2. Bakar, N.; Abu-Siada, A.; Islam, S. A review of dissolved gas analysis measurement and interpretation techniques. *IEEE Electr. Insul. Mag.* **2014**, *30*, 39–49. [CrossRef]
3. Wani, S.A.; Gupta, D.; Farooque, M.U.; Khan, S.A. Multiple incipient fault classification approach for enhancing the accuracy of dissolved gas analysis (DGA). *IET Sci. Meas. Technol.* **2019**, *13*, 959–967. [CrossRef]
4. Christodoulou, C.A.; Vita, V.; Mitropoulou, A.; Oikonomou, D.S.; Ekonomou, L. Interface construction for the computation of the optimum installation position of metal oxide surge arresters in medium voltage substations. In Proceedings of the Recent Advances in Energy & Environment, Changsha, China, 4–6 December 2010.
5. Christodoulou, C.A.; Vita, V.; Maris, T.I. Lightning Protection of Distribution Substations by Using Metal Oxide Gapless Surge Arresters Connected in Parallel. *Int. J. Power Energy Res.* **2017**, *1*, 1–7. [CrossRef]
6. Christodoulou, C.A.; Vita, V.; Ekonomou, L. Studies for the more effective protection of MV/LV substations against lightning overvoltages Department of Electrical and Electronic Engineering Educators. *Int. J. Circuits Electron.* **2017**, *2*, 6–10.
7. Christodoulou, C.A.; Vita, V.; Voglitsis, D.; Milushev, G.; Ekonomou, L. A Heuristic method for the reduction of the outage rate of high-voltage substations due to atmospheric overvoltages. *Appl. Sci.* **2018**, *8*, 273. [CrossRef]
8. IEC 60599-2015. *Mineral oil-filled electrical equipment in service—Guidance on the interpretation of dissolved and free gases analysis*; Norwegian Electrotechnical Committee: Mountain View, CA, USA, 2005.
9. Jahromi, A.; Piercy, R.; Cress, S.; Service, J.; Fan, W. An approach to power transformer asset management using health index. *IEEE Electr. Insul. Mag.* **2009**, *25*, 20–34. [CrossRef]
10. Naderian, A.; Cress, S.; Piercy, R.; Wang, F.; Service, J. An Approach to Determine the Health Index of Power Transformers. In Proceedings of the Conference Record of the 2008 IEEE International Symposium on Electrical Insulation, Vancouver, BC, Canada, 9–12 June 2008; pp. 192–196.
11. Hernanda, I.G.N.S.; Mulyana, A.C.; Asfani, D.A.; Negara, I.M.Y.; Fahmi, D. Application of health index method for transformer condition assessment. In Proceedings of the TENCON 2014—2014 IEEE Region 10 Conference, Kuala Lumpur, Malaysia, 14–16 April 2014; pp. 1–6.
12. Abu-Siada, A.; Hmood, S.; Islam, S. A new fuzzy logic approach for consistent interpretation of dissolved gas-in-oil analysis. *IEEE Trans. Dielectr. Electr. Insul.* **2013**, *20*, 2343–2349. [CrossRef]
13. Bakar, N.A.; Abu-Siada, A.; Cui, H.; Li, S. Improvement of DGA interpretation using scoring index method. In Proceedings of the ICEMPE 2017 International Conference on Electric Power Equipment, Zhangzhou, China, 22–25 October 2017; pp. 502–506.
14. Abu-Siada, A.; Arshad, M.; Islam, S. Fuzzy logic approach to identify transformer criticality using dissolved gas analysis. In Proceedings of the IEEE PES General Meeting, PES 2010, Providence, RI, USA, 25–29 July 2010; pp. 1–5.

15. Gumilang, H.; Ansori, E.; Siregar, R.; Subrata, I.; Ika S, H.; Aenul, R.; Yuliastuti, E.; Setiawan, A. Condition assessment method for power transformer as a part of condition based maintenance program in PLN P3B Jawa Bali. In Proceedings of the 2012 IEEE International Conference on Condition Monitoring and Diagnosis, Bali, Indonesia, 23–27 September 2012; pp. 269–272.
16. Abu-Siada, A.; Islam, S. A new approach to identify power transformer criticality and asset management decision based on dissolved gas-in-oil analysis. *IEEE Trans. Dielectr. Electr. Insul.* **2012**, *19*, 1007–1012. [CrossRef]
17. Ashkezari, A.D.; Ma, H.; Saha, T.; Ekanayake, C. Application of fuzzy support vector machine for determining the health index of the insulation system of in-service power transformers. *IEEE Trans. Dielectr. Electr. Insul.* **2013**, *20*, 965–973. [CrossRef]
18. Mahmoudi, N.; Samimi, M.H.; Mohseni, H. Experiences with transformer diagnosis by DGA: Case studies. *IET Gener. Transm. Distrib.* **2019**, *13*, 5431–5439. [CrossRef]
19. Mharakurwa, E.T.; Nyakoe, G.N.; Akumu, A.O. Power Transformer Fault Severity Estimation Based on Dissolved Gas Analysis and Energy of Fault Formation Technique. *J. Electr. Comput. Eng.* **2019**, *2019*, 10. [CrossRef]
20. Arshad, M.; Islam, S.; Khaliq, A. Fuzzy logic approach in power transformers management and decision making. *IEEE Trans. Dielectr. Electr. Insul.* **2014**, *21*, 2343–2354. [CrossRef]
21. Hmood, S.; Masoum, M.A.S.; Islam, S.M.; Abu-Siada, A. Method Standardization of DGA Interpretation Techniques using Fuzzy Logic Approach. In Proceedings of the 2012 IEEE International Conference on Condition Monitoring and Diagnosis, Bali, Indonesia, 23–27 September 2012; pp. 929–932.
22. Hooshmand, R.A.; Parastegari, M.; Forghani, Z. Adaptive neuro-fuzzy inference system approach for simultaneous diagnosis of the type and location of faults in power transformers. *IEEE Electr. Insul. Mag.* **2012**, *28*, 32–42. [CrossRef]
23. Islam, S.M.; Wu, T.; Ledwich, G. A novel fuzzy logic approach to transformer fault diagnosis. *IEEE Trans. Dielectr. Electr. Insul.* **2000**, *7*, 177–186. [CrossRef]
24. Huang, Y.-C.; Sun, H.-C. Dissolved gas analysis of mineral oil for power transformer fault diagnosis using fuzzy logic. *IEEE Trans. Dielectr. Electr. Insul.* **2013**, *20*, 974–981. [CrossRef]
25. Wani, S.A.; Farooque, M.U.; Khan, S.A.; Gupta, D.; Khan, M.A. Fault severity determination in transformers using dissolved gas analysis (DGA). In Proceedings of the 12th IEEE International Conference Electronics, Energy, Environment, Communication, Computer, Control: (E3-C3), INDICON 2015, New Delhi, India, 17–20 December 2015; pp. 1–6.
26. IEEE Std C57.104-2008. *(Revision of IEEE Std C57.104-1991)*; IEEE: Piscataway Township, NJ, USA, 2008.
27. Lee, S.-J.; Kim, Y.-M.; Seo, H.-D.; Jung, J.-R.; Yang, H.-J.; Duval, M. New methods of DGA diagnosis using IEC TC 10 and related databases Part 2: Application of relative content of fault gases. *IEEE Trans. Dielectr. Electr. Insul.* **2013**, *20*, 691–696.
28. Duval, M.; DePablo, A. Interpretation of gas-in-oil analysis using new IEC publication 60599 and IEC TC 10 databases. *IEEE Electr. Insul. Mag.* **2001**, *17*, 31–41. [CrossRef]
29. Duval, M.; Lamarre, L. The duval pentagon-a new complementary tool for the interpretation of dissolved gas analysis in transformers. *IEEE Electr. Insul. Mag.* **2014**, *30*, 9–12.
30. Gumilang, H. Typical Concentration Value and Typical Fault Type Based on DGA Test of Power Transformers in PLN TJBT. In Proceedings of the IEEE Conference on Power Engineering and Renewable Energy, Solo, Indonesia, 29–31 October 2018; pp. 1–4.
31. Pattanadech, N.; Sasomponsawatline, K.; Siriworachanyadee, J.; Angsusatra, W. The conformity of DGA interpretation techniques: Experience from transformer 132 units. In Proceedings of the 2019 IEEE 20th International Conference on Dielectric Liquids (ICDL), Roma, Italy, 23–27 June 2019; pp. 1–4.
32. Benmahamed, Y.; Teguar, M.; Boubakeur, A. Application of SVM and KNN to Duval Pentagon 1 for transformer oil diagnosis. *IEEE Trans. Dielectr. Electr. Insul.* **2017**, *24*, 3443–3451. [CrossRef]
33. Farooque, M.U.; Wani, S.A.; Khan, S.A. Artificial neural network (ANN) based implementation of Duval pentagon. In Proceedings of the 2015 International Conference on Condition Assessment Techniques in Electrical Systems (CATCON), Bangalore, India, 10–12 December 2015; pp. 46–50.
34. Faiz, J.; Soleimani, M. Dissolved gas analysis evaluation in electric power transformers using conventional methods a review. *IEEE Trans. Dielectr. Electr. Insul.* **2017**, *24*, 1239–1248. [CrossRef]

35. IEEE Std C57.104-2019. *IEEE Guide for the Interpretation of Gases Generated in Mineral Oil-Immersed Transformers*; IEEE: Piscataway Township, NJ, USA, 2019.
36. Gumilang, H. Typical Gas Concentration Values and Typical Rate of Gas Increase on DGA Test in PLN UIT-JBT. In Proceedings of the International Conference on High Voltage Engineering and Power Systems, Denpasar, Indonesia, 1–4 October 2019.
37. Prasojo, R.A.; Suwarno. Power transformer paper insulation assessment based on oil measurement data using SVM-classifier. *Int. J. Electr. Eng. Inf.* **2018**, *10*, 661–673. [CrossRef]
38. Ibrahim, K.; Sharkawy, R.M.; Temraz, H.K.; Salama, M.M.A. Selection criteria for oil transformer measurements to calculate the Health Index. *IEEE Trans. Dielectr. Electr. Insul.* **2016**, *23*, 3397–3404. [CrossRef]
39. Wei Fei, S.; Liang Liu, C.; Bin Miao, Y. Support vector machine with genetic algorithm for forecasting of key-gas ratios in oil-immersed transformer. *Expert Syst. Appl.* **2009**, *36*, 6326–6331. [CrossRef]
40. Basuki, A.; Suwarno. Online dissolved gas analysis of power transformers based on decision tree model. In Proceedings of the 4th IEEE Conference on Power Engineering and Renewable Energy, ICPERE 2018—Proceedings, Solo, Indonesia, 29–31 October 2018.
41. Kartojo, I.H.; Wang, Y.-B.; Zhang, G.-J.; Suwarno. Partial Discharge Defect Recognition in Power Transformer using Random Forest. In Proceedings of the 2019 IEEE 20th International Conference on Dielectric Liquids (ICDL), Roma, Italy, 23–27 June 2019; pp. 1–4.
42. Li, J.; Zhang, Q.; Wang, K.; Wang, J.; Zhou, T.; Zhang, Y. Optimal dissolved gas ratios selected by genetic algorithm for power transformer fault diagnosis based on support vector machine. *IEEE Trans. Dielectr. Electr. Insul.* **2016**, *23*, 1198–1206. [CrossRef]
43. Liu, J.; Zhao, Z.; Tang, C.; Yao, C.; Li, C.; Islam, S. Classifying Transformer Winding Deformation Fault Types and Degrees Using FRA Based on Support Vector Machine. *IEEE Access* **2019**, *7*, 112494–112504. [CrossRef]
44. Zeng, B.; Guo, J.; Zhu, W.; Xiao, Z.; Yuan, F.; Huang, S. A transformer fault diagnosis model based on hybrid grey wolf optimizer and LS-SVM. *Energies* **2019**, *12*, 4170. [CrossRef]
45. Shang, H.; Xu, J.; Zheng, Z.; Qi, B.; Zhang, L. A novel fault diagnosis method for power transformer based on dissolved gas analysis using hypersphere multiclass support vector machine and improved D–S evidence theory. *Energies* **2019**, *12*, 4017. [CrossRef]