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ORIGINAL RESEARCH PAPER

Interpreting dissolved gases in transformer oil: A new method based on the analysis of labelled fault data

Arnaud Nanfak[1] | **Samuel Eke**[1] | **Charles Hubert Kom**[1] | **Ruben Mouangue**[2] | **Issouf Fofana**[3]

[1] Laboratory of Energy, Materials, Modelling and Methods, National Higher Polytechnic School of Douala, University of Douala, Douala, Cameroon

[2] Laboratory of Combustion and Green Technologies, Department of Energetic Engineering, UIT, University of Ngaoundere, Ngaoundere, Cameroon

[3] Research Chair on the Aging of Power Network Infrastructure (ViAHT), University of Quebec in Chicoutimi, Chicoutimi, Canada

Correspondence
Arnaud Nanfak, Laboratory of Energy, Materials, Modelling and Methods, National Higher Polytechnic School of Douala, University of Douala, P.O. Box 2701, Douala, Cameroon.
Email: nanfak.arnaud@yahoo.fr

Abstract

In this contribution, a new dissolved gas analysis (DGA) method combining key gases and ratio approaches for power transformer fault diagnostic is presented. It is based on studying subsets and uses the five main hydrocarbon gases including hydrogen (H_2), methane (CH_4), ethane (C_2H_6), ethylene (C_2H_4), and acetylene (C_2H_2). The proposed method uses 475 samples from the dataset divided into subsets formed from the maximum and minimum(s) concentrations of the whole dataset. It has been tested on 117 DGA sample data and validated on the International Electrotechnical Commission (IEC) TC10 database. The performance of the proposed diagnostic method was evaluated and compared with the following diagnostic methods: IEC ratios method, Duval's triangle (DT), three ratios technique (TRT), Gouda's triangle (GT), and self-organizing map (SOM) clusters. The results found were analysed by computer simulations using MATLAB software. The proposed method has a diagnosis accuracy of 97.42% for fault types, as compared to 93.16% of TRT, 96.58% of GT method, 97.25% of SOM clusters method and 98.29% of DT method. However, in terms of fault severity, the proposed method has a diagnostic accuracy of 90.59% as compared to 78.90% of SOM clusters method, 83.76% of TRT, 88.03% of DT method, and 89.74% of GT method.

1 | INTRODUCTION

Power transformers are the most expensive and important elements of power systems. They are crucial for the safety and stability of network operations. Indeed, the failure of a power transformer can lead to a major breakdown of the power grid, leading to outages, costly repairs and huge financial costs [1]. Therefore, early detection of transformer faults is imperative in the process of operating and maintaining power system networks. Chromatographic analysis of dissolved gas in oil, namely dissolved gas analysis (DGA) is one of the most widely used techniques for the early detection of faults inactive parts of transformers [2, 3]. Its popularity stems from the fact that this technique is non-intrusive and can be used for real-time monitoring. The principle of the method consists of periodically taking samples of transformer insulation oil to obtain the composition of gases dissolved in the oil due to the degradation of the insulation system [4]. Identification of the different dissolved gases is made possible by gas chromatography discovered in the 1940s [5]. Gas production is favoured by the temperature level and/or the energy produced by the fault. Depending on the type of fault, different types of decomposition processes may occur. When electrical or thermal faults occur in transformer oil, it degrades, generating combustible gases such as hydrogen (H_2), methane (CH_4), ethane (C_2H_6), ethylene (C_2H_4), and acetylene (C_2H_2). When decomposition occurs in cellulosic insulation, the gases generated are carbon monoxide (CO) and carbon dioxide (CO_2), which indicates a thermal fault. Other gases such as oxygen (O_2) and nitrogen (N_2) are also produced [6]. Once the gases have been identified and quantified, the result still needs to be interpreted to assess the condition of the transformer. Several methods have been proposed in the literature to predict the occurrence of faults and to determine their types by interpreting the concentration of the gases detected [7]. Several standards from different committees and organizations, such as International Electrotechnical Commission (IEC) 60559-1999, Institute of Electrical and Electronics Engineers (IEEE) C57.104-1991, and International Council on Large Electric Systems (CIGRE) TF 15.01.01 provide guidelines for DGA interpretation.

Generally, conventional diagnostic methods using dissolved gases can be divided into three main categories: key gas, graphical and gas ratio methods [8]. The key gas method is based on the correlation of key gases generated with the fault type. In this method, the fault type is identified by the percentage of the generated gases as suggested by IEEE C57.104-2019 [9]. The graphical methods are based on a graphical representation visualizing the different types of faults. Each side of these graphs represents the relative proportions of key gases concentrations or combinations. The most popular graphical methods are Duval's triangle (DT) [10] and Duval's pentagon (DP) [11]. Other graphic methods exist in the literature such as Mansour's pentagon [12], Gouda's heptagon [13], or Gouda's triangle (GT) [14]. Gas ratio methods are based on the correlation of ratio of fault gas concentrations with incipient fault types. These methods take into account the ratios of key gases to develop a code that is supposed to give an indication of fault type. These include, among others, Doernenburg's ratios method (DRM) [15], Roger's ratios method (RRM) [16], conventional IEC ratios method (IRM) [17], and three ratios technique (TRT) of Gouda et al. [18].

The conventional DGA methods of interpretation have certain drawbacks in terms of precision and uncertainty [19]. In order to overcome the difficulties posed by traditional methods in interpreting test results, a major effort has been made to develop intelligent diagnosis in this area. For this purpose, several methods have used artificial intelligence (AI) including expert system (EPS) [20], artificial neural network (ANN) [21–23], genetic algorithm (GA) [24], fuzzy logic theory [25–27], rough sets theory (RST) [28], Grey system theory (GST) [29], swarm intelligence (SI) algorithms [30, 31], data mining technology [32], self-organizing map (SOM) [33] and machine learning (ML) [34–36] for the diagnosis of transformer faults based on DGA data. The current existing conventional and intelligent methods are carried out by means of a sample dataset with the corresponding labelled faults. The size of the training data is a limitation for conventional methods because they require interpretation by human experts [37]. As a result, many of these techniques are based on a reduced amount of data, thus increasing the probability of misdiagnosis.

In this paper, a new diagnostic model combining key gas and gas ratio methods is proposed. It is based on multi-studying dataset (subset) and six ratios of H_2, CH_4, C_2H_6, C_2H_4, and C_2H_2. This method solves the problem of the size of the dataset by creating subsets made from combining maximum and minimum(s) sample concentrations of the main dataset. The ratio approach was used to distinguish between the different faults in each subset. The proposed diagnostic method was carried on using 475 samples dataset, tested on 117 samples DGA data. The classification performance of the proposed method is validated on IEC TC10 database and compared with following conventional methods DT, IRM, RRM, TRT, and DRM.

The remaining part of this paper is organized as follows: A brief description of the types of faults detectable by DGA, and the relationships between the gases produced and the corresponding faults is given in Section 2. Section 3 is devoted to brief review of gas ratio methods. The principle and the flow chart of proposed method are presented in Section 4. The test performance of proposed method and its comparison with conventional methods using IEC TC10 database are presented in Section 5. Finally, Section 6 concludes the paper.

2 | FAULT TYPES AND DGA

2.1 | Transformer fault types

The three major types of power transformer faults which can be reliably identified during a visual inspection are partial discharges, thermal overheating, and arcing [38]. Partial discharges and arcing refer to electrical faults and correspond to the deterioration of insulation due to high electrical stress. Thermal faults refer to the deterioration of the insulation system as a result of a rise in abnormal temperature. Such rises result from overheating of conductors, short circuits, overheating of windings due to Foucault's currents, loose connections, and insufficient cooling [5]. Based on IEC 60599, these major fault types can be further classified into 6 types of transformer faults, summarized in Table 1.

TABLE 1 Fault classification according to IEC 60599 and IEEE C57.104 standard

Acronyms	Faults
PD	Partial discharge
D_1	Low energy discharge
D_2	High energy discharge
T_1	Low temperature thermal fault $T < 300°C$
T_2	Medium temperature thermal fault $300°C < T < 700°C$
T_3	High temperature thermal fault $T > 700°C$

2.2 | Relationship between faults and dissolved gas produced

The two main causes of gas formation in an operating transformer are electrical and thermal stresses. Each type of fault degrades the oil or paper differently, each producing its amount of dissolved gas. The quantities are more or less important depending on the intensity of the particular fault. The nature of the gases formed and their relative proportions provide information on the type of stress, its intensity and the type of materials affected [39]. When an electric arc discharge occurs, large amounts of hydrogen and acetylene are produced, with minor amounts of methane and ethylene. For such a failure, acetylene typically accounts for 20% to 70% and hydrogen for 30% to 90% of the total hydrocarbons. Carbon dioxide and carbon monoxide can also be formed if the cellulose is present at the fault site. In some cases, the oil may carbonize [40]. The occurrence of thermal faults leads to the degradation of oil and paper. Oil overheating produces ethylene and methane with small amounts of hydrogen and ethane. Traces of acetylene can be formed if the fault is serious or involves electrical contacts. Large quantities of carbon dioxide and carbon monoxide are produced when thermal faults attack cellulose.

Hydrocarbon gases, such as methane and ethylene, are formed if the fault involves an oil-impregnated structure [7].

3 | GAS RATIO METHODS

The gas ratio methods are conventional methods that use key gas ratios for fault diagnosis. In this section, a brief review of these methods is presented.

3.1 | Doernenburg's ratio method

The DRM is the first method using the DGA approach. It was designed in 1794 in order to evaluate the three main faults types. Table 2 presents Doernenburg ratios according to the fault type and corresponding diagnostics. DRM is applied if the minimum concentration of one of H_2, CH_4, C_2H_4, and C_2H_2 gases exceeds twice limit values (Table 3) and one of the others gases exceeds the same limit values [41].

TABLE 2 Fault diagnosis by DRM [9]

Fault type	Doernenburg ratios			
	$\frac{CH_4}{H_2}$	$\frac{C_2H_2}{C_2H_4}$	$\frac{C_2H_2}{CH_4}$	$\frac{C_2H_6}{C_2H_2}$
Thermal decomposition	> 1.0	< 0.75	< 0.3	> 0.4
Corona	< 0.1	/	< 0.3	> 0.4
Arcing	0.1–1.0	> 0.75	> 0.3	< 0.4

TABLE 3 Acceptable limits for DRM [42]

Gas	H_2	CH_4	C_2H_6	C_2H_4	C_2H_2	CO
Limit (ppm)	100	120	65	50	1	350

3.2 | Roger's ratio method

The Rogers Ratio Method takes into account the ratios of H_2, CH_4, C_2H_6, C_2H_4, and C_2H_2 to develop code allowing fault diagnosis. In Table 4, ratio range and corresponding codes are listed. The corresponding diagnostics for the various code combinations are presented in Table 5 [9].

TABLE 4 Roger codes

Ratio	Ratio range	Code
$R_1 = C_2H_2/C_2H_4$	$R_1 < 0.1$	0
	$0.1 \leq R_1 \leq 3$	1
	$R_1 > 3$	2
$R_2 = CH_4/H_2$	$R_2 < 0.1$	0
	$0.1 \leq R_2 \leq 1$	1
	$R_2 > 1$	2
$R_3 = C_2H_4/C_2H_6$	$R_3 < 1$	0
	$1 \leq R_3 \leq 3$	1
	$R_3 > 3$	2

TABLE 5 Fault diagnosis by RRM

Fault type	R_1	R_2	R_3
Normal	0	0	0
Low energy density arcing-PD	0	1	0
Arcing-high energy discharge	1	0	2
Low temperature thermal	0	0	1
Thermal < 700°C	0	2	1
Thermal > 700°C	0	2	2

3.3 | IEC ratio method

The IEC ratio method takes into account the same ratios as RRM and the faults are classified into nine categories. The same codes of the three ratios in Table 4 are used in Table 6 which presents code combination according to the IRM faults diagnostics.

TABLE 6 Fault diagnosis by IRM [16]

Fault type	R_1	R_2	R_3
Normal	0	0	0
Partial discharges of low energy density	1	0	0
Partial discharges of high energy density	1	1	0
Discharges of low energy	0	1 → 2	1 → 2
Discharges of high energy	0	1	2
Thermal fault of low temperature < 150°C	0	0	1
Thermal fault of low temperature range 150–300°C	2	0	0
Thermal fault of medium temperature range 300–700°C	2	0	1
Thermal fault of high temperature range > 700°C	2	0	2

3.4 | Three ratios technique

The TRT proposed by Gouda et al. [18] uses three new gas ratios to classify fault types and their severity, as shown in Table 7. In this method, the R_1 ratio is used to classify thermal, arcing, and partial discharge faults. The R_3 ratio, also used in the above diagnostic techniques, is used to separate thermal and electrical faults, and so it is used to confirm the type of R_1 ratio fault. The R_2 ratio is used to assess the degree of severity of thermal, electrical and partial discharge faults. It is used to distinguish between low (PD_1) and high (PD_2) partial discharge faults, low (D_1) and high (D_2) energy discharge faults and also very low (T_0), low (T_1), medium (T_2) and high (T_3) temperature thermal energy faults [14]. The corresponding diagnostics for the various code combinations, inspired by the flowchart described in [14], are presented in Table 8.

TABLE 7 Gouda codes

Ratio	Ratio range	Code
$R_1 = \frac{C_2H_6+C_2H_4}{H_2+C_2H_2}$	$R_1 < 0.05$	0
	$0.05 \leq R_1 \leq 0.9$	1
	$R_1 > 0.9$	2
$R_2 = \frac{C_2H_2+CH_4}{C_2H_4}$	$R_2 < 1$	0
	$1 \leq R_2 \leq 3.5$	1
	$R_1 > 3.5$	2
$R_3 = \frac{C_2H_2}{C_2H_4}$	$R_3 < 0.05$	0
	$0.05 \leq R_3 \leq 0.5$	1
	$R_3 > 0.5$	2

TABLE 8 Fault diagnosis by TRT

Fault type	Severity of fault	R_1	R_2	R_3
High temperature thermal T > 700°C	T_3	1 or 2	0	0 or 1
Medium temperature thermal 300°C < T < 700°C	T_2	1 or 2	1	0 or 1
Low temperature thermal 150°C < T < 300°C	T_1	1 or 2	2	0 or 1
Low temperature thermal T < 150°C	T_0	1	/	0
Low partial discharge	PD_1	0	1 or 2	0 or 1
High partial discharge	PD_2	0	1 or 2	2
High arcing discharge	D_2	0 or 1	0 or 1	2
Low arcing discharge	D_1	1 or 2	2	2
Mix of electrical and thermal fault	DT	2	0 or 1	2

This technique shall be applied when at least one of the concentrations of dissolved gases exceeds the normal limits as shown in Table 9.

TABLE 9 Limit concentrations of dissolved gases for the application of TRT [43]

Gas	H_2	CH_4	C_2H_6	C_2H_4	C_2H_2	CO	CO_2
Limit (ppm)	100	120	65	50	1	350	2500

4 | PROPOSED METHOD FOR TRANSFORMERS FAULTS DIAGNOSTIC

4.1 | Principle of the method

This article proposes a diagnostic method for power transformer faults that combines the key gas and gas ratio approaches. It is mainly based on the decomposition of the studying dataset into studying subsets which are then studied individually using the ratios method approach. Six gas ratios involving the five main hydrocarbon gases formed in transformer oil, namely H_2, CH_4, C_2H_6, C_2H_4, and C_2H_2 are used. The subsets obtained by decomposing the main dataset result from the combination of maximum and minimum(s) sample concentrations of the main dataset. The gas ratio approach is used to determine the different faults in each subset. As each subset is treated independently of the others, this allows more flexibility on the ratios to be taken into account and on the ratio ranges to be used for development of the model of each subset (sub-model). The final diagnostic model is obtained by combining the different sub-models obtained with each subset. Table 10 shows the subsets resulting from combinations having hydrogen as maximum concentration. A total of 75 studying subsets can be created from the main dataset. Table 11 lists the definition of the gas ratios used, while Figure 1 illustrates the principle of the proposed method.

TABLE 10 Possible studying subsets of H_2

Key gases concentrations		
Maximum	Minimum (s)	Studying subsets
H_2	CH_4	1
	C_2H_6	2
	C_2H_4	3
	C_2H_2	4
	CH_4 & C_2H_6	5
	CH_4 & C_2H_4	6
	CH_4 & C_2H_2	7
	C_2H_6 & C_2H_4	8
	C_2H_6 & C_2H_2	9
	C_2H_4 & C_2H_2	10
	CH_4 & C_2H_6 & C_2H_4	11
	CH_4 & C_2H_6 & C_2H_2	12
	CH_4 & C_2H_4 & C_2H_2	13
	C_2H_6 & C_2H_4 & C_2H_2	14
	CH_4 & C_2H_6 & C_2H_4 & C_2H_2	15

TABLE 11 Gas ratio used

Ratio	Expression
R_1	$\frac{CH_4+C_2H_6}{H_2+CH_4+C_2H_6+C_2H_4+C_2H_2}$
R_2	$\frac{CH_4+C_2H_4}{H_2+CH_4+C_2H_6+C_2H_4+C_2H_2}$
R_3	$\frac{C_2H_6}{CH_4+C_2H_4}$
R_4	$\frac{CH_4+H_2}{H_2+CH_4+C_2H_6+C_2H_4+C_2H_2}$
R_5	$\frac{C_2H_4+C_2H_2}{H_2+CH_4+C_2H_6+C_2H_4+C_2H_2}$
R_6	$\frac{C_2H_2}{C_2H_4}$

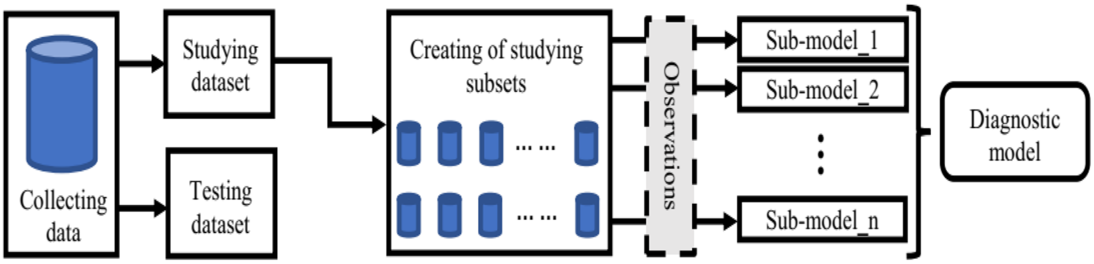

FIGURE 1 Schematic view of the new DGA method

TABLE 12 Studying dataset of example

No.	H_2	CH_4	C_2H_6	C_2H_4	C_2H_2	Actual
1	54.54	71.93	9.72	93.37	6.58	T_3
2	20	80.2	24.6	68.6	0	T_2
3	15.9	55.98	22.33	137.25	0.21	T_3
4	2.369	119.69	21.891	20.15	0	T_1
5	131.7	116.55	19.4	183.97	0.32	T_3
6	73.8	148	38.9	181	1.76	T_3
7	18.19	21.99	6.58	46.92	3.97	T_3
8	116.17	180.83	52.48	278.18	5.36	T_3
9	50.18	171.12	74.7	148.69	0	T_2
10	7238.97	695.16	231.3	2394.3	2308.92	D_2
11	50.35	65.58	21.05	99.13	0.96	T_3
12	120.45	210.91	35.7	285.39	15.86	T_3
13	5.48	48.82	96.81	489.57	0.3	T_3

N°	H_2	CH_4	C_2H_6	C_2H_4	C_2H_2	Actual
14	25.4	54.97	8.72	77.84	10.47	T_3
15	7911.85	947.43	96.93	907.19	4844.48	D_1
16	34.76	5.52	2.09	4.97	10.36	D_1
17	110.4	112	32.5	80.8	0	T_1
18	170	300	44	580	300	T_3
19	180	340	52	6303	340	T_3
20	17	21	11	145	21	T_3
21	90	160	54	330	160	T_3
22	139	52.2	6.8	62.8	52.2	D_2
23	421	135	27.7	351	135	D_2
24	71.6	20.2	2.7	34.6	20.2	D_2
25	730	750	190	1300	750	D_2

4.2 | Example of application of the method

This example illustrates the application of the proposed method to a dataset of 25 samples (Table 12). The first step in the method is to create subsets from the samples in the studying dataset. In the second step, each subset is studied individually and the corresponding sub-model is proposed. The third and last step consists of grouping all the sub-models into a single program to have the diagnostic model. These three steps are presented in Figure 2. A generalization to a larger database made it possible to have the flowchart of the diagnostic method presented in Table B1 and the pseudo code in Appendix A. Examples of numerical application on samples 5 (purple), 10 (red), 17 (blue) and 25 (green) from Table 12 can be seen in Table B1.

5 | RESULTS AND DISCUSSION

5.1 | Data collection

The present study was carried out using 592 samples covering the six faults classes with actual fault types collected from several sources as presented in Table 13 below: 144 data samples from [44], 339 data samples collected from [45], 64 data samples from [19], 20 data from tab. 2 of [46] and 25 data from tabs. 1 and 2 of [47].

In order to conduct the new proposed method, the DGA data was divided into studying and testing dataset as shown in Table 14. The studying dataset is composed of samples labelled of dissolved gas and is used for the implementation of flow chart of the proposed method. The testing dataset is used for verification of observations made in each subset.

5.2 | Results and discussion

Implementation of the proposed method was performed using MATLAB software and the algorithm was programmed in .m codes. Table 15 presents an overview of the fault diagnostic accuracy obtained by comparing studying and testing datasets.

Considering the diagnostic accuracy results obtained from the studying dataset, it is clear that the proposed method performs better at detecting PD, D_2 and T_3 faults, with accuracy greater than or equal to 90%. A fairly good accuracy, close to 70%, was reported for faults D_1 and T_2 while an accuracy of 82.6% was assigned for fault T_1. In summary, 83.36% of the dissolved gas samples were well diagnosed, i.e. 396 out of 475

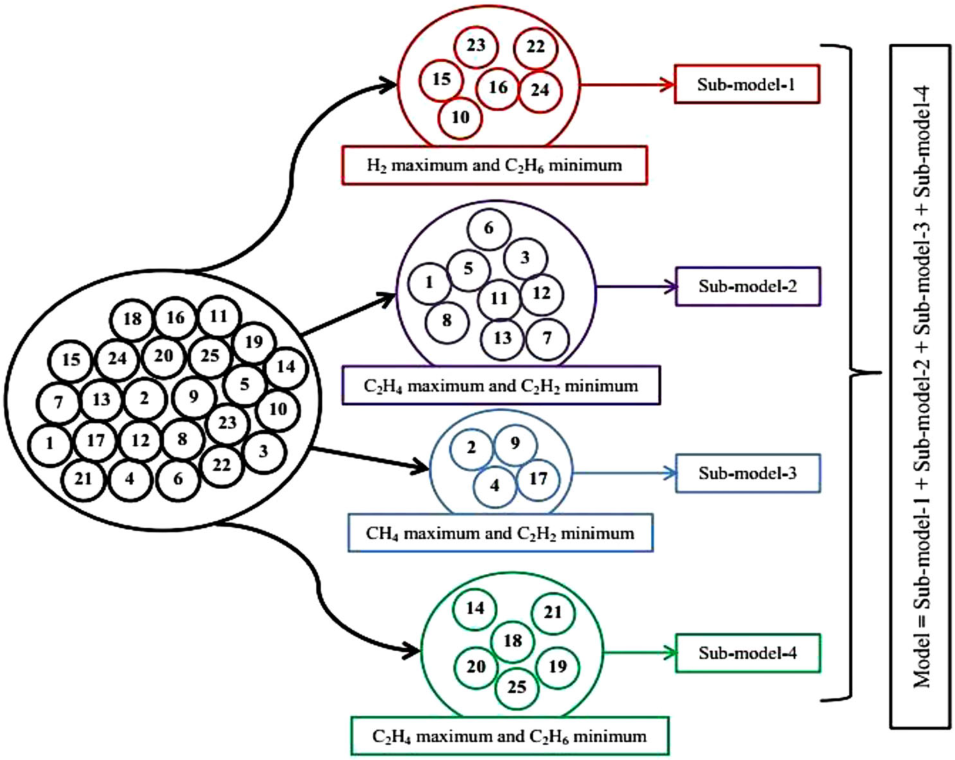

FIGURE 2 Example of application of the steps of the proposed method

TABLE 13 Distribution of collected data according to references

	Fault types						
Ref.	**PD**	**D_1**	**D_2**	**T_1**	**T_2**	**T_3**	**Total**
[44]	16	35	15	29	19	30	144
[45]	32	51	74	85	41	56	339
[19]	0	32	32	0	0	0	64
[46]	7	2	2	0	5	4	20
[47]	0	7	18	0	0	0	25
Total	55	127	141	114	65	90	592

TABLE 14 Composition of studying and testing dataset

	Fault types						
	PD	**D_1**	**D_2**	**T_1**	**T_2**	**T_3**	**Total**
Studying dataset	44	102	113	92	52	72	475
Testing dataset	11	25	28	22	13	18	117
Total	55	127	141	114	65	90	592

TABLE 15 Fault diagnosis accuracy

	Fault diagnosis accuracy (%)						
	PD	**D_1**	**D_2**	**T_1**	**T_2**	**T_3**	**Total**
Studying dataset	90.90	72.54	90.26	82.60	71.15	93.05	83.36
Testing dataset	90.90	84	96.42	72.72	100	94.44	88.88

data sets. Based on the diagnostic accuracies obtained from the testing dataset, it appears that the observations made on the studying dataset were well carried out in the measure that its diagnostic precision was higher.

5.3 | Validation and comparison with other conventional methods using IEC TC10 database

The IEC TC 10 database contains 117 cases of fault for transformers in service, which were identified by visual inspection [38]. This data is not part of the new DGA proposed method. In order to validate this proposed model, this DGA database was used. The diagnostic results are presented in Table C1 and the average diagnostic accuracies by equipment type are summarized in Table 17.

Table 16 shows the equipment's abbreviations of the IEC TC10 database. In Table 17, the fault types refer to the three

TABLE 16 Abbreviations used for equipment type

Abbreviations	**Equipment**
P	Power transformer without communication OLTC
U	Power transformer with communication OLTC
R	Reactor
I	Instrument transformer
B	Bushing
C	Cable

TABLE 17 Average diagnosis accuracy of diagnosis models validated with IEC TC10 database

	Average diagnosis accuracy (%)											
	IRM		DT		TRT		GT		SOM clusters		Proposed	
Equipment type	Severity	Fault type	Severity	Fault type	Severity	Fault type	Severity	Fault type	Severity	Fault type	Severity	Fault type
P	63.88	86.11	88.88	97.22	86.11	94.44	86.11	94.44	77.78	100	88.88	97.22
U	77.27	86.36	90.91	100	95.45	100	95.45	100	72.73	95.45	100	100
R	75	87.50	90.62	96.87	84.37	93.75	93.75	96.88	84.36	96.88	90.62	96.87
I	58.33	58.33	100	100	83.33	83.33	91.67	91.67	91.67	100	100	100
B	0	40	40	100	20	60	60	100	60	100	40	80
C	100	100	100	100	100	100	100	100	50	50	100	100
S	71.42	85.71	71.42	100	71.42	100	85.71	100	/	/	85.71	100
Empty	0	0	100	100	100	100	100	100	/	/	100	100
Total	66.67	81.19	88.03	98.29	83.76	93.16	89.74	96.58	78.90	97.25	90.60	97.43

main faults, i.e. partial discharges, thermal overheating, and arcing. As for severity, it refers to the three main faults: i.e. PD for partial discharge, D_1 and D_2 for arcing, and T_1, T_2 and T_3 for thermal overheating. The results obtained are compared with those obtained with IRM [16], DT [10], TRT [18], GT [14] and SOM clusters [33].

Tables 18 and 19 summarize the comparison between proposed diagnostic method and other diagnostic methods obtained with 117 cases of IEC TC10 databases.

TABLE 18 Comparison between proposed method and conventional methods in terms of severity

DGA methods	Unresolved diagnostic (%)	Wrong diagnostic (%)	Error (%)	Diagnostic accuracy (%)
IRM	14.53	18.80	33.33	66.67
DT	00.85	11.11	11.97	88.03
TRT	00.85	15.38	16.24	83.76
GT	00.00	10.26	10.26	89.74
SOM cl.	00.00	21.10	21.10	78.90
Proposed	00.00	09.40	09.40	90.60

TABLE 19 Comparison between proposed method and conventional methods in terms of fault type

DGA methods	Unresolved diagnostic (%)	Wrong diagnostic (%)	Error (%)	Diagnostic accuracy (%)
IRM	14.53	04.28	18.81	81.19
DT	00.00	01.71	01.71	98.29
TRT	00.85	05.99	06.84	93.16
GT	00.00	03.42	03.42	96.58
SOM cl.	00.00	02.75	02.75	97.25
Proposed	00.00	02.57	02.57	97.43

The diagnostic accuracies with the IEC TC10 database for the different methods are presented in terms of the equipment and distributed according to severity and fault type. Considering the diagnostic accuracy obtained from the equipment, the proposed method could be used to detect and classify faults in P, U, R, I, and C equipment. For power transformers without communicating OLTC, the proposed method has diagnostic accuracy of 88.88% and 97.22% respectively in terms of severity and fault type. However, for power transformers with communicating OLTC, the diagnostic accuracy is 100% for both types. Out of the 117 cases including all equipment, the proposed method has diagnostic accuracy of 90.60% and 97.43% for severity and fault type respectively.

The use of subsets makes it possible on the one hand to propose empirical methods to diagnose power transformers using a large number of labelled data and on the other hand to take into account all the characteristics of the sample subsets created. However, the multiplication of studying datasets increases the work of the human expert, who no longer confines himself to observations allowing detection and classification of faults in a single set, but in several sets at the same time. Although the new diagnostic method is more constraining in terms of the work carried out, it offers several avenues for improving the performance of existing methods. Also, it can be used to propose a method with dynamic ratios according to the different subsets created. It could even be used to combine several methods into one by applying them to the different subsets created.

6 | CONCLUSION

In this paper, a new conventional DGA method for fault diagnosis of power transformers is proposed. This method is based on multi datasets combining the key gases and gas ratio approaches. The key gases approach is used to form the different studying subsets from the combination of maximum and minimum(s) sample gas concentration of main dataset. The gas ratio approach is used to detect and classify faults of each studying subset. The dataset used in this paper contains 709 labelled samples covering six fault types. The first group of 592 samples is used for the implementation and evaluation of the diagnostic model proposed. Taking into account the subjectivity of the testing dataset, the performance of proposed diagnostic model was validated using the second group of data consisting of the 117 samples from the IEC TC10 database. The proposed method has a diagnosis accuracy of 97.42% for fault types, as compared to 93.16% of TRT, 96.58% of GT method, 97.25% of SOM clusters method, and 98.29% of DT method. In terms of fault severity, however, the proposed method has the highest diagnostic accuracy of 90.60% compared to 78.90% of SOM clusters method, 83.76% of TRT, 88.03% of DT method and 89.74% of GT method. The main advantage of the proposed method is that it can be formalized insofar as the schematic approach is clear and comprehensible. Whereas this is not the case with the conventional methods existing in the literature, which present their flow chart without the methodical approach that made it possible. The use of studying subsets makes it possible to implement conventional diagnostic methods using large databases leading to the proposal of a more efficient diagnostic model. In addition, it offers many possibilities in the improvement of existing conventional methods, in the implementation of combined or even hybrid diagnostic approaches. The proposed model appears to be a promising approach to support a new generation of DGA diagnosis and to overcome the complexities.

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APPENDICES

The pseudo code describes step by step how the method can be reproduced by everyone. In this pseudo code, it is indicated how the flowchart can be transformed into a code with two examples. Table B1 presents the flow chart of the proposed diagnostic method and Table C1 shows the diagnostic results obtained with the conventional methods and the proposed method, using IEC TC10 database.

APPENDIX A: PSEUDO CODE

1. Input dissolved gas sample concentrations
2. Compute the gas ratios R_1 to R_6 (Table 11)
3. Compute total dissolved gas sample concentrations

$$T = H_2 + CH_4 + C_2H_6 + C_2H_4 + C_2H_2;$$

4. Determination of maximum and minimum(s) sample concentrations

$$C_{max} = \max([H_2, CH_4, C_2H_6, C_2H_4, C_2H_2]);$$
$$C_{min} = \min([H_2, CH_4, C_2H_6, C_2H_4, C_2H_2])$$

5. Determination of subsets

```
if Cmax == H2
    if Cmin == CH4
        N = SM1;
    elseif Cmin == C2H6
        N = SM2;
    elseif Cmin == C2H4
        N = SM3;
    elseif Cmin == C2H2
        N = SM4;
    elseif Cmin == CH4 & C2H6
        N = SM5;
        ⋮
        elseif Cmin == CH4 & C2H6 & C2H4 & C2H2
        N = SM15;
end
elseif Cmax == CH4
    if Cmin == H2
        N = SM16;
    elseif Cmin == C2H6
        N = SM17;
    ⋮
    elseif Cmin == H2 & C2H6 & C2H4 & C2H2
        N = SM30;
end
elseif Cmax == C2H6
    if Cmin == H2
        N = SM31;
    elseif Cmin == CH4
    N = SM32;
    ⋮
    elseif Cmin == H2 & CH4 & C2H4 & C2H2
        N = SM45;
end
elseif Cmax == C2H4
        if Cmin == H2
        N = SM46;
    elseif Cmin == CH4
        N = SM47;
:
```

```
        elseif Cmin == H2 & CH4 & C2H6 & C2H2
            N = SM60;
    end
    else
        if Cmin == H2
            N = SM61;
        elseif Cmin == CH4
            N = SM62;
    :
        elseif Cmin == H2 & CH4 & C2H6 & C2H4
            N = SM75;
    end
    end
```

6. Construction of the model

```
    Switch N
            case SM1
                if R1 <= 0.15
                    disp('Low energy discharge: D1')
                else
                    disp('High energy discharge: D2')
                end
            :
            case SM3
                if R5(i,1) < 0.05
                    if R6(i,1) >= 0.40
                        disp('Partial Discharge: PD')
                    else
                        disp('Low energy discharge: D1')
                    end
                else
                    if R2(i,1) > 0.15
                        disp('High energy discharge: D2')
                    else
                        disp('Low energy discharge: D1')
                    end
                end
            :
            otherwise
                disp('ND')
    end
```

TABLE B1 Flow chart of the proposed diagnostic model of power transformers

Key Gases		Ratios						Concentration		Fault type					
Max.	Minimum(s)	R_1	R_2	R_3	R_4	R_5	R_6	T	C_2H_6	PD	D_1	D_2	T_1	T_2	T_3
H_2	CH_4	≤0.15	x	x	x	x	x	x	x		✓				
		>0.15										✓			
	C_2H_6	x	≥0.20	≥0.10	≥0.65	x	≥4	x	x						✓
							<4				✓				
				<0.10			x					✓			
			<0.20	x							✓				
		x	x	x	<0.65	≥0.40	≥0.45					✓			
			≥0.23			<0.40						✓			
			<0.23								✓				
			x	≥0.10		x	<0.45				✓				
			≥0.20	<0.10		≥0.40						✓			
			<0.20								✓				
			x			<0.40						✓			
	C_2H_4	x	x	x	x	<0.05	≥0.40	x	x	✓					
							<0.40				✓				
		x	>0.15	x	x	≥0.05	x					✓			
			≤0.15								✓				
	C_2H_2	x	≥0.15	>1	x	x	≤10	x	x		✓				
							>10						✓		
		≥0.15	<0.15				x			✓					
		<0.15									✓				
		x	x	≤1	x	≥0.15	≤15					✓			
						]0.1; 0.15[								✓	
						≤0.1				✓					
					≥0.75	x	>15			✓					
			≤0.45		<0.75								✓		
			>0.45											✓	
	CH_4 & C_2H_6	x	x	x	x	x	x	x	x		✓				
	C_2H_6 & C_2H_4	x	x	≤0.1	x	x	x	x	x	✓					
				>0.1							✓				
	C_2H_6 & C_2H_2	x	x	≤0.1	x	x	x	x	x	✓					
				>0.1							✓				
	C_2H_4 & C_2H_2	x	x	x	x	≤0.05	x	x	x	✓					
						>0.05					✓				
	C_2H_6 & C_2H_4 & C_2H_2	x	x	≤0.1	x	x	x	x	x	✓					
				>0.1							✓				
CH_4	H_2	x	x	≥0.1	x	x	x	x	x			✓			
				<0.1										✓	
	C_2H_6	x	x	x	x	x	x	x	x			✓			
	C_2H_4	x	x	x	x	x	x	x	x				✓		
	C_2H_2	≥0.4	x	≥0.15	x	≥0.25	x	x	x					✓	

(Continues)

TABLE B1 (Continued)

				<0.15	≥0.55			≥1500							✓
								<1500						✓	
					<0.55			x						✓	
		<0.4		x	x								✓		
		x	x	x	≥0.90	<0.25	x	x					✓		
			≥0.60	≥0.25	<0.90								✓		
				<0.25										✓	
		≥0.775	<0.60	x							✓				
		<0.775											✓		
	H_2 & C_2H_4	x	x	x	x	x	x	x	x				✓		
	H_2 & C_2H_2	x	x	x	x	x	x	x	x				✓		
	C_2H_4 & C_2H_2	x	x	x	x	x	x	x	x				✓		
	H_2 & C_2H_4 & C_2H_2	x	x	x	x	x	x	x	x				✓		
C_2H_6	H_2	x	x	x	≥0.1	x	x	x	x			✓			
					<0.1										✓
	CH_4	x	x	x	x	x	x	x	x			✓			
	C_2H_4	x	x	x	x	≥0.1	x	x	x			✓			
		x	x	x	≥0.30	<0.1						✓			
					<0.30								✓		
	C_2H_2	≥0.60	x	x	x	≥0.10	x	x	≥0.1			✓			
									<0.1				✓		
		<0.60							x				✓		
		≥0.65	≥0.35	x	x	<0.10	x		≥0.1						✓
									<0.1				✓		
			<0.35						x				✓		
		<0.65	≥0.25						≥0.1	✓					
			<0.25									✓			
			x						<0.1				✓		
	H_2 & C_2H_2	x	x	x	x	x	x	x	x				✓		
	C_2H_4 & C_2H_2	x	x	x	x	x	x	x	x	✓					
C_2H_4	H_2	x	x	x	x	x	x	x	x						✓
	CH_4	≥0.10	x	x	x	x	x	x	x			✓			
		<0.10									✓				
	C_2H_6	x	≥0.60	x	x	x	x	x	x						✓
			<0.60									✓			
	C_2H_2	≥0.45	≥0.70	≥0.15	≥0.10	x	x	x	x					✓	
		<0.45													✓
		x			<0.10	≥0.70									✓
						<0.70								✓	
			<0.70		x	x			≥0.10				✓		
		≥0.45							<0.10						✓
		<0.45												✓	
		x	x	<0.15	x	x	x	x	x						✓
	H_2 & C_2H_2	x	x	x	x	x	x	x	x					✓	
	C_2H_6 & C_2H_2	x	x	x	x	x	x	x	x						✓
	H_2 & CH_4 & C_2H_2	x	x	x	x	x	x	x	x						✓

(Continues)

TABLE B1 (Continued)

	H_2 & C_2H_6 & C_2H_2	x	x	x	x	x	x	x	x						✓
	H_2 & CH_4 & C_2H_6 & C_2H_2	x	x	x	x	x	x	x	x						✓
C_2H_2	H_2	x	x	x	x	x	x	x	x			✓			
	CH_4	x	≥0.15	x	x	x	x	x	x			✓			
			<0.15								✓				
	C_2H_6	≥0.10	≥0.20		≥0.40	x	x	x	x			✓			
				≥0.10	<0.40						✓				
				<0.10								✓			
			<0.20	x	x							✓			
		<0.10	≥0.10	≥0.10	≥0.40	x	x				✓				
					<0.40							✓			
				<0.10	≥0.30							✓			
					<0.30						✓				
			<0.10	x	≥0.15							✓			
					<0.15						✓				
	C_2H_4	≥0.10	x	x	x	x	x	x	x			✓			
		<0.10									✓				
	H_2 & CH_4	x	x	x	x	x	x	x	x			✓			
	CH_4 & C_2H_6	x	x	x	x	x	x	x	x		✓				
	C_2H_6 & C_2H_4	x	x	≥0.15	x	x	x	x	x		✓				
		x	x	<0.15	x	x	x	x	x			✓			
	H_2 & C_2H_6 & C_2H_4	x	x	x	x	x	x	x	x			✓			
	CH_4 & C_2H_6 & C_2H_4	x	x	x	x	x	x	x	x			✓			

TABLE C1 Diagnostic model validated with the IEC TC10 database

H_2	CH_4	C_2H_6	C_2H_4	C_2H_2	Equip.	Act.	IRM	DT	TRT	GT	SOM	Prop.
57	24	2	27	30	B	D1	D_2	D_2	D_2	D_2	D_2	D_2
1000	500	1	400	500	B	D1	D_2	D_2	D_2	D_2	D_2	D_2
8266	1061	22	0,001	0,001	B	PD	ND	PD	PD	PD	PD	PD
0,001	18900	410	540	330	B	T_1/T_2	ND	T_1	D1	T_1	T_1/T_2	T_1
40000	400	70	600	6	B	T_1/T_2	ND	T_3	ND	T_1	T_1/T_2	PD
210	22	6	6	7	C	D1	D_1	D_1	D_1	D_1	D_1	D_1
150	130	9	55	30	C	D_2	D_2	D_2	D_2	D_2	T_2	D_2
7940	2000	355	3120	5390	I	D_2	D_2	D_2	D_2	D_2	D_2	D_2
33046	619	58	2	0,001	I	PD	PD	PD	PD	PD	PD	PD
92600	10200	0,001	0,001	0,001	I	PD	D_1	PD	PD	PD	PD	PD
9340	995	60	6	7	I	PD	ND	PD	PD	PD	PD	PD
26788	18342	2111	27	0,001	I	PD	NF	PD	T_1	PD	PD	PD
36036	4704	554	5	10	I	PD	ND	PD	PD	PD	PD	PD
37800	1740	249	8	8	I	PD	PD	PD	PD	PD	PD	PD
40280	1069	1060	1	1	I	PD	PD	PD	PD	PD	PD	PD
360	610	259	260	9	I	T_1/T_2	T_2	T_2	T_2	T_2	T_1/T_2	T_1
960	4000	1290	1560	6	I	T_1/T_2	T_2	T_2	T_2	T_2	T_1/T_2	T_2
1	27	49	4	1	I	T_1/T_2	ND	T_1	NF	N	T_1/T_2	T_1
24700	61000	26300	42100	1560	I	T_1/T_2	T_2	T_2	T_2	T_2	T_3	T_2
305	100	33	161	541	P	D_1	D_1	D_1	D_1	D_1	D_1	D_1
595	80	9	89	244	P	D_1	D_2	D_1	D_1	D_1	D_1	D_1
78	20	11	13	28	P	D_1	D_1	D_1	D_1	D_1	D_2	D_1
95	10	0,001	11	39	P	D_1	D_1	D_1	D_1	D_1	D_2	D_1
645	86	13	110	317	P	D_1	D_2	D_1	D_1	D_1	D_1	D_1
1230	163	27	233	692	P	D_1	D_2	D_1	D_1	D_1	D_1	D_1
1330	10	20	66	182	P	D_1	ND	D_2	D_2	D_2	D_1	D_1
75	15	7	14	26	P	D_2	D_1	D_2	D_2	D_2	D_1	D_1
1820	405	35	365	634	P	D_2	D_2	D_2	D_2	D_2	D_2	D_2
60	5	2	21	21	P	D_2	ND	D_2	D_2	D_2	D_2	D_2
2770	660	54	712	763	P	D_2	D_2	D_2	D_2	D_2	D_2	D_2
260	215	35	334	277	P	D_2	D_2	D_2	D_2	D_2	D_2	D_2
440	89	19	304	757	P	D_2	D_2	D_2	D_2	D_2	D_1	D_2
545	130	16	153	239	P	D_2	D_2	D_2	D_2	D_2	D_2	D_2
755	229	32	404	460	P	D_2	D_2	D_2	D_2	D_2	D_2	D_2
1170	255	18	312	325	P	D_2	D_2	D_2	D_2	D_2	D_2	D_2
1500	395	28	395	323	P	D_2	D_2	D_2	D_2	D_2	D_2	D_2
1570	1110	175	1780	1830	P	D_2	D_2	D_2	D_2	D_2	D_2	D_2
7150	1440	97	1210	1760	P	D_2	D_2	D_2	D_2	D_2	D_2	D_2
20000	13000	1850	29000	57000	P	D_2	D_2	D_2	D_2	D_2	D_2	D_2
3090	5020	323	3800	2540	P	D_2	ND	D_2	D_2	D_2	D_2	D_2
3700	1690	128	2810	3270	P	D_2	D_2	D_2	D_2	D_2	D_2	D_2
12	18	4	4	0,001	P	T_1/T_2	T_2	T_1	NF	T_1	T_1/T_2	T_1
14	44	124	7	1	P	T_1/T_2	ND	T_1	T_1	T_1	T_1/T_2	T_1
48	610	29	10	0,001	P	T_1/T_2	T_1	PD	T_1	PD	T_1/T_2	T_1
66	60	2	7	0,001	P	T_1/T_2	ND	T_1	NF	N	T_1/T_2	PD

(Continues)

TABLE C1 (Continued)

H_2	CH_4	C_2H_6	C_2H_4	C_2H_2	Equip.	Act.	IRM	DT	TRT	GT	SOM	Prop.
1270	3450	520	1390	8	P	T_1/T_2	T_2	T_2	T_2	T_2	T_1/T_2	T_2
3420	7870	1500	6990	33	P	T_1/T_2	T_3	T_2	T_2	T_2	T_1/T_2	T_3
6	2990	29990	26076	67	P	T_3	T_1	T_3	T_3	T_3	T_3	T_3
107	143	34	222	2	P	T_3	T_3	T_3	T_3	T_3	T_2	T_3
400	940	210	820	24	P	T_3	T_3	T_2	T_2	T_2	T_2	T_3
290	966	299	1810	57	P	T_3	T_3	T_3	T_3	T_3	T_2	T_3
290	1260	231	820	8	P	T_3	T_3	T_2	T_2	T_2	T_2	T_3
2500	10500	4790	13500	6	P	T_3	T_2	T_3	T_3	T_3	T_3	T_2
6709	10500	1400	17700	750	P	T_3	T_3	T_3	T_3	T_3	T_3	T_3
8800	64064	72128	95650	0,001	P	T_3	T_2	T_3	T_3	T_3	T_3	T_3
60	10	4	4	4	R	D_1	D_1	D_1	D_2	D_1	D_1	D_1
385	60	8	53	159	R	D_1	D_2	D_1	D_1	D_1	D_1	D_1
1790	580	321	336	619	R	D_1	D_1	D_1	D_1	D_1	D_2	D_1
120	25	1	8	40	R	D_1	D_1	D_1	D_1	D_1	D_1	D_1
2177	1049	207	440	705	R	D_1	D_1	D_1	D_1	D_1	D_1	D_1
4230	690	5	196	1180	R	D_1	D_1	D_1	PD	D_1	D_1	D_1
6454	2313	121	2159	6432	R	D_1	D_2	D_1	D_1	D_1	D_1	D_2
7600	1230	318	836	1560	R	D_1	D_1	D_2	D_2	D_1	D_1	D_1
90	28	8	31	32	R	D_2	D_2	D_2	D_2	D_2	D_1	D_2
4419	3564	668	2861	2025	R	D_2	D_2	D_2	D_2	D_2	T_3	D_2
5000	1200	83	1000	1100	R	D_2	D_2	D_2	D_2	D_2	D_2	D_2
99	170	20	200	190	R	D_2	ND	D_2	D_2	D_2	D_2	D_2
110	62	90	140	250	R	D_2	D_1	D_2	D_2	D_2	D_2	D_2
120	31	0,001	66	94	R	D_2	D_2	D_2	D_2	D_2	D_2	D_2
220	77	22	170	240	R	D_2	D_2	D_2	D_2	D_2	D_2	D_2
245	120	18	131	167	R	D_2	D_2	D_2	D_2	D_2	D_2	D_2
305	85	25	197	130	R	D_2	D_2	D_2	D_2	D_2	D_2	D_2
530	345	85	266	250	R	D_2	D_2	D_2	D_2	D_2	D_2	D_2
535	160	16	305	680	R	D_2	D_2	D_2	D_2	D_2	D_2	D_2
810	580	111	570	490	R	D_2	D_2	D_2	D_2	D_2	D_2	D_2
1900	530	35	383	434	R	D_2	D_2	D_2	D_2	D_2	D_2	D_2
2800	2800	234	3500	3600	R	D_2	D_2	D_2	D_2	D_2	D_2	D_2
5100	1430	0,001	1140	1010	R	D_2	D_2	D_2	D_2	D_2	D_2	D_2
5900	1500	68	1200	2300	R	D_2	D_2	D_2	D_2	D_2	D_2	D_2
8200	3790	250	4620	5830	R	D_2	D_2	D_2	D_2	D_2	D_2	D_2
480	1075	298	1132	0,001	R	T_1/T_2	T_3	T_3	T_3	T_3	T_1/T_2	T_3
2031	149	20	3	0,001	R	T_1/T_2	PD	PD	PD	PD	T_1/T_2	PD
1	8	8	100	6	R	T_3	T_3	T_3	T_3	T_3	T_2	T_3
12705	23498	6047	34257	5188	R	T_3	ND	T_3	T_3	T_3	T_3	T_3
300	700	280	1700	36	R	T_3	T_3	T_3	T_3	T_3	T_2	T_3
1550	2740	816	5450	184	R	T_3	T_3	T_3	T_3	T_3	T_3	T_3
3910	4290	626	6040	1230	R	T_3	ND	T_3	T_3	T_3	T_3	T_3
4	1	2	7	52	U	D_1	D_1	D_1	D_1	D_1	D_2	D_1
543	120	41	411	1880	U	D_1	D_1	D_1	D_1	D_1	D_1	D_1
1900	285	31	957	7730	U	D_1	D_1	D_1	D_1	D_1	D_1	D_1

(Continues)

TABLE C1 (Continued)

H_2	CH_4	C_2H_6	C_2H_4	C_2H_2	Equip.	Act.	IRM	DT	TRT	GT	SOM	Prop.
13	3	1	3	6	U	D_2	D_1	D_2	D_2	D_2	D_1	D_2
10000	6730	345	7330	10400	U	D_2	D_2	D_2	D_2	D_2	D_2	D_2
13500	6110	212	4510	4040	U	D_2	D_2	D_2	D_2	D_2	D_2	D_2
34	21	4	49	56	U	D_2	D_2	D_2	D_2	D_2	D_2	D_2
137	67	7	53	104	U	D_2	D_2	D_2	D_2	D_2	D_1	D_2
310	230	54	610	760	U	D_2	D_2	D_2	D_2	D_2	D_2	D_2
420	250	41	530	800	U	D_2	D_2	D_2	D_2	D_2	D_2	D_2
620	325	38	181	244	U	D_2	D_2	D_2	D_2	D_2	D_1	D_2
800	160	23	260	600	U	D_2	D_2	D_2	D_2	D_2	D_2	D_2
1570	735	87	1330	1740	U	D_2	D_2	D_2	D_2	D_2	D_2	D_2
2850	1115	138	1987	3675	U	D_2	D_2	D_2	D_2	D_2	D_2	D_2
7020	1850	0,001	2960	4410	U	D_2	D_2	D_2	D_2	D_2	D_2	D_2
32930	2397	157	0,001	0,001	U	PD	PD	PD	PD	PD	PD	PD
1450	940	211	322	61	U	T_1/T_2	D_1	DT	T_2	T_2	T_1/T_2	T_2
3675	6392	2500	7691	5	U	T_1/T_2	T_3	T_3	T_3	T_3	T_1/T_2	T_1
100	200	110	670	11	U	T_3	T_3	T_3	T_3	T_3	T_2	T_3
150	22	9	60	11	U	T_3	D_2	T_3	T_3	T_3	T_3	T_3
860	1670	30	2050	40	U	T_3	T_3	T_3	T_3	T_3	T_3	T_3
1860	4980	0,001	10700	1600	U	T_3	ND	T_3	T_3	T_3	D_2	T_3
8	0,001	0,001	43	101	S	D_1	ND	D_2	D_2	D_1	/	D_1
35	6	3	26	482	S	D_1	D_1	D_1	D_1	D_1	/	D_1
6870	1028	79	900	5500	S	D_1	D_1	D_1	D_1	D_1	/	D_1
10092	5399	530	6500	37565	S	D_1	D_1	D_1	D_1	D_1	/	D_1
210	43	12	102	187	S	D_2	D_2	D_2	D_2	D_2	/	D_2
1084	188	8	166	769	S	D_2	D_1	D_1	D_1	D_1	/	D_1
1100	1600	221	2010	26	S	T_3	T_3	T_3	T_3	T_3	/	T_3
650	81	170	51	270		D_1	ND	D_1	D_1	D_1	/	D_1

ND, no detection; NF, no fault; Prop., proposed.