DGA Results Comparison between ANN Methods and Tested Sampling from Sonelgaz-GRTE Transformers Fleet

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Abstract: **Transformer insulation aging diagnosis is important for all the condition assessment. Dissolved gas analysis (DGA) is one of the most useful techniques and tools to detect the incipient faults in large oil filled transformers. Various methods have been developed to interpret DGA results. Among them are the Key Gas, Rogers Ratio, Logarithmic Nomograph, Dorenenburg, IEC Ratio and Duval Triangle. This paper uses the DGA data from different cases to test the accuracy and consistency of these methods in interpreting the transformer condition. It also describes the structure and specific features of transformer insulation ageing diagnosis based on artificial neural networks. MATLAB programs using neural network were developed to automate and to compare the evaluation of each method with those of Sonelgaz – Grte findings.**

Index Terms: **Transformer, Insulation Aging, DGA, interpretation methods, Artificial Neural Network (ANN), Fault gases.**

1. Introduction

As a major apparatus in a power system, the power transformer is vital to system operation. Techniques for diagnosis and incipient-fault detection are valuable. A transformer is subject to electrical and thermal stresses which could break down the insulating materials and release gaseous decomposition products. Overheating, corona and arcing are three primary causes of fault related gases.

Principally, the fault related gases commonly used are hydrogen (H_2), carbon monoxide (CO), carbon dioxide (CO,), methane (CH_4), acetylene (C_2H_2), ethane (C_2H_6), and ethylene (C_2H_4). The analysis of dissolved gases is a powerful tool to diagnose developing faults in power transformers. Many diagnostic criteria have been used for the interpretation of the dissolved gases. These methods would find the relationship between the gases and the fault conditions, some of which are obvious and others may not be apparent (hidden relationships).

However, much of the diagnostics relies on experts to interpret the results correctly. New computer-aided techniques can consistently diagnose incipient-fault conditions for the novice and in some cases may provide further insight to the expert. Expert system and fuzzy-set approach have been developed to reveal some of the hidden relationships in transformer fault diagnosis**.** Expert system derives the decision rules from the previous experience while the fuzzy-set represents the decision rules by using vague quantities. Artificial neural network method (ANN) has also been used for this purpose since the hidden relationships between the fault types and dissolved gases can be recognized by ANN through training process. A two-step ANN approach is presented in this paper. The accuracy of the **ANN** is carefully verified. With two ANNs, high diagnosis accuracy is obtained. **[1]**

2. Dissolved Gases -in-Oil Analysis

Dissolved gases-in-oil analysis (DGA) is a common practice in transformer fault diagnosis. Electrical insulation such as mineral oils and cellulosic materials degrade under excessive thermal and electrical stresses, forming by product gases which can serve as indicators of the type of stress and its severity. Dissolved gas-in-oil concentrations, relative proportion of gases, and gas generation rates (gassing rates) are used to estimate the condition of a transformer. Commonly used gases include hydrogen (H_2), methane (CH_4), acetylene (C_2H_2) ethylene (C_2H_4), ethane (C_2H_6), carbon monoxide (CO), and carbon dioxide (CO_2). These gases are extracted from the oil under high vacuum and analyzed by Gas Chromatograph to get each gas concentration separately. By interpretation of gas contents, the developing faults in the power transformers can be diagnosed. Many diagnostic techniques have been developed for the interpretation of these gases. **[2]**

This technique includes the conventional key gas method, ratio methods, and recently, the artificial intelligent methods. The key gas method relates key gases to fault types and attempts to detect four fault types (overheating of oil, overheating of cellulose, partial discharge, and arcing) based on key gas

contents (C_2H_4, CO, H_2, C_2H_2). The ratio methods are coding systems that assigns certain combination of codes to a specific fault type.

The Codes are generated by calculating gas ratios and comparing the ratios to predefined ratio intervals. A fault condition is detected when a code combination fits the code pattern of the fault. Because the number of possible code combination is larger than the number of fault types, “no decision” often results from the ratios Methods such **as** Doemenburg Ratios, Rogers Ratios and IEC Ratios. All of these methods are able to detect thermal decomposition, partial discharge, and arcing faults.

In an actual diagnosis process, other information such as the variability of dissolved-gas data and the influence of loading and environmental factors on these data is usually also taken into consideration. Recently, application of artificial intelligence (AI) has shown very promising results in DGA. These techniques include expert system, fuzzy logic, evolutionary algorithm, and artificial neural network (ANN). **[3]**

The Artificial Neural Network method can be used more accurately for this purpose since the hidden relationships between the fault types and dissolved gases can be recognized by ANN through training process. **[2]**

3. Gas ratio methods

In condition monitoring, the advantage of using ratio methods is that, they overcome the issue of volume of oil in the transformer by looking into the ratio of gas pairs rather than absolute values. The ratio methods considered in this paper are Rogers Ratio Method and IEC Method.

3.1 Rogers Ratio Method:

The Roger’s method utilizes four ratios, CH4/H2, C2H6/CH4, C2H4/C2H6 and C2H2/C2H4. Diagnosis of faults is accomplished via a simple coding scheme based on ranges of ratios. Four conditions are detectable, i.e. normal ageing, partial discharge with or without tracking, thermal fault and electrical fault of various degrees of severity.

Ratios	Range	Code
CH4/H2	≤ 0.1 >0.1<1 ≥1 < 3 ≥3	5 0 1 2
C2H6/CH4	<1 ≥1	0 1
C2H4/C2H6	<1 ≥1<3 ≥3	0 1 2
C2H2/C2H4	<0.5 ≥0.5<3 ≥3	0 1 2

Tab.1-Roger’s Ratio Codes **[4]**

N°	Code				diagnosis
1	0	0	0	0	Normal
2	5	0	0	0	Partial discharge of low energy
3	1,2	0	0	0	Overheating < 150°C
4	1,2	1	0	0	Overheating 150-200°C
5	0	1	0	0	Overheating 200-300°C
6	0	0	1	0	Conductor Overheating
7	1	0	1	0	Overheating by Winding circulating current
8	1	0	2	0	Overheating by Core and tank circulating currents
9	0	0	0	1	Arcing of low energy
10	0	0	1,2	1,2	Arcing of high energy
11	0	0	2	2	continuous sparking to floating potential
12	5	0	0	1,2	Partial discharge with high energy

Tab.2-Roger’s Fault Diagnosis Table **[4]**

3.2. IEC Method:

For diagnosis scheme recommended by IEC originated from Rogers’ method, except that the ratio C2H6/CH4 was dropped since it only indicated a limited temperature range of decomposition. Four conditions are detectable, i.e. normal ageing, partial discharge of low and high energy density, thermal faults and electrical faults of various degrees of severity. In this method three gas ratios are used to interpret the faults.

Table 3 and 4 shows the codes for different gas ratios depending on the range of gas ratios and their interpretation. But, the drawback of these ratio methods is that it fails to cover all ranges of data and quite often ratios fall outside the scope of the tables. In this paper, an Artificial Neural Network approach was used to overcome the above drawback of ratio methods

defined range of the gas ratio	Codes of different gas ratios		
	$\frac{C_2H_2}{C_2H_4}$	$\frac{CH_4}{H_2}$	$\frac{C_2H_4}{C_2H_6}$
<0.1	0	1	0
0.1-1	1	0	0
1-3	1	2	1
>3	2	2	2

Tab.3: IEC Ratio Codes **[5]**

N	Fault type			
1	No fault	0	0	0
2	Partial discharge with low energy density	0	1	0
3	Partial discharge with high energy density	1	1	0
4	Discharge of low energy	1, 2	0	1, 2
5	Discharge of high energy	1	0	2
6	Overheating < 150°	0	0	1
7	Overheating 150°<T< 300°	0	2	0
8	Overheating 300°<T< 700°	0	2	1
9	Overheating T> 700°	0	2	2

Tab.4- IEC Fault Diagnosis Table **[5]**

4. Artificial Neural Networks

The ability of Artificial Neural Networks **(ANN)** in mapping functional relationships has become then as an attractive approach that can be used in several types of problem**.** This characteristic is particularly important when the relationship among the process variables is non-linear and/or not well defined, and thus difficult to model by conventional techniques.
An artificial neural network is a dynamic system that consists of highly interconnected and parallel non-linear processing elements that shows extreme efficiency in computation. The main benefits of using ANN'S on the oil contamination processes are the following:

- The ability of learning and therefore generalization.
- The facility of implementation in hardware.
- The capacity of mapping complex systems without the necessity of knowing the eventual mathematical models associated with them.
- The possibility of time reduction involved with tests in laboratory. **[6]**

An ANN is characterized by having in its architecture many low-level processing units with a high degree of interconnectivity via weighted connections. Among many ANN concepts, the most commonly used is the Multilayer Feed forward Neural Network (Figure 1).

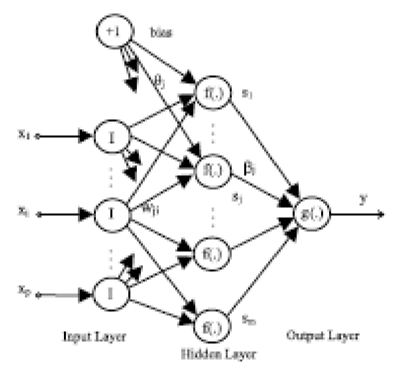


Fig.1. ANN topology

For this ANN, each neuron in a hidden layer H calculates:

$$S_j = f(\sum_{i=1}^{n} x_i w_{ij} + \theta_j) \qquad (1)$$

Where $\mathbf{x_i}$ is the **i-th** input to the net, **wij** is the weight of the connection from input neuron **i** to hidden neuron **j**, θ_j is the bias of the **j-th** hidden neuron and f (-) is the activation function of the neuron. **[7]**

5. Topology of the used ANN

We will use the networks of neurons with training supervised especially of the multi-layer networks, pulled by the algorithm of Back propagation which remains more used. The algorithm of Levenberg - Marquardt has a good robustness for the diagnosis by networks of neurons and seems to be most effective according to the researchers in this field. The architecture of the RNA (a number of hidden layers, a number of neurons) is a significant factor deciding on the quality of the training more than the parameters of training. One made this architecture one base on the functions of Matlab.

The choice of the characteristics of input is a first essential stage. To have been a very careful choice, so that these inputs, reflect the characteristics of the problem.

The number of neurons in the layer of input will be equal to the number of data input and the number of neurons in the layer of output will be defined according to the number of variables and the answers which you seek. In my case, five principal precursory gases with failures in transformers, H_2, CH_4, C_2H_6, C_2H_4 and C_2H_2, are selected like characteristics of input.

5.1. Inputs:

Inputs of the ANN, therefore, the vectors of the codes of the ratios of concentrations of H_2, CH_4, C_2H_6, C_2H_4 and C_2H_2 in ppm. It is different for each method.

5.2. Outputs:

The outputs which we want are the types of defect which to occur from the input, who are discharges partial of weak and strong energy, the electric arc and overheats it or the case normal, if the data of input does not act of a failure to the transformer. In each standard method, different type defect.

5.3. Hidden Layer:

The use of a great number of hidden layers not recommended. The large majority of the problems of standards of classification, used only, one has more than two hidden layers. The number of neurons in the hidden layer is generally defined in an empirical way.

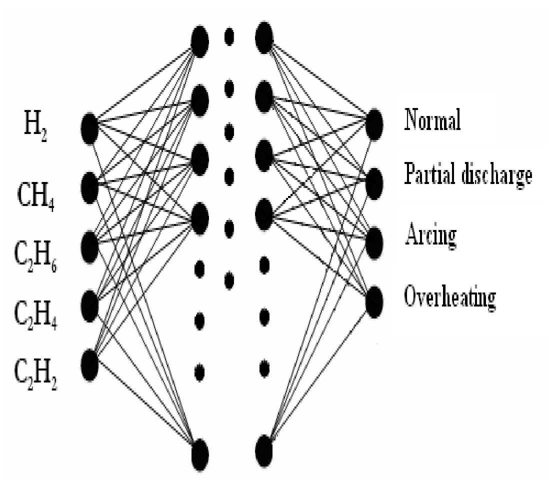


Fig.2- Topology of ANN used

5.4.Transfer function:
sigmoid tangent **(logsig)** most common of function of activation is used in the networks of neurons.

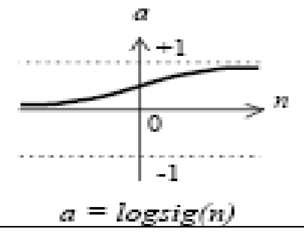


Fig .3. Transfer function log- Sigmoid

The optimization of the RNA used in the diagnosis is carried out by changing topology of the network and the criterion of optimization is based on the exactitude of the results.

The methods of ratio considered in this research are the method of ratio of Rogers and the method of the CEI.

5.5. Data of inputs:
They are the gas concentrations found in the analysis chromatographic test of samples taken on the life of the transformer (formation) or suspected in the sample (net value under normal conditions of use).

The bank of data of the diagnoses made on the park of the transformers of the area of SETIF enabled us to see the sensitivity of our program and the level of its reproducibility. The comparison of the results obtained is made compared to software DELTA X used in the laboratories of Sonelgaz-GRTE [J DUCKARM] or the data of share and others are examined to see established convergences. **[9]**
Concentrations of principal gases in ppm:

Samples	H_2	CH_4	CO	CO_2	C_2H_4	C_2H_6	C_2H_2	Known Fault
1	6	9	25	290	10	4	< 1	Overheating
2	1046	2809	681	7820	321	675	7	DP
3	127	76	879	3471	23	32	49	ARC
4	230	402	90	600	579	176	< 1	Overheating
5	<1	115	469	3319	16	147	<1	Overheating
6	39	33	991	3280	9	7	2	Normal
7	72	278	53	610	176	289	< 1	Overheating
8	1	39	361	4081	9	36	1	Normal
9	239	41	841	4964	59	21	227	ARC
	17	15	292	6956	78	20	35	ARC

Tab .5. Samples data **[8]**

6. Application of ANN to DGA

6.1. Diagnosis using the method of the CEI:

The vector of inputs E = [C1, C2, C3] = [code $\frac{C_2H_2}{C_2H_4}$, code $\frac{CH_4}{H_2}$, code $\frac{C_2H_4}{C_2H_6}$] (codes obtained according to the method of CEI (see table 3)

The vector of exit S = [S1, S2, S3, S4, S5, S6, S7, S8, S9] (nine defects found by the method of CEI (see table 4)

The network of neuron with the method of the CEI is composed of layer of input of 3 neurons; the hidden layers contain a variable number of neurons and the exit with 9 neurons.

The output produces real numbers between 0 and 1 indicating the probability of existence of a defect among the nine defects indicated by standards CEI. The models of formation for the method of the CEI are shown in table 6.

inputs			outputs								
C1	C2	C3	S1	S2	S3	S4	S5	S6	S7	S8	S9
0	0	0	1	0	0	0	0	0	0	0	0
0	1	0	0	1	0	0	0	0	0	0	0
1	1	0	0	0	1	0	0	0	0	0	0
1,2	0	1,2	0	0	0	1	0	0	0	0	0
1	0	2	0	0	0	0	1	0	0	0	0
0	0	1	0	0	0	0	0	1	0	0	0
0	2	0	0	0	0	0	0	0	1	0	0
0	2	1	0	0	0	0	0	0	0	1	0
0	2	2	0	0	0	0	0	0	0	0	1

Tab.6 - Database Trained By IEC Method

6.2. Diagnosis using the method of Rogers:

The vector of inputs E = [C1, C2, C3, C4] = [code $\frac{CH_4}{H_2}$, code $\frac{C_2H_6}{CH_4}$, code $\frac{C_2H_4}{C_2H_6}$, code $\frac{C_2H_2}{C_2H_4}$] (codes obtained according to the method of Rogers (see table 1)

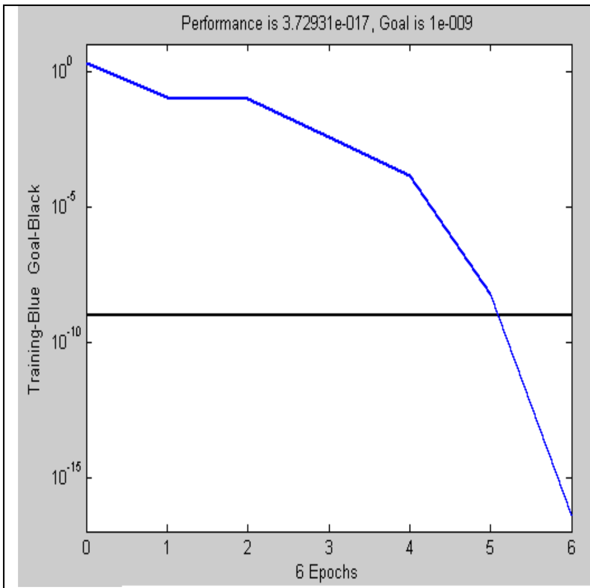
The vector of output S = [S1, S2, S3, S4, S5, S6, S7, S8, S9, S10, S11, S12] (12 defects found by the method of Rogers (see table 2)

The network of neuron with the method of Rogers is composed of layer of input of 4 neurons; the hidden layers contain a variable number of neurons and the output with 12 neurons.

The output produces real numbers between 0 and 1 indicating the probability of existence of a defect among the nine defects indicated by the method of Rogers. The models of formation for the method of Rogers are shown in table 7.

inputs				outputs											
C1	C2	C3	C4	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12
0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
1,2	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
1,2	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0
0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0
0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0
1	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0
1	0	2	0	0	0	0	0	0	0	0	1	0	0	0	0
0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0
0	0	1,2	1,2	0	0	0	0	0	0	0	0	0	1	0	0
0	0	2	2	0	0	0	0	0	0	0	0	0	0	1	0
5	0	0	1,2	0	0	0	0	0	0	0	0	0	0	0	1

Tab.7 – Database Trained By Rogers Method



Two hidden layer with 1 and 18 neuron

Fig.8. Training phase error using LM method

7. Results

Once the training is completed, the network needs to be tested. In order to test the trained network, 10 test samples given in Table 5 were considered with a known cause of fault.

The results obtained during testing are presented in Table 8. From Table 8 it is observed that the trained network made a correct diagnosis in 8 out of 10 cases in Rogers Methods and 7 out of 10 cases in IEC Method.

samples	Actual fault	Predicted fault from ANN	
		IEC Method	Rogers Method
1	Overheating	Overheating	Overheating
2	DP	Overheating	Overheating
3	ARC	ARC	ARC
4	Overheating	Overheating	Overheating
5	Overheating	Overheating	Overheating
6	Normal	DP	Normal
7	Overheating	Overheating	Overheating
8	Normal	Overheating	Overheating
9	ARC	ARC	ARC
10	ARC	ARC	ARC

Tab.8 – Results of DGA by ANN

8. Conclusions:

DGA has been recognized as an important tool in condition monitoring of power transformer. The main advantage of using ratio methods is that, volume of oil involved in the dissolution of gas is not required as only ratios of gases are involved. But the drawback is that they fail to cover all ranges of data. Therefore an ANN approach is used to overcome the drawback. The results obtained through ANN are highly reliable.

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