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Transformer incipient fault diagnosis on the basis of energy-weighted DGA using an artificial neural network

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Abstract: In this paper, a transformer incipient fault diagnosis model has been developed with the help of an artificial neural network (ANN), taking into account the difference in the energy required to produce the different fault gases. The key fault gases are indicative of the fault type prevailing in the transformer. However, in conventional studies, the energy difference in fault gas formation is not considered while adopting the key gas method for fault diagnosis. In this work, a weighting factor has been used to take into account this relative difference in energy requirement for various fault gas formations. The fault gas concentrations have been suitably weighted by their respective weighting factors before being used in the incipient fault diagnosis process. A backpropagation ANN has been appropriately trained using the weighted fault gas concentration for transformer incipient fault identification. The model has been trained to identify fault types as enlisted in the transformer fault-interpreting standard IEC-599. The developed ANN model has been tested for its diagnostic capability using a reported fault database. The comparative diagnosis results presented here show clear improvement in the diagnosis of transformer internal faults using the energy-weighted ANN model over the unweighted ANN model.

Key words: Power transformer, fault diagnosis, dissolved gas analysis, artificial neural networks

1. Introduction

Electrical utilities have to ensure satisfactory operation of various critical pieces of equipment, such as a power transformer, so as to maintain continuity of supply. These pieces of equipment need continuous monitoring to determine any possible incipient fault that may develop well before any severe damage takes place. This requires a clear understanding of all possible incipient faults that can develop in a transformer [1].

Internal faults in transformers are of essentially two types: thermal and electrical. The incipient thermal and electrical faults developing in an oil-immersed transformer may cause its oil to decompose, resulting in the release of some gases that get dissolved in the oil [2,3].

The concentrations of the various gases released depend on the fault types and temperature [1–3]. Dissolved gas analysis (DGA) is a proven tool for the identification of an incipient fault on the basis of dissolved gases in the insulating oil of the transformer. A number of international standards such as IEEE C57.104 [4] and those of the IEC [5,6] define the methods for transformer incipient fault diagnosis based on DGA results. These standards, even though they are being used very commonly, may provide misleading diagnosis or no diagnosis for some cases. A wrong diagnosis or unresolved diagnosis can have a severe impact on the life of the transformer.

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Various elaborate algorithms have been suggested to improve the diagnosis of the available ratio-based methods for a more reliable diagnosis, as in [2–3,7–10]. Furthermore, several soft computing techniques have also been used in various studies to overcome the shortcomings of the different standard methods. Some of the popular soft computing methods that have been adopted to improve the reliability of DGA-based transformer incipient fault identification are fuzzy logic [11–14], ANNs [15–17], wavelet networks [18,19] and the adaptive neuro-fuzzy inference system (ANFIS) [20–23]. However, these intelligent techniques have their own limitations and hence the degree of the reliability of the method would depend on how these methods are adopted to circumvent their limitations.

As stated earlier, the occurrence of a fault in an oil-immersed transformer results in the decomposition of the oil, which in turn causes gases to be released. The concentration of the various gases formed depends on the energy content of the fault or severity of fault [24–26]. However, most fault diagnosis studies do not take into account the fault energy criteria for fault identification. Methane (CH_4) and acetylene (C_2H_2) are weighted equally even though there is a prominent difference in the energy required for their formation.

In this paper, an ANN model for transformer incipient fault identification has been developed. Another ANN model has been used to study the impact of considering the energy level of various gas formations on the fault diagnosis by suitable weighting of fault gas concentrations. The training data for the ANN model have been prepared for the fault cases listed in IEC-599, taking gas concentrations as inputs rather than ratios. The diagnostic capability of both the methods are comparatively studied using a known fault database comprising 100 fault cases obtained from published literature [27].

2. DGA and the concept of weighted DGA

Transformers are normally considered as stable components of power system, but faults in them can result in significant financial loss and can severely deter the power system's functioning. Development of faults during transformer operation are mainly attributed to localized stress concentrations, formed due to poor design and manufacturing flaws, inadequate stress protection features, insufficient cooling, large leakage flux, etc. Persistent faults in transformers may lead to eventual catastrophic failure of the transformer [1]. Hence, faults in transformers need to be identified and tended to as early as possible.

Transformer internal faults are of primarily three types: partial discharge or corona, thermal heating, and electrical arcing. Corona mainly occurs due to discharges taking place in gas-filled bubbles in oil or voids in paper insulations. A breakdown of transformer insulation takes places upon the occurrence of any of these faults, which results in the release of gases in the transformer. These gases are dissolved in the transformer oil and their concentration depends on the fault type. The constituent gases produced as a result of transformer oil decomposition are categorized into three groups: 1) hydrogen and hydrocarbons - hydrogen (H_2), methane (CH_4), ethane (C_2H_6), ethylene (C_2H_4), acetylene (C_2H_2); 2) carbon oxides - CO and CO_2; and (iii) nonfault gases - O_2 and N_2 [4,21]. The formation of these fault gases is a function of temperature and hence the fault type, i.e. the type and concentration of gas produced as a result of decomposition of the insulating oil is suggestive of the possible transformer incipient fault type. Table 1 gives a list of the gases evolved due to insulation breakdown and the possible transformer incipient fault [8].

The gases produced in a transformer in the event of an internal fault occurring in a transformer dissolve in the insulating oil as well as occupying the empty space of the unit. Apart from the concentration of individual gases, even the solubility of the fault gases differs at different temperatures. The key to an effective transformer incipient fault diagnosis is the accurate identification of the gases dissolved in the transformer oil

Table 1. Interpretation of gases dissolved in oil.

Dissolved gas	Possible fault type
Hydrogen (H_2)	Corona, partial discharge
Methane (CH_4)	Arcing
Ethane (C_2H_6)	Thermal fault
Ethylene (C_2H_4)	Thermal fault
Acetylene (C_2H_2)	Electrical fault (arcing)
Carbon monoxides (CO)	Cellulose deterioration
Carbon dioxide (CO_2)	Cellulose deterioration
Oxygen (O_2)	Seal fault

or the identification of gases in the empty space of the Buchholz relay. A number of methods have been used over the last few decades for the identification of these gases with DGA being one prominent method among them, being adopted very commonly. This method identifies both the combustible and noncombustible gases dissolved in transformer oil. Once the concentration of gases dissolved in transformer oil has been estimated, their presence can be interpreted to determine the possible incipient fault existing in the transformer.

Due to the difference in the energy requirement for the formation of the primary incipient faults, i.e. partial discharge, thermal faults, and arcing, there is a noticeable difference in the composition of decomposed gas dissolved in oil or available in the gas blanket. For each fault type, depending on the fault energy, a particular gas would form the main constituent of the gas composition. The identity and relative concentration of this key gas can provide information on the possible fault type [28,29].

IEC-599 is a recognized standard adopted for fault interpretation based on DGA results. It is a ratio method, having three gas ratios from five fault key gases as its input. This standard helps identify eight faults of PD, thermal, and arcing type apart from the no-fault condition [5–6,27–29].

One major issue overlooked by the DGA-based transformer incipient fault interpretation methods is the energy required to produce a particular fault gas. The severity of faults differs for each of the fault types discussed earlier. Maximum energy dissipation takes place with electrical faults while less dissipation occurs with thermal faults and corona has the least intensity of energy dissipation [2,3]. The type and concentration of the fault gases produced depends on the fault type and its severity [4]. There is a pronounced difference in the energy required for the production of each type of fault gas [24,25]. The partial discharge type of fault has a significant amount of hydrogen and a smaller concentration of methane. The gases released during a thermal fault are mainly hydrogen, methane, ethane, and ethylene. The relative concentration of these gases is temperature-dependent. At lower temperatures of less than 300 $^\circ$C, mainly methane and ethane are produced with a lesser concentration of ethylene. As the fault temperature increases above 300 $^\circ$C, the concentration of ethylene dominates over the other gas concentrations. At temperatures of about 1000 $^\circ$C, the presence of acetylene may also be noticed. Electrical arcing faults are high-energy faults, in which the main gas constituents are hydrogen and acetylene. The concentration of acetylene is greater for electrical faults than for other fault types [4–6]. If the transformer internal faults involve paper insulation, carbon monoxide and carbon dioxide are produced in significantly large quantities. Therefore, if this energy difference in the formation of fault gases is taken into account, it would certainly aid in the identification of the more severe faults.

Energy-weighted dissolved gas analysis (EWDGA) is the method of weighting the individual gas concentrations by a factor derived from the relative energy required for its formation. The energy-weighted concentration of a fault gas can be depicted by the following equation:

Energy-weighted gas concentration = Gas concentration $\times$ Weighting factor (1).

The incorporation of the energy content of the fault gases requires the estimation of an appropriate weighting factor from the thermodynamic decomposition model of the fault gases. The weighting factor is evaluated from the relative enthalpies of formation of the fault gases. The enthalpy of formation of different fault gases has a noticeable difference. The energy content in the faults producing acetylene (C_2H_2) is more pronounced than that of the faults releasing CH_4. In conventional DGA studies, this significant difference in the energy content of the fault gases is neglected. Equal weightage is given to the formation of 100 ppm of CH_4 in 10 days and to the formation of 100 ppm of C_2H_2 in an equal number of days, while thermodynamic study clearly states that the energy required for the formation of 100 ppm of C_2H_2 is much more than that required for the production of 100 ppm of CH_4 [24]. The transformer oil decomposition leading to the formation of fault gases is studied through a decomposition model involving an n-octane molecule. The n-octane molecule is selected because it possesses paraffinic traits and properties similar to those compounds that would decompose to produce the fault gases [24–26].

The weighting factors are indicative of the fault severity and are obtained by normalizing the respective enthalpies of formation of the fault gases. The normalized or relative enthalpies are shown in Table 2.

Table 2. Fault gas weighting factors derived from their enthalpies of formations [22].

Fault gas type	Enthalpy of formation (ΔH_f°)	Relative enthalpy (weighting factor)
CH_4	77.7	1.00
C_2H_6	93.5	1.20
C_2H_4	104.1	1.34
H_2	128.5	1.65
C_2H_2	278.3	3.58

3. The ANN model

The ANN primarily functions to process information aided by an effective nonlinear mapping of the input space and the output space. It finds its importance in its ability to learn from an elaborate arrangement of well-interconnected neurons. The artificial neurons form a layered structure consisting of well-defined input and output layers, which may be separated from one another by one or more hidden layers, as shown in Figure 1. The hidden layers help in realizing more complex problems. The neurons of the different layers are interconnected and trained using a learning algorithm, which may be supervised, unsupervised, or hybrid. If the information is processed only in the forward direction, the ANN structure follows a feedforward topology. If feedback is provided to any of the neuron units it is said to follow a feedback or recurrent topology. An ANN network aptly trained can handle problems of any quantum, owing to its superior learning and generalization ability.

The backpropagation (BP) algorithm is considered as the most popular supervised learning algorithm for the training of feedforward ANN systems. The governing concept of the BP algorithm is to minimize the sum-squared errors, calculated as a difference between the computed and expected output. This is referred to

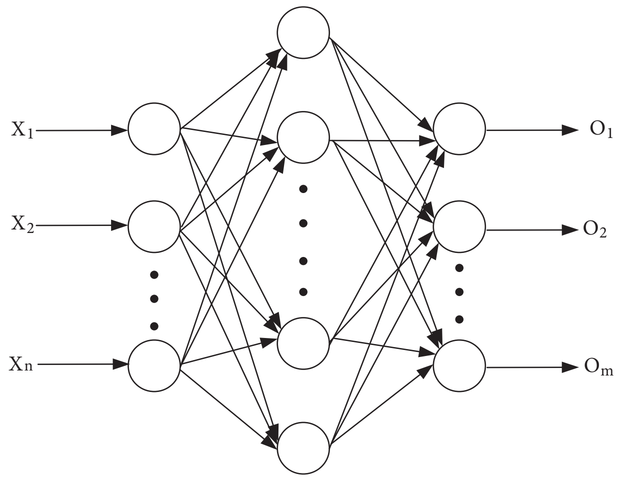

Figure 1. The layered architecture of a feedforward neural network.

as the generalized delta rule. The reduction in error is continued until the completion of the learning process, where the ANN is said to have been trained over the complete training dataset.

The training is initiated with some random weights which, in the due course of learning, are adjusted so as to render the error to a minimum value. The BP algorithm is motivated to minimize the sum-squared error following the gradient descent approach [16,17].

4. ANN-based transformer incipient fault diagnosis

The assessments of the diagnostic capability of the ANN-based fault identification models have been carried out in MATLAB software. The ANN models have been trained suitably using the key gases to identify the fault type prevailing in the transformer. In order to achieve an acceptable level of accuracy in the fault diagnosis model, it is essential that the training data be prepared with utmost care. The accuracy of the ANN model shows a great dependency on the accuracy of the training data. Care should also be taken to ensure that the training data cover the entire range of the input space so as to prevent any unresolved or wrong diagnosis. The training dataset has been developed using the key gas concentrations for extended fault cases covering eight fault types and a no-fault case as shown in Table 3. The training dataset comprising fault gas concentrations has been prepared in-line with the IEC-599 standard. The faulty transformer gas concentration data in [27] was relied upon in the development of training data of suitable ranges. For each fault type in the IEC standard, care has been taken to include gas concentrations in the upper and lower limits as well as in the median range for appropriate ANN learning. The concentration of one of the two gases in a ratio is set within the limiting ranges of that fault type, while the other gas concentration is calculated from the value of the ratio for that particular fault case. The motivation behind this is to obtain a more reliable fault diagnosis model with little or no possibility of an unresolved condition. Furthermore, this would also enable us to validate the outcome of the models with that of a known interpretation standard such as IEC-599. The transformer fault diagnosis procedure has been depicted through the flow diagram shown in Figure 2. Separate ANN models have been used for the DGA- and EWDGA-based diagnosis and these are described in the following sections.

Table 3. Transformer fault cases as stated by IEC-599 [6].

S. no.	Fault type	Fault code
1	No fault	F0
2	Partial discharge with low energy density	F1
3	Partial discharge with high energy density	F2
4	Discharge (arc) with low energy	F3
5	Discharge (arc) with high energy	F4
6	Thermal faults of temperatures of <150 °C	F5
7	Thermal faults of temperatures between 150 and 300 °C	F6
8	Thermal faults of temperatures between 300 and 700 °C	F7
9	Thermal faults of temperatures of >700 °C	F8

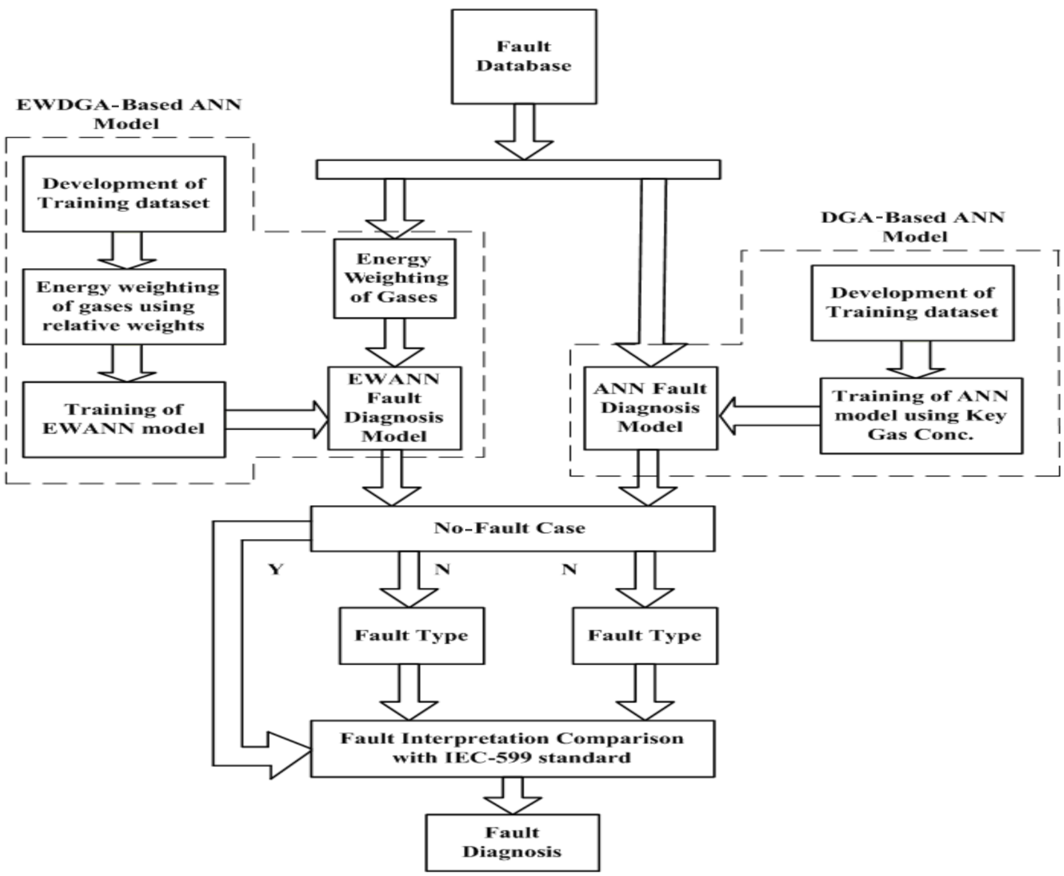

Figure 2. The transformer fault diagnosis process based on the DGA and EWDGA ANN model.

4.1. DGA using ANN

Many works have been carried out in the implementation of DGA using the ANN. The sole purpose of this model is to obtain a comparative diagnostic analysis of the two ANN models. The inputs to the ANN are the five key gases of H_2, CH_4, C_2H_6, C_2H_4, and C_2H_2 and the outputs are the eight possible fault types and a no-fault condition as given in Table 3. A multilayer ANN model trained with a BP algorithm and using sigmoid as its activation function has been used as the network architecture. An extensive training dataset comprising 250 sample data covering all the possible fault types has been developed to train the neural network. The optimum number of neurons for the neural network was selected as 35, corresponding to minimum error as shown in Figure 3. The performance of the neural network has been tested using a known fault database consisting of fault cases derived from [27].

4.2. EWDGA using ANN

The ANN model for EWDGA has also been developed in a manner similar to that for DGA. It also uses a multilayered architecture comprising input, output, and hidden layers. The input to the ANN is again the key gases, which have been weighted appropriately by a weighting factor. This weighting factor is a constant value and is dependent on the amount of energy required to produce a particular fault gas [26]. The outputs are the different fault conditions that may exist in the transformer (F1–F8) and one no-fault condition (F0). The neuron levels are decided based upon a trial approach and have been selected as 40, corresponding to the minimum error as shown in Figure 4. The training dataset comprises 250 samples of weighted key gas concentrations encompassing all the possible fault types. The diagnostic capability of the developed model was checked by the same fault database as that used in the DGA-based ANN model.

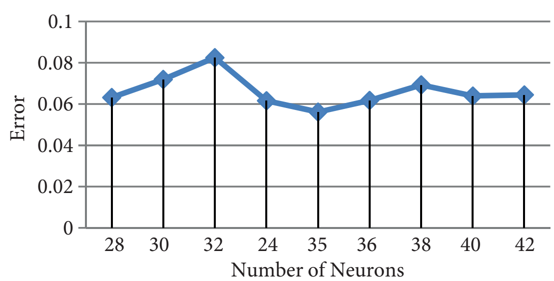

Figure 3. Neuron selection for DGA using ANN.

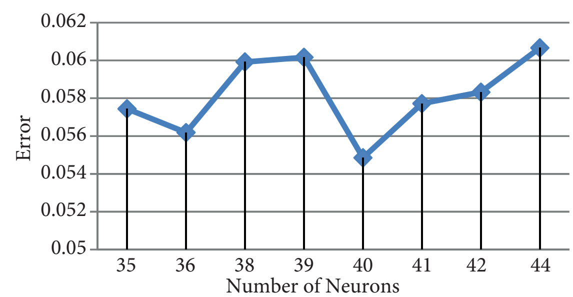

Figure 4. Neuron selection for EWDGA using ANN.

5. Results and discussion

The diagnostic performances of the DGA- and EWDGA-based ANN models have been tested for 100 known fault cases. The output of these models when compared against the known fault type, as derived from the IEC-599 standard, provides information on the reliability of these models. Table 4 presents the concentrations of key gases for 12 faulty transformers from the fault database along with the expected (known) fault type.

Table 5 shows the fault diagnosis of the DGA-based ANN model along with the expected output as per the IEC-599 standard. The output pattern has nine values corresponding to fault types F0–F8. The element of the vector that has the maximum value corresponds to the possible fault prevalent in the transformer. It is evident from the table that the ANN model based on DGA incorrectly diagnoses five of the twelve cases presented here. For transformer fault case no. 1, the model diagnoses it as an arcing discharge of low energy density type, whereas the standard determines it as a high energy density discharge. Similar wrong diagnoses can be observed for fault cases 3, 6, 9, and 10.

The ANN modeled for the EWDGA method has also been tested for its diagnostic capability using the 12 sample cases of Table 4. In order to validate the EWDGA-based ANN model a comparison of two of the fault cases (Case No. 5 and Case No. 11) diagnosed by the EWDGA-based ANN model is done with the outcome of the ANN method presented in [20] and the comparative results are given in Table 6. It can be seen that the

Table 4. Gas concentrations of ten faulty transformers [25].

Transformer fault case no.	Gas concentration (in ppm)							Known fault type
	H_2	CH_4	C_2H_2	C_2H_4	C_2H_6	CO	CO_2	
1	6454	2313	6432	2159	121	3628	225	F4
2	305	100	541	161	33	440	3700	F3
3	1230	163	692	233	27	130	115	F4
4	33,046	619	–	2	58	51	1	F1
5	796	999	31	1599	234	389	1334	F8
6	34	21	56	49	4	95	315	F4
7	960	4000	6	1560	1290	15,800	50,300	F7
8	6	2990	67	26,076	29,990	6	26	F6
9	2500	10,500	6	13,500	4790	530	2310	F7
10	300	700	36	1700	280	760	9250	F8
11	37,800	1740	8	8	249	56	197	F2
12	1450	940	61	322	211	2420	3560	F5

Table 5. ANN-based DGA results.

Transformer fault case no.	Known fault type	Output values	Fault type
1	F4	[–0.0404 0.08271 –0.0526 0.9734 –0.1149 –0.1658 –0.0359 –0.0925 0.38773]	F3
2	F3	[–0.0762 0.0226 –0.0713 0.6737 0.5940 –0.0615 0.1426 –0.1509 –0.0498]	F3
3	F4	[0.0427 0.0171 0.0048 0.6568 0.7702 –0.0932 0.0198 –0.1627 –0.0694]	F4
4	F1	[0.0164 0.7246 0.6362 –0.0024 –0.0124 –0.0761 0.0005 0.0058 –0.0034]	F1
5	F8	[0.0803 0.0787 –0.0626 0.0492 0.0854 0.1232 –0.1995 0.4234 0.4102]	F7
6	F4	[0.1009 –0.02108 0.0199 0.3654 0.2181 0.0895 0.00563 0.1124 0.1052]	F3
7	F7	[–0.0424 –0.0193 0.03401 –0.1647 –0.1372 0.06917 0.4217 0.5885 0.2435]	F7
8	F6	[–0.3156 1.2610 0.4428 –0.1179 –0.1162 0.7736 1.3143 –0.1134 –0.2148]	F6
9	F7	[–0.4483 –0.2852 0.6743 0.1692 –0.2551 –0.0914 0.74133 0.4687 –0.0938]	F6
10	F8	[0.0799 0.0633 –0.0806 0.0552 0.1024 0.1618 –0.2088 0.4136 0.4039]	F7
11	F2	[0.0057 0.7975 0.6003 –0.0314 0.0057 –0.0131 –0.0009 0.0286 –0.0019]	F1
12	F5	[0.0767 0.0613 0.0257 0.2357 0.1357 0.4673 0.0489 0.1964 0.1412]	F5

diagnosis of the EWDGA-based ANN model conforms to the diagnosis of the IEC-599 standard as well as the ANN model from [20] for both fault cases.

The results of transformer fault diagnosis using the EWDGA-based ANN method for the 12 sample fault cases are presented in Table 7. The EWDGA model is able to identify the transformer incipient fault types to a fair degree of accuracy. It can be seen from the output pattern that most of the fault diagnoses conform with that of the IEC standard fault interpretation, except for fault cases 6 and 9. For fault case 6, the EWDGA-based ANN model interprets the fault to be a low-energy discharge fault (F3) while the IEC-599 standard diagnoses

Table 6. Comparison of outputs of EWDGA model with the ANN model of reference [20].

Transformer fault case no.	Fault as per IEC-599 standard	ANN model in [20]		EWDGA-based ANN model	
		Input type	Diagnosed fault type	Input type	Diagnosed fault type
5	F8	Gas ratio	F8	Gas Concentration	F8
11	F2		F2		F2

it as a high-energy arcing discharge (F4). Similarly, the expected fault type for transformer fault case 9 is a thermal fault with temperature ranging between 300 and 700 °C (F7), while the model wrongly diagnoses it as a thermal fault with temperature greater than 700 °C (F8). Both the DGA- and EWDGA-based ANN models were extensively used to diagnose 100 fault cases and the results of this diagnostic test are summarily presented in Table 8.

Table 7. ANN-based EWDGA results.

Transformer fault case no.	Known fault type	Output values	Fault type
1	F4	[0.1269 –0.8596 0.8805 0.2297 1.0370 –0.0888 0.0399 0.0783 –0.4534]	F4
2	F3	[–0.1120 –0.0186 –0.0221 0.7825 0.1238 0.2457 –0.1617 0.0110 0.1467]	F3
3	F4	[–0.0040 –0.1416 0.1335 0.5823 0.6867 0.1613 –0.0365 –0.0796 0.0952]	F4
4	F1	[0.0963 0.7147 0.5022 0.0939 –0.1277 0.0323 –0.0803 0.0892 –0.0224]	F1
5	F8	[–0.0139 –0.4319 0.4054 –0.2383 0.3353 –0.0469 –0.0558 0.4479 0.5991]	F8
6	F4	[0.0747 –0.0447 0.0490 0.4777 0.2550 –0.0197 0.0177 0.0936 0.0956]	F3
7	F7	[0.1130 –0.0774 0.0484 –0.1531 0.1961 0.0158 0.0968 0.9010 –0.1388]	F7
8	F6	[0.2972 0.1660 –1.2663 0.4912 –1.1672 –0.1778 1.6503 –1.1333 1.3404]	F6
9	F7	[0.9883 0.0187 –0.0882 –0.8844 –2.1782 1.3297 –0.4382 0.3872 1.8337]	F8
10	F8	[–0.0253 –0.4486 0.3776 –0.1577 0.3745 –0.1340 0.0475 0.3970 0.5701]	F8
11	F2	[–0.1077 0.6849 0.8751 0.0688 –0.0767 0.0217 0.1064 0.0602 –0.1254]	F2
12	F5	[0.1403 –0.0355 0.0964 –0.0233 0.3321 0.5118 –0.1032 0.2271 0.1383]	F5

Table 8. Summary of transformer fault diagnosis.

	DGA-based ANN model	EWDGA-based ANN model
No. of faulty cases tested	100	100
No. of correct diagnosis	53	86
No. of wrong diagnosis	47	14
Accuracy	53%	86%

In this paper, an attempt has been made to incorporate the essential information of the significant difference in the energy content of the fault gases in the fault diagnosis process, which was ignored in earlier studies. In view of this, the accuracy of the given EWDGA model is found to be comparable to the accuracies of the models presented in various other studies. Table 9 gives a comparison of the accuracies of the transformer incipient fault diagnostic models presented in various studies.

Table 9. Comparison of accuracies with other fault diagnosis models.

Method	Input type	% Accuracy
IEC method [30]	Gas ratios	50.26
Refined IEC method [30]		66.06
IEC-based ANN [31]	Gas ratios	80
ANN [32]	Gas concentrations	89
IEC-599 [10]	Gas ratios	77.78
Dual of Duval triangle [10]	Relative gas concentrations	90.6
EWDGA-based ANN model	Gas concentrations	86%

6. Conclusion

In this work, a modified form of DGA, based on the energy content of the fault gases along with their concentrations, is used to investigate the prevailing incipient fault in the transformer. The EWDGA model does not present a new diagnosis model but attempts to use the model in conjunction with the existing interpretation standard, incorporating the essential information on the energy content of the fault gases. It has been observed for the entire fault database comprising 100 fault cases that the EWDGA-based ANN model gave an accuracy of 86% in comparison to the DGA-based ANN model, which gave an accuracy of only 53% for the same fault database. It has also been seen that the ANN model for the EWDGA system gives encouraging results in terms of fault diagnosis and its accuracy is comparable and in some cases even better than the conventional fault diagnosis techniques.

Therefore, it is evident from this study that making use of the energy content of the fault gases certainly aids in the fault diagnosis process and makes the diagnosis of transformer incipient faults, particularly the higher energy content (thermal) faults, easier.

Nomenclature

ANN	Artificial neural network
DGA	Dissolved gas analysis
EWDGA	Energy-weighted dissolved gas analysis
BP	Backpropagation
H_2	Hydrogen
CH_4	Methane
C_2H_6	Ethane
C_2H_4	Ethylene
C_2H_2	Acetylene
F0	No fault
F1	Partial discharge with low energy density
F2	Partial discharge with high energy density
F3	Discharge (arc) with low energy
F4	Discharge (arc) with high energy

F5	Thermal faults of temperatures of <150 °C
F6	Thermal faults of temperatures between 150 °C and 300 °C
F7	Thermal faults of temperatures between 300 °C and 700 °C
F8	Thermal faults of temperatures of >700 °C
ΔH_f°	Enthalpy of formation

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