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Full Length Research Paper

Artificial neural networks applied to DGA for fault diagnosis in oil-filled power transformers

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Dissolved Gas Analysis (DGA) is a popular method to detect and diagnose different types of faults occurring in power transformers. This objective is obtained by employing different interpretations of dissolved gases in the mineral oil insulation of such transformers. This paper engages these interpretations and applies appropriate Artificial Neural Networks (ANN) to classify the different faults. Each interpretation method needs special neural network to determine the occurred fault. Three ANNs are applied to this aim. The classification results and some typical examples are presented to validate the networks.

Key words: DGA, duval triangle, ANN, power transformer faults.

INTRODUCTION

Faults in power transformers can significantly decline the longevity of mineral oil insulation of those transformers. It is essential to detect and eliminate the occurred fault very soon preventing any jeopardous results. Insulating mineral oils under faults release gases which dissolve in the oils. The distribution of these gases relates to the type of fault. Analysis of the dissolved gases can result in very useful information in the maintenance programs. The advantages of dissolved gas analysis can be briefly stated as (DiGiorgio, 1996):

(i) Advance warning of developing faults.
(ii) Determining the improper use of units.
(iii) Status checks on new and repaired units.
(iv) Convenient scheduling of repairs.
(v) Monitoring of units under overload.

There are different detection and interpretation methods (DiGiorgio, 1996; Duval, 2006). IEC and ANSI/IEEE standards are among the most prestigious sources for the dissolved and free gas interpretations (ANSI/IEEE C57.104; IEC 60599). Each interpretation method has its own pros and cons. These methods will be shortly discussed and evaluated.

The term of ‘fault gases’ is used to hint the gases which are originated through the faults. These fault gases are Methane (CH_4), Ethane (C_2H_6), Ethylene (C_2H_4), Acetylene (C_2H_2), Hydrogen (H_2), Carbon monoxide (CO), Carbon dioxide (CO_2), and the non-fault gases are Nitrogen (N_2), and Oxygen (O_2).

In addition to the oil, insulating papers also provide some gases under faults. The percentage of released gases under different faults is stated in Table 1. Corona, pyrolysis (over heating), and arcing in the oil and pyrolysis in the cellulose are considered as different types of faults in Table 1.

As a result, each of these gases can individually represent type fault. Table 2 presents such a conclusion (Jakob, 2003; Lewand, 2003).

There are different methods to measure the value of fault gases of the oil. The total combustible gases (TCG) and gas blanket analysis are such methods which take a sample of the space above the insulating oil in the power

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Table 1. Percentage of each released gas under different faults.

Fault type	H_2 (%)	CO_2 (%)	CO (%)	CH_4 (%)	C_2H_6 (%)	C_2H_4 (%)	C_2H_2 (%)
Corona in oil	88	1	1	6	1	0.1	0.2
Pyrolysis in oil	16	TRACE	TRACE	16	6	41	TRACE
Arcing in oil	39	2	4	10	TRACE	6	35
Pyrolysis in cellulose	9	25	50	8	TRACE	4	0.3

Table 2. Interpretation based on a single released gas amount.

Gases	Indication
Hydrogen	Partial discharge, heating, arcing
Methane ,Ethane, Ethylene	“Hot metal” gases
Acetylene	Arcing
Carbon oxides	Cellulose insulation degradation

transformers (DiGiorgio, 1996). TCG has the advantage of high speed analysis and continues monitoring but it is not able to collect noncombustible gases such as Carbon dioxide, Nitrogen, and oxygen. The gas blanket analysis is capable of sampling both combustible and noncombustible fault gases.

In general, both of the mentioned methods suffer from some disadvantages. Indeed, these methods can not be engaged to detect fault gases in transformers which are full of oil and do not contain any gas blanket above their insulating oil. Furthermore, since the faults are often originated from the bottom of the oil, it takes time to the released gases to saturate the oil at first and then penetrate in the gas blanket. Therefore, the total time of the analysis will be significantly augmented.

Dissolved Gas Analysis (DGA) is the most popular informative method to this aim. In this method, a sample of oil containing dissolved fault gases is taken from the oil of the unit; then the fault gases are detached from the sample. Eventually, each gas is separated from the others and the value of each gas is derived in part per million level (ppm). The main advantage of DGA is the quick detection of the gases right after occurrence of a fault. All these methods provide the value of fault gases in the oil. Now it is required to interpret the attained values to determine the type of the occurred fault.

There are some interpretation methods which classify the faults according to the obtained gases values. Artificial neural networks are employed to solve these pattern classifications for three popular interpretation methods in this paper.

DORNENBURG PLOT

This earlier IEEE method plots two different ratios in two axes. Three different faults, Thermal, arcing, and corona, can be detected by using this method.

A multilayer perceptron neural network is designed to simulate Dornenburg interpretation. Construction of this network is presented in Figure 1. This configuration contains 10 neurons in the first layer and three neurons in the last one. Inputs nodes are ratios of C_2H_2/C_2H_4 and CH_4/H_2 and three outputs represent three types of faults. Each output node is assigned to a special type of fault hence the neuron which is high in its output indicates that which fault is occurred.

Transfer function of all the neurons of the two layers is the step function. When the input of a step function is negative, the output becomes zero and correspondingly the output is unity when the input is at least zero. The first layer is designed to make all the decision boundaries and the second one plays an OR rule to create three different classes of the three faults. Each input is applied to all the neurons of the first layer by a weight. All of the neurons include biases. Abbreviated notation of this network is also presented in Figure 2 (Hagan, 1996)

Weight and bias matrixes are evaluated as (1) to (4):

$$W^1 = \begin{bmatrix} 1 & -1 & 0 & 1 & 0 & -1 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & -1 & 0 & 1 & 0 & -1 & 1 \end{bmatrix} \quad (1)$$

$$b^1 = \begin{bmatrix} 0 & 2 & -1 & -2 & 0.07 & 5.83 & 0 & -5.84 & 1 & -0.07 \end{bmatrix}^T \quad (2)$$

$$W^2 = \begin{bmatrix} 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 \end{bmatrix}^T \quad (3)$$

$$b^2 = \begin{bmatrix} -2.5 & -3.5 & -2.5 \end{bmatrix}^T \quad (4)$$

This network has been simulated in the Matlab software and the classification problem has been solved. A large amount of random inputs have been applied as inputs and Figure 3 has been obtained. Red areas are corresponding to thermal faults, green areas represent

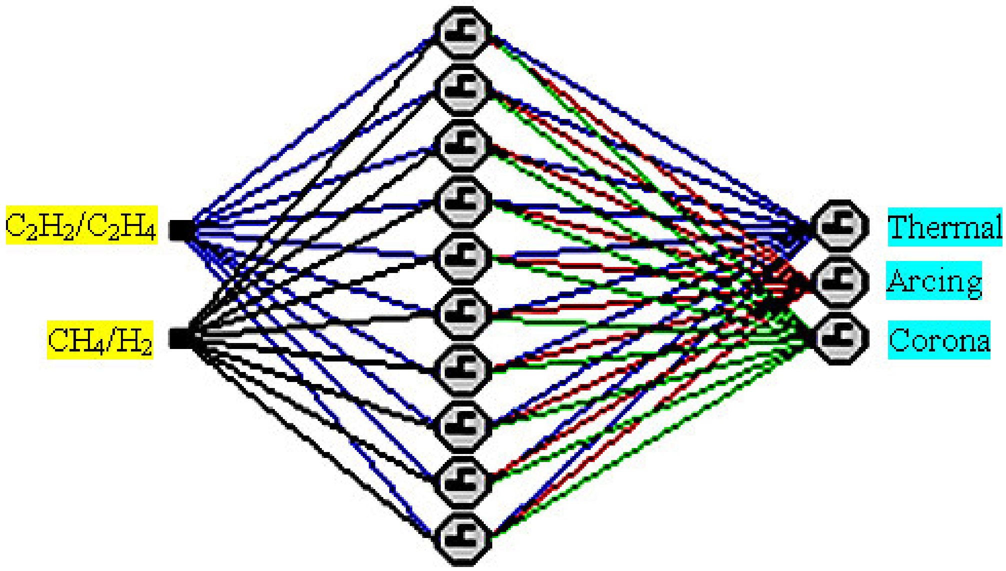

Figure 1. Multilayer perceptron for Dornenburg method.

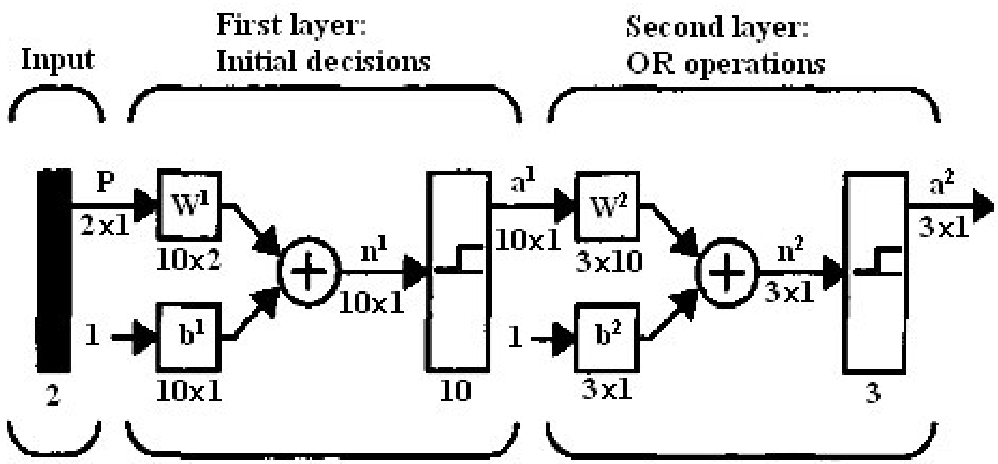

Figure 2. Configuration of the three layer perceptron.

arcing faults, and blue areas indicate corona faults.

VALIDATION OF THE NETWORK

Some experimental data and the type of fault have been presented in (Jakob, 2003). To validate the results of the proposed neural network, these data have been engaged. All of the values are in ppm.

The data presented in Table 3 have been obtained by the method of DGA under normal operation of the power transformer (Jakob, 2003). The proposed neural network is employed to judge about the condition. Figure 4 indicates that the network correctly selects the normal condition.

One year later, this unit was tested once again. The obtained data indicated that the unit was under thermal runaway condition. Table 4 represents the data. The neural network notices that the unit is under heating fault (Figure 4).

Engineers removed the unit from the power system to repair. The unit was tested again after installation. The data of Table 5 and Figure 4 prove that the unit was under normal condition.

Red areas are corresponding to thermal faults, green areas represent arcing faults, and blue areas indicate

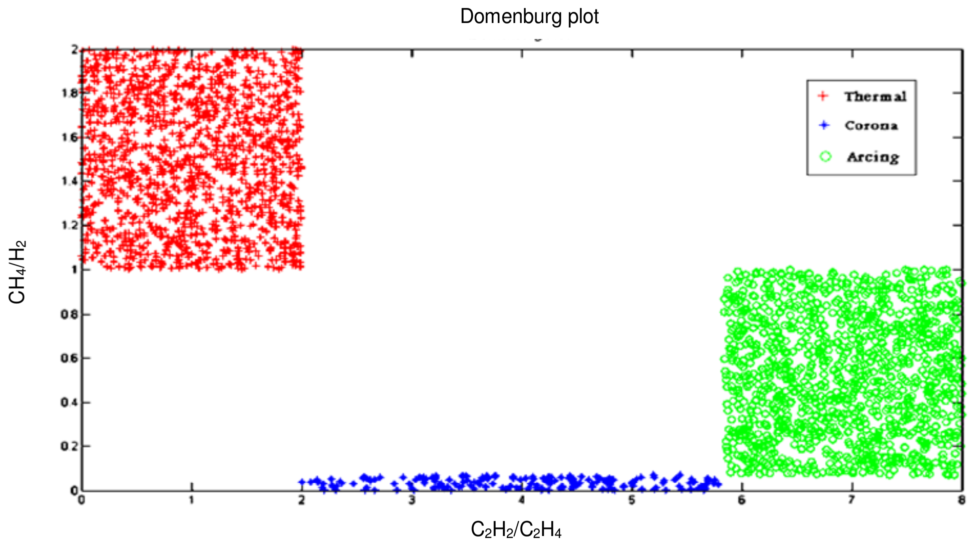

Figure 3. Dornenburg plot attained by two layer perceptron neural network.

Table 3. Experimental data on February 25, 1993.

Date	C_2H_2	CH_4	C_2H_6	C_2H_4	H_2	CO	CO_2
02/25/93	0	5	1	4	34	71	350

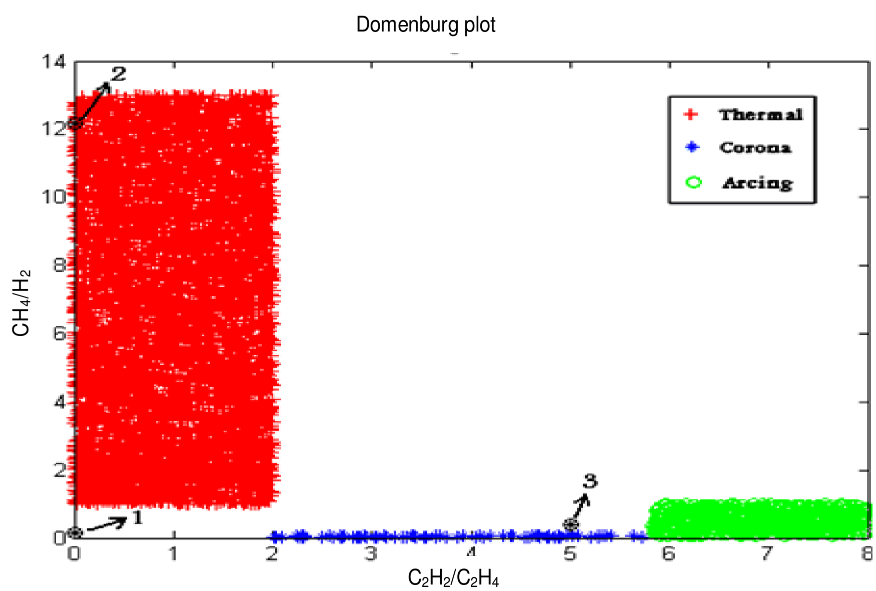

Figure 4. Three condition plot of the unit; 1, 3: Normal, 2: Thermal fault.

corona faults. All of the other areas show normal condition. Therefore point 1 indicates normal condition. Point 2 is situated in red areas hence the transformer is operating under overheat condition and it is required to remove the transformer and eliminate the occurred fault or repair the unit. After repairing the transformer, it should

Table 4. Experimental data on February 25, 1994.

Date	C_2H_2	CH_4	C_2H_6	C_2H_4	H_2	CO	CO_2
02/25/94	44	1812	576	3143	149	33	645

Table 5. Experimental data after repairs on February 27, 1994.

Date	C_2H_2	CH_4	C_2H_6	C_2H_4	H_2	CO	CO_2
02/27/94	44	1812	576	3143	149	33	645

Table 6. C. E.G. B. fault gas ratios developed by Rogers.

Ratio	Range	Code
CH_4/H_2	≤ 0.1	5
	> 0.1 < 1	0
	≥ 1 < 3	1
	≥ 3	2
C_2H_6/CH_4	< 1	0
	≥ 1	1
C_2H_4/C_2H_6	< 1	0
	≥ 1 < 3	1
	≥ 3	2
C_2H_2/C_2H_4	< 0.5	0
	≥ 0.5 < 3	1
	≥ 3	2

be installed and tested by DGA and related equipments. It is done and point 3 proves that the new condition is normal and the unit can satisfy the network requirements.

ROGERS METHOD

Central Electric Generating Board (CEGB) of Great Britain has employed a method developed by Rogers, IEEE method (Duval, 2006), in which four ratios of fault gases are calculated to generate a four digit code presenting in Table 6 and 7. Table 6 illustrates circumstance of developing the digits and Table 7 describes the fault diagnosis assigning to each of the digits.

A competitive neural network has been developed and proposed in the Matlab software to simulate the Rogers method. This network is presented at Figure 5.

Table 7. C. E. G. B. diagnostics developed by Rogers.

Code				Diagnosis
0	0	0	0	Normal
5	0	0	0	Partial discharge
1,2	0	0	0	Slight overheating < 150°C
1,2	1	0	0	Slight overheating 150 - 200°C
0	1	0	0	Slight overheating 200 - 300°C
0	0	1	0	General conductor overheating
1	0	1	0	Winding circulating currents
1	0	2	0	Core and tank circulating currents, overheated joints
0	0	0	1	Flashover, no power follow through
0	0	1,2	1,2	Arc, with power follow through
0	0	2	2	Continuous sparking to floating potential
5	0	0	1,2	Partial discharge with tracking (note CO)
CO_2 / CO > 11				Higher than normal temperature in insulation

Indeed this type is a Hamming network by two layers. The weights of the first layer are desired prototypes. All the inputs, the four ratios plus CO_2/CO, are compared to the first layer weights and the hamming distances are calculated. The less is the hamming distance, the more is the output of the neuron which has a linear transfer function. The outputs of the first layer then become the inputs of second layer, competitive layer. The second layer contains recurrent neurons in which the outputs represent one time less than the inputs. Each output of the second layer is back propagated to its input by a weight equal to unity however all the other outputs feed the input of that neuron by a "-ε" weighted loop. "ε" is much less than unity and should be less than $\frac{1}{S-1}$ where S is the number of neurons in the first layer. It is important to note that the second layer has the same number of neurons in the first one.

After following the outputs of the first layer into the second one and passing a few iterations, the neuron which has had the biggest initial value wins the competition, global winning neuron. The winning neuron has unity on its output while all of the other neurons are zero on their outputs. As a result an input which is more near to one of the weights of the first layer, will take all the other inputs, so called winner-takes all (WTA). 'D' block represents a time delay. To prevent drawing a complex diagram, which will nor be readily readable, abbreviate notation of this network is only presented. For simplification, the second layer can be replaced by a competitive layer and since all of the biases are zero and the output of a linear transfer function is equal to its input, Figure 5 can be redrawn as Figure 6.

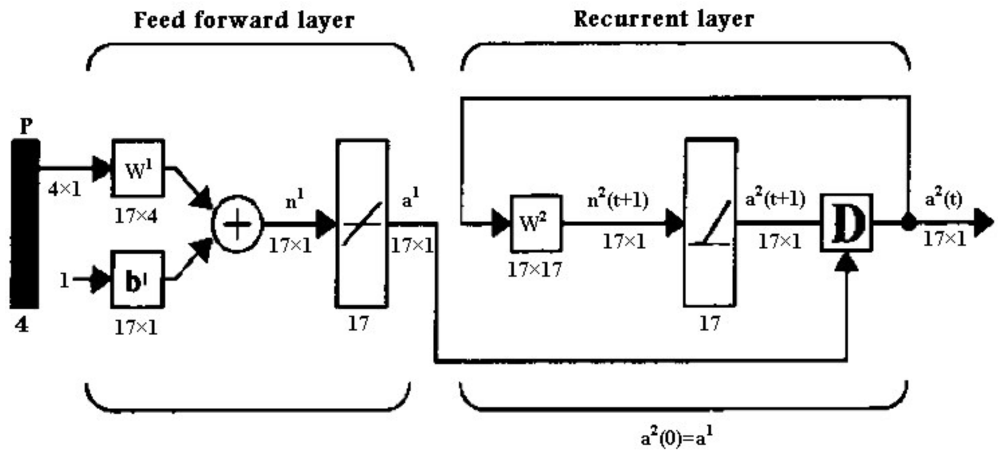

Figure 5. Hamming network for Rogers method.

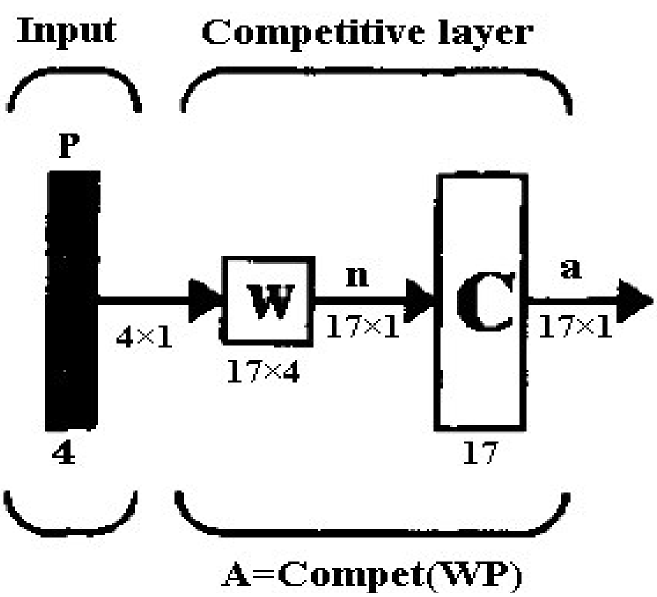

Figure 6. Hamming network of Figure 5 with a competitive layer.

This network has been simulated in the Matlab software. The weights of the first layer are the codes stated in table X hence it is not required to rewrite here. The simulator prompts this network while $CO_2/CO<11$. As this ratio outmatches 11, the network is interrupted and the output is set to a value indicating that the temperature of the insulation is higher than the normal value.

VALIDATION OF THE NETWORK

A bushing soaked in oil has been tested by DGA (Jakob, 2003). Table 8 represents the obtained data. John Stead has stated on his presented paper at the 1996 Doble Conference that this unit has been under partial discharge condition.

Table 8. Bushing overwhelmed on oil under partial discharge.

Gas	Value in ppm
Hydrogen	19132
Oxygen	4041
Nitrogen	50767
Carbon monoxide	537
Methane	1256
Carbon dioxide	1459
Ethylene	11
Ethane	409
Acetylene	0.2

These data were applied to the neural network. The network produced codes: [5 0 0 0] which demonstrates the correctness of the decision, partial discharge fault. As another instance, suppose Table 9 presented in (Lewand, 2003). The unit is subjected in high temperature overheating of the oil. Applying these data to the proposed neural network eventuated codes [0 1 2 0] which means that the temperature of the insulation is higher than normal.

DUVAL TRIANGLE

The dual triangle was first developed in 1974 (Duval, 2006). It uses only three hydrocarbon gases (CH4, C_2H_2, and C_2H_4). The three sides of the triangle are expressed in triangular coordinates (X, Y, Z) representing the relative proportions of CH_4, C_2H_4 and C_2H_2, from 0 to

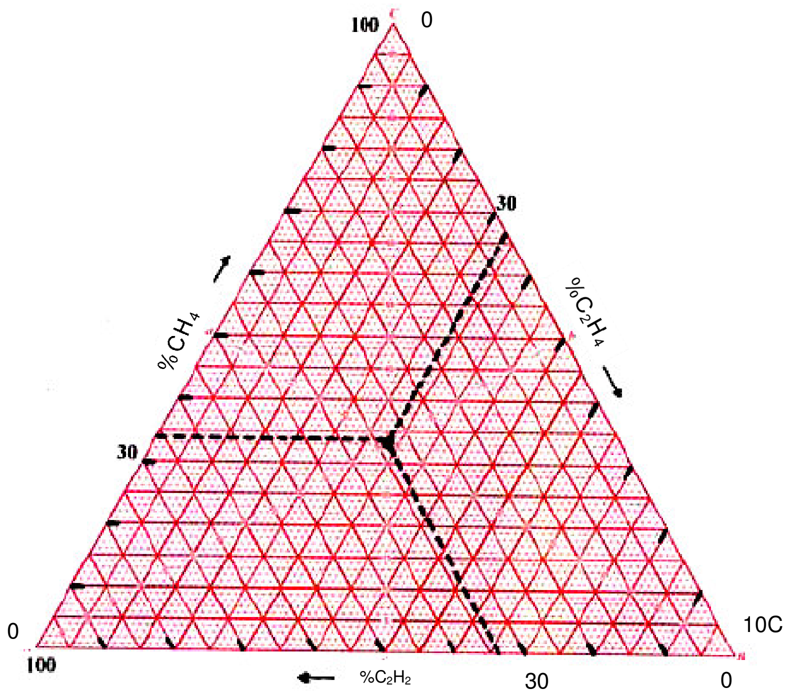

Figure 7. Example of triangular graphical plot.

Table 9. Value of fault gases under high temperature, McGraw Edison Transformer, 400 MVA, 345 KV, 1969.

Gas	Value in ppm
Hydrogen	7040
Methane	17700
Ethane	4200
Ethylene	21700
Acetylene	165
Carbon Monoxide	67
Carbon Dioxide	1040

Table 10. Faults detectable by Duval triangle.

Symbol	Fault
PD	Partial discharge
D1	Discharges of low energy
D2	Discharges of high energy
T1	Thermal fault, T <300℃
T2	Thermal fault, 300<T<700℃
T3	Thermal fault, T>700℃
DT	Mixtures of electrical and thermal faults

100% for each gas.

In order to display a DGA result in the triangle, one must start with the concentrations of the three gases, (CH_4) =A, (C_2H_4) =B, and (C_2H_2) =C, in ppm.

First calculate the sum of these three values: ($CH_4+C_2H_4+C_2H_2$) =S, in ppm, then calculate the relative proportion of the three gases, in %:

$X=\%CH_4=100(A/S)$, $Y=\%C_2H_4=100(B/S)$, $Z=\%C_2H_2=100(C/S)$.

X, Y and Z are necessarily between 0 and 100%, and (X+Y+Z) should always 100%. Plotting X, Y and Z in the triangle provide only one point in the triangle.

For example, if the DGA results are A=B=C=100 ppm, X=Y=Z=33.3%, which corresponds to only one point in the centre of the triangle, as indicated in Figure 7. Duval triangle can diagnose the fault types of Table 10. These faults are shown in Figure 8.

Michel Duval found his proposed method the most suitable. He has presented Table 11 to demonstrate his claim.

A three layer perceptron has been proposed here to simulate Duval triangle. This network is presented in Figure 9.

This neural network has been simulated in the Matlab software. Many random inputs have been applied to the network to indicate its performance. Figure 10 presents the results.

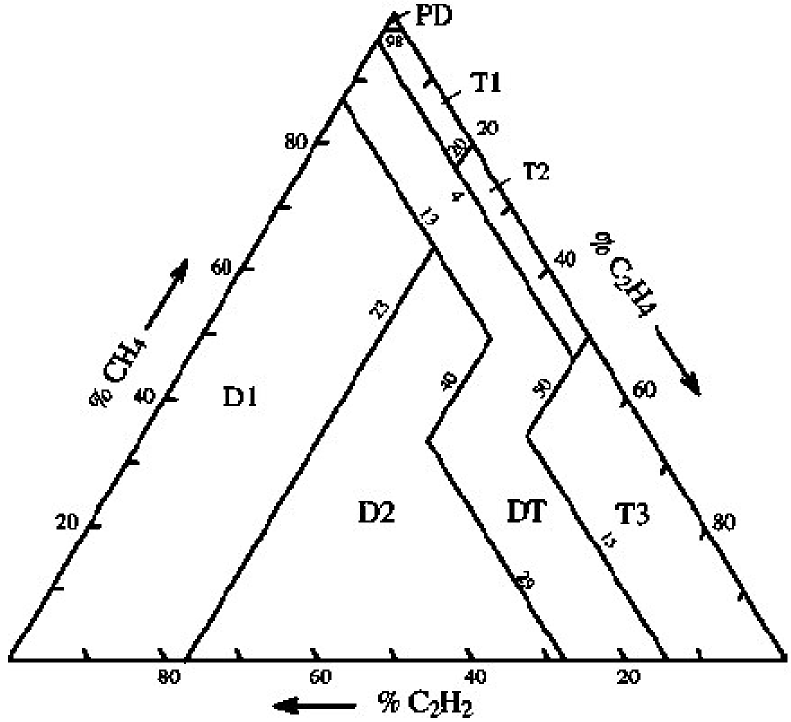

Figure 8. Fault dispersal on Duval triangle.

Table 11. Comparing faults of diagnostic methods by Duval.

Diagnostic method	% Unresolved diagnoses	% Wrong diagnoses	%Total
Key gases	0	58	58
Rogers	33	5	38
Dornenburg	26	3	29
IEC	15	8	23
Triangle	0	4	4

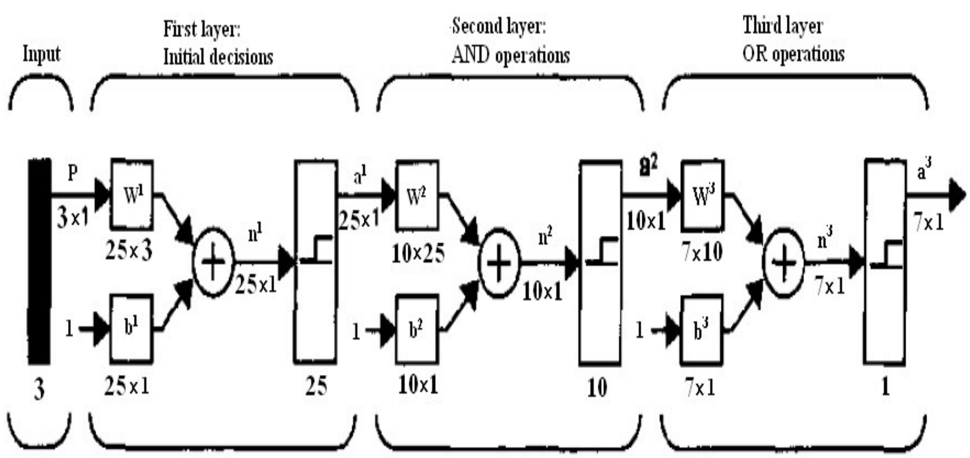

Figure 9. Three layer neural network for Duval triangle.

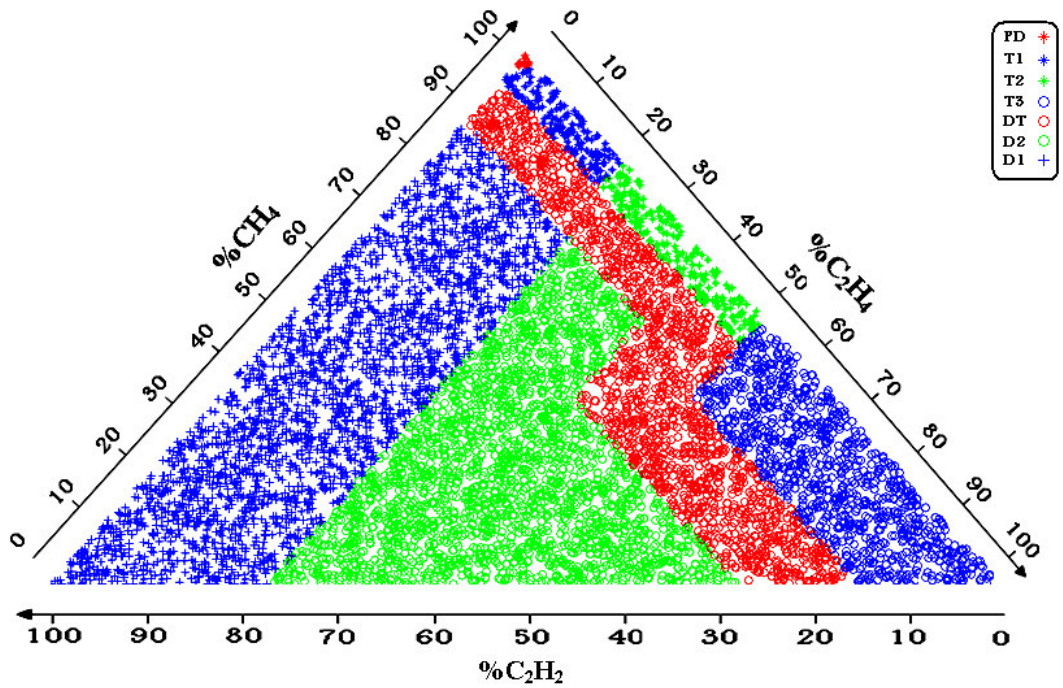

Figure 10. Duval triangle plot obtained by the three layer perceptron neural network.

Table 12. Examples of DGA cases (concentrations in percent).

Fault	CH_4	C_2H_4	C_2H_2
PD	99	1	0
D1	38	12	50
D2	15	50	35
T2	69	30	1
T3	20	75	5

It is comprehended from Figure 10 that the proposed neural network can successfully classify the seven faults of Duval method. It is important to note that the input is three dimensional and a conversion has been applied to a two dimensional plot. For instance, When C_2H_2=CH_4= C_2H_4=%33, X (horizontal axis) will be equal to:

$$X = 100 - \left(\%C_2H_2 + \frac{Y}{\tan(\frac{\pi}{3})} \right)$$

Correspondingly, Y (vertical axis) will be:

$$Y = \%CH_4 \times \cos(\frac{\pi}{6}) \quad (6)$$

VALIDATION OF THE NETWORK

Michel Duval has engaged some experimental data of DGA to indicate the correctness of his triangle (Duval, 2006). These data are presented in Table 12.

All of the cases in Table 12 have been presented to the proposed neural network and Figure 11 indicates the results. All the five points corresponding to the faults of Table 12 have been plotted in Figure 11. Circumstance of drawing the points on such a plot is also shown by thin lines connected to the points. By a glance on the figure, it can be understood that the faults are correctly classified.

CONCLUSION

Appropriate design of artificial neural networks can help simulate the interpretation methods of fault diagnoses in power transformers. Three well-known methods were engaged and a neural network was designed for each of them in this paper. Validation results for the proposed networks prove that they can predict the occurred faults correctly.

As a matter of fact, interpretation methods of fault gases are theoretic and it is required to employ artificial intelligences such as neural networks to realize them. Therefore, once DGA detects the value of all the fault gases in the insulating mineral oil of a transformer, a

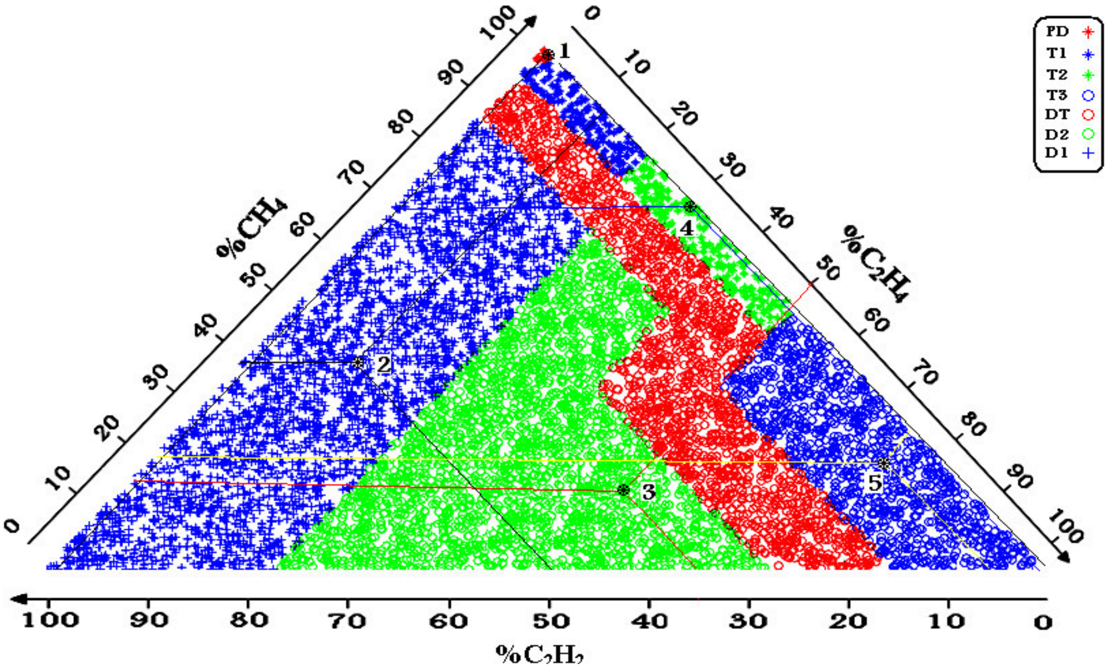

Figure 11. Decision making about the faults of table XV by the neural network.

neural network allocating to a desired interpretation method is selected. Eventually, the designed neural network can be employed to real-time decision making of any fault resulting in continues monitoring of that unit. Each neural network has its own characteristics and it is not possible to make comparisons in most cases; hence, for each type of the fault interpretation method, an appropriate network can be previously defined.

REFERENCES

DiGiorgio JB (1996-2005). Dissolved Gas Analysis of Mineral Oil Insulating Fluids. NTT copyrighted material.

Duval M (2006). Dissolved Gas Analysis and the Duval Triangle. Fifth AVO New Zealand International Technical Conference.

Jakob (2003). Dissolved Gas Analysis – Past, Present and Future. Weidmann Electrical Technology, Technical Library.

Lewand LR (2003). Using Dissolved Gas Analysis to Detect Active Faults in Oil-Insulated Electrical Equipment. Doble Engineering Company, Practicing Oil analysis Magazine, Issue Number: 200303.

Hagan MT, Demuth HB, Beale M (1996). Neural Network Design. PWS Publishing Company.

ANSI/IEEE C57.104. IEEE Guide for the Interpretation of Gases Generated in Oil-Immersed Transformers –Description. IEEE Standard.

IEC 60599. Mineral oil-impregnated electrical equipment in service - Guide to the interpretation of dissolved and free gases analysis. IEC Standard.