Neural Network Based Dissolved Gas Analysis Using Gas Composition Patterns Against Fault Causes

J. H. Sun*, K. H. Kim** and P. B. Ha***

Abstract - This study describes neural network based dissolved gas analysis using composition patterns of gas concentrations for transformer fault diagnosis. DGA samples were gathered from related literatures and classified into six types of faults and then a neural network was trained using the DGA samples. Diagnosis tests were performed by the trained neural network with DGA samples of serviced transformers, fault causes of which were identified by actual inspection. Diagnosis results by the neural network were in good agreement with actual faults.

Keywords: Neural Network, Dissolved Gas Analysis (DGA), Transformer Diagnosis

1. Introduction

Transformer insulation systems using cellulose impregnated with mineral oils provided a high degree of reliability [1-2]. However, incipient faults in these insulation systems can occur under certain operating conditions and the insulation systems can break down as a result of the development of these incipient faults. Power transformer reliability improves when these faults are detected and eliminated before they are permitted to progress into problems of severe magnitude.

In the case of oil immersed power transformers, when sufficient energy dissipated by faults is applied to insulation oil and solid insulation such as cellulosic paper or press board, the bonds between its molecules may be broken. Depending on the level of energy according to fault causes such as arcing, overheating and partial discharge, various bonds are broken forming different kinds of molecules. Combustible and non-combustible gases are generated in the process of recombining formed molecules and are dissolved into oil. Assorted gas compositions result from different dissipated energy levels according to fault causes [3]. Therefore, the analysis of these gases provides useful information relating to fault conditions. This has been understood for a long time and Dissolved Gas-in-oil Analysis (DGA) has been widely applied by many utilities and researches for assistance in identifying incipient faults of power transformers.

Much effort has been given to the development of techniques using attributes like the ratio of specific dissolved gas concentrations, their generation rates and combustible gas concentrations [5-9]. Gas ratio methods or key gas methods are used for classification of fault causes in most conventional DGA. Gas ratio methods such as the Doernenburg method, the Rogers method and IEC 60599, which are the most commonly used ratio methods assign a certain combination of gas ratios to a specific fault type. The ratio methods have the advantage that their approaches are comparatively simple and they can be computer programmed since fault causes are determined by numerical limitations of gas ratios. However, some combinations of gas ratios may have no diagnostic decision when the ratio does not fall within a certain range due to causes such as error in the measuring system or simultaneous generation of different types of faults. In key gas methods such as gas pattern and IEEE standard method, fault causes are identified by leading gases. Since this method does not employ the use of numerical limitations, proper diagnosis will be based greatly on experience. Therefore, the search of a reliable diagnostic method using DGA in power transformers is still a topic of interest to many utilities.

Recently, some studies have reported the use of neural networks using DGA for achievement of better diagnosis performance for power transformers [10-12]. These studies are mainly based on neural networks trained according to conventional DGA criteria or using only three types of main fault causes such as arcing, partial discharge as output features, and overheating. These approaches can still include the above mentioned conventional DGA problems and since the fault types of transformers are greatly varied, the three types of outputs may not provide sufficient information to diagnose diverse fault types.

This study describes neural network based dissolved gas analysis(NNDGA) for fault diagnosis of oil immersed

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power transformers. DGA samples were gathered from related literatures and composition patterns of gas concentrations for DGA samples were obtained according to fault causes. A neural network using the scaled gradient descent algorithm was trained with the DGA samples. Fault diagnosis using NNDGA was performed with the DGA samples of faulted transformers, fault causes of which were identified by visual inspection. Diagnosis results using NNDGA were compared with actual fault causes.

2. Evolution of Gas in Oil

Most power transformers use mineral oil as a dielectric and coolant. Abnormal conditions can occur within a transformer because of electrical, thermal, mechanical and environmental stresses. These conditions result in the occurrence of various faults such as arcing, overheating and partial discharge and lead to decomposition of the oil.

As oil is decomposed, various types of hydrocarbon gases are generated according to energy levels that mainly depend on the temperatures of the fault location with fault types. Fig. 1 shows the decomposition gases of oil with fault types. As can be seen in Fig. 1, mineral insulating oil is composed of a blend of different hydrocarbon molecules and scission of some of the C-H and C-C bonds may occur as a result of faults like arcing, overheating and partial discharge with the formation of unstable fragments in radical and ionic form, which recombine rapidly into gas molecules such as hydrogen (H-H), methane (CH_3-H), ethane (CH_3-CH_3), ethylene (CH_2=CH_2) and acetylene (CH≡CH) [13]. In the relation between fault types and their energy levels from Fig. 1, the notable hydrocarbon gas for each of the faults will be as follows.

- arcing: hydrogen, acetylene
- overheating: ethylene, ethane, methane,
- partial discharge: hydrogen

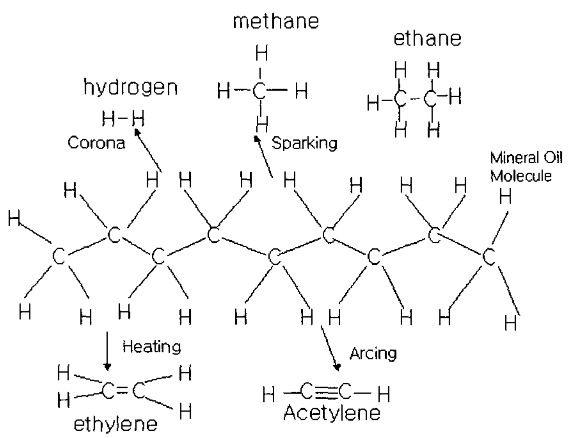


Fig. 1 Typical gases of oil with fault types

3. Classification of Dga Data for Training

Principally, the oil fault related gases commonly used are hydrogen (H2), methane (CH4), ethane (C2H4), acetylene (C2H2) and ethylene (C2H6). They have been used in the conventional DGA methods like key gases, IEC code, Rogers and Dornenburg. Seventy-eight DGA samples containing ppm concentrations of the above mentioned five gases were gathered from various literatures [3, 9-15] and all samples were used as training data. A set of the training data used are shown in Table 1. Fault causes such as arcing, overheating and partial discharge can be indicated by consideration of the inspection results in Table 1. The samples were classified in three types of faults, arcing, overheating and partial discharge. Table 2 shows each of the corresponding sample numbers among a total of 190 DGA samples against 3 types of fault causes. A gas composition pattern provides information on fault conditions such as temperature of fault point, fault cause, fault severity and so on. In this study, in order to obtain more detailed fault information from the DGA, gas composition patterns of sample data for each fault cause were searched. A total of six types of gas composition patterns were obtained and classified as shown in Fig. 2. Fig. 3 shows the obtained six types of gas patterns and the percentage of each gas to the summation of five gases plotted against the gas order of C_2H_2, H_2, C_2H_4, CH_4 and C_2H_6. In Fig. 3, two types of gas patterns are given for the arc case, arc 1 and arc 2 and three types of gas patterns are given in the overheat case, overheat 1, overheat 2 and overheat 3, and 1 type is given in PD case.

Table 1 A set of training data

H2	CH4	C2H2	C2H4	C2H6	Total	Inspection Results
3030	15200	22	6680	1530	26772	Damage due to mismatched joints in a multiple conductor causing high circulating currents between individual conductors
888	22	24	23	14	971	Discharge like corona
1280	1450	62	978	83	3853	Heating of pressure plate making contact with core
640	530	2	364	53	1589	Loose connection
16000	1470	3880	1800	76	23226	Short between turns and ground
13500	6110	4040	4510	212	28372	Turn to turn short circuit
6800	1160	2820	424	30	11234	Turn to turn short circuit
2500	10500	6	13500	4790	31296	Loose bolt causing the core to contact with its clamping frame
755	2260	84	4120	700	7919	Heating due to circulating currents in metal structures
860	2460	5	2920	1000	8138	Heating of tie rod due to stray flux

Since six types of gas composition patterns have characteristic curve patterns, fault causes can be inferred from recognition of those curve patterns. These six patterns are used as output vectors of NNDGA as described in the next session.

Table 2 DGA sample number classified against fault causes

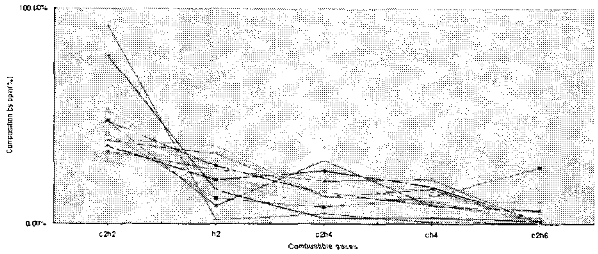
Fault causes	DGA sample number
Arcing	73
Overheating	105
PD	12
Total	190

Fault Causes	Pattern Name	Sample Number
Arcing	arc1	24
	arc2	49
Overheating	overheat1	78
	overheat2	18
	overheat3	9
PD	PD	12

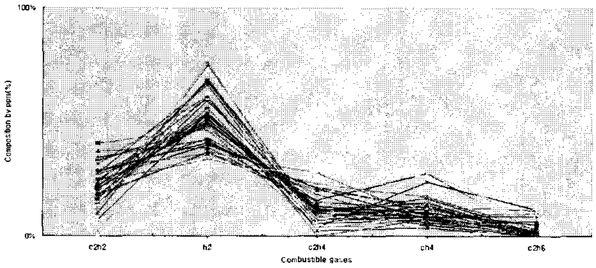
Fig. 2 Classification of gas composition pattern

4. Neural Network Design

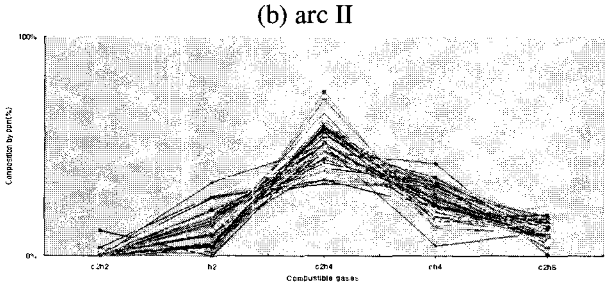
The dissolved gases in oil show characteristic gas composition patterns according to fault types but conventional DGA methods have no diagnostic decisions in the case of any gas patterns. Neural networks have been used extensively in applications where pattern recognition is needed. Therefore, properly trained neural network DGA can identify the relationship between fault causes and those gas patterns. A neural network design for training includes selection of layer number, input features, output features, the number of hidden nodes and weighted connections. In this study, the scaled gradient descent algorithm that prevents training from being driven to a minimum local point was used as the training algorithm of the NNDGA, and its architecture is shown in Fig. 4. As can be seen in Fig. 4, three layers were used in order to avoid slow training. Six gas concentrations in ppm including total gas, which means the summation of the other five gases, are presented in the input nodes. An error of 0.001, which was considered acceptable in this study, was used as the goal error value. NNDGA was trained until reaching the error goal of 0.001. Since 210 hidden nodes showed the smallest epoch number during training, a NNDGA configuration based on the node number was selected for NNDGA testing and the average epoch number from 10 trials of training at 210 hidden nodes was 1180.



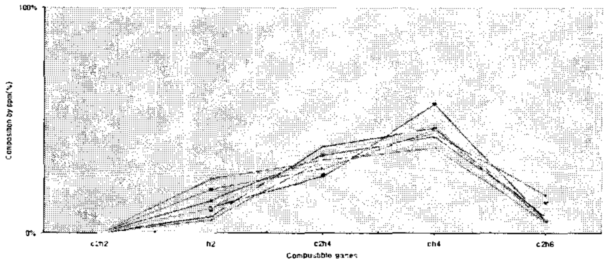
(a) arc I



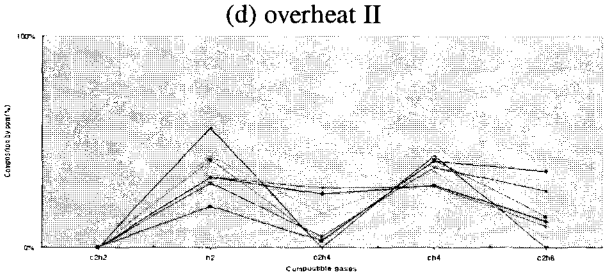
(b) arc II



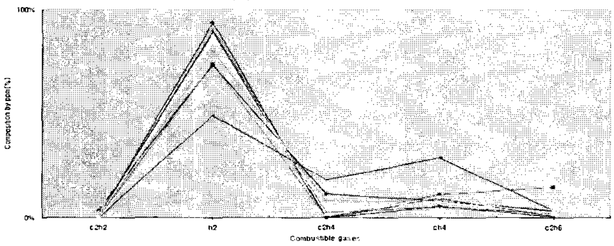
(c) overheat I



(d) overheat II



(e) overheat III



(f) PD

Fig. 3 Gas composition patterns

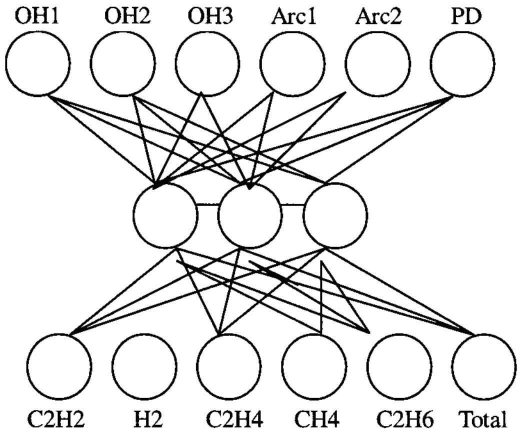


Fig. 4 Architecture of NNDGA

An activation function transforms input vectors multiplied by synaptic weights into output vectors. The log sigmoid activation function was used in each node so that outputs range from 0 to 1. The output layer consists of six nodes, which represent six types of faults mentioned in the previous session. Fig. 5 shows a typical error trend with epoch number under determined training configuration during training.

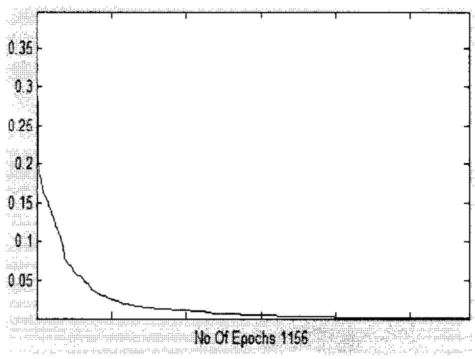


Fig. 5 Typical error trend for NNDGA

Graphic user interface (GUI) was used for training and diagnosis. The GUI panel consists of a main window, input and output windows and control buttons. The main window shows not only accuracies of output vectors as bar type graphs but also error trend and gas composition pattern, which have been introduced in Fig. 3 as curve type graphs. Input windows show six gas concentrations entered in ppm and output windows display accuracy of each output vector as numbers in the range of 0 to 1. Control buttons include training start, diagnosis start button and so on. The GUI panel will be shown in the next session.

5. Transformer Diagnostic Tests

Four test samples for NNDGA testing with unknown data were taken from DGA results of faulty transformers in service and their fault causes were identified by actual inspection. Table 3 shows five gas concentrations in ppm and the inspection results of each test sample.

Table 3 Example data and inspection results

Example No.	C2H2	H2	C2H4	CH4	C2H6	Inspection Results
1	2	22	429	127	89	Core grounding strap had carbonized due to recurring current
2	61	22	33	30	0	Arc discharge at loose press board supporting bolt
3	0	16	45	104	471	The insulation cover of the core pressure ring had been carbonized due to eddy current.
4	2495	15994	0	0	99	Arc had been developed from lead winding to frame due to insufficient insulation distance.

As we can see in the Table 3, it seems that the fault cause of test sample 1 is overheat due to recurring current generated by multi-grounding of the core. The fault cause of sample 2 is arc due to floating discharge according to incorrect grounding of the bolt and the fault cause of sample 3 is overheating of the coil pressure ring caused by the eddy current. Lastly, the fault cause of sample 4 is arc generated by insufficient insulation between grounding and high voltage winding. Diagnosis tests were performed by the trained NNDGA with four DGA samples in Table 4. Fig. 6 shows a gas composition pattern GUI for sample 1. It is indicated that pattern © of the six gas composition patterns in Fig. 3 corresponds to the pattern of DGA data under testing. Fig 7, which is the test result for sample 1, shows GUI displaying output accuracy as a bar graph and number. The accuracies of NNDGA against six output vectors of the four test samples obtained from performing output accuracy GUI as in Fig. 6 are provided in Table 4.

In sample case 1, overheat 1 of output accuracy 0.99 can be indicated as a fault cause since the accuracy of the other causes are close to 0. In sample case 2, arc 1 of output accuracy 0.80 and in sample case 3 case, overheat 2 of output accuracy 0.83 can each be indicated as fault causes. In sample case 4, both arc 2 of output accuracy 0.50 and PD of output accuracy 0.75, which are low values compared to the above three cases, can be indicated as fault causes. Fault causes of sample cases 1, 2 and 3 indicated by NNDGA are in good agreement with those analyzed by inspection results in Table 3 but the fault cause of sample case 4 exhibits slight deviation from that by inspection since the fault causes by NNDGA were PD and arc2 but fault cause by actual inspection was arc. This mismatch is considered to be due to the lack of PD cases for training, which is 12 cases of a total of 190 fault cases in Table 2, or the possibility of actual PD generation during sufficient time before evolving to arc.

Table 4 Accuracies of NNDGA against output vectors

Sample No.	Arc1	Arc2	Over-heat1	Over-heat2	Over-heat3	PD
1	0.01	0.01	0.99	0.01	0.01	0.00
2	0.80	0.36	0.03	0.02	0.01	0.00
3	0.01	0.00	0.00	0.83	0.40	0.00
4	0.00	0.50	0.00	0.00	0.00	0.75

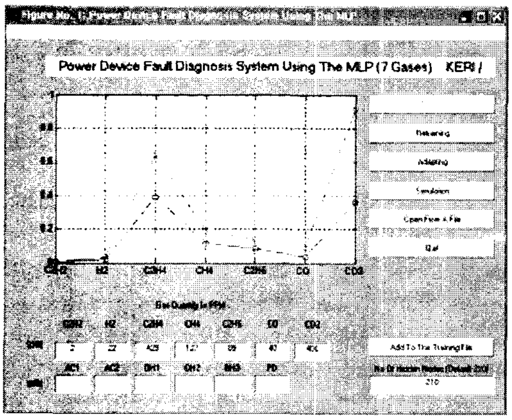


Fig. 6 Example of gas composition pattern GUI

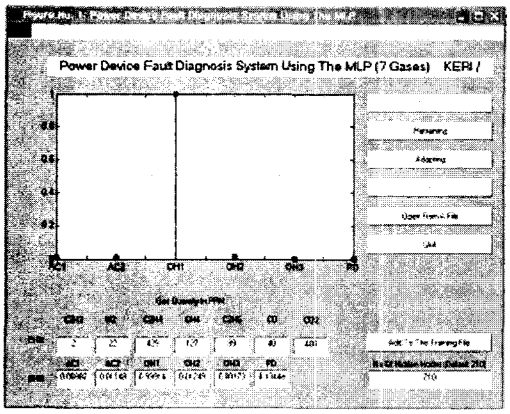


Fig. 7 Example of output accuracy GUI

6. Conclusion

In this paper, we described neural network based dissolved gas analysis using composition patterns of gas concentrations. 190 sample data including concentrations in ppm of five gases were taken from the published literatures for training. Six gas composition patterns were obtained from the classification of the composition patterns of five gases for three types of fault causes. Among those patterns, arcing had two types of patterns of arc I and arc II, overheat had three types of patterns of overheat I, overheat II and overheat III, and partial discharge had only one type of pattern. These six patterns were used as output attributes of NNDGA. The architecture of NNDGA for the optimal training was decided and GUI was used for training and testing. Four sample DGA data obtained from a faulty transformer in service and were tested by NNDGA. It was indicated that the diagnosis results by NNDGA agreed with visual inspection results for the most part but in the PD case more sample data for training were needed for the increase of output accuracy.

Hereafter, it is considered that further study on the database construction and NNDGA training for the relationship between gas composition patterns and fault phenomena for more DGA samples taken from faulty transformers in service is needed for a more reliable diagnosis.

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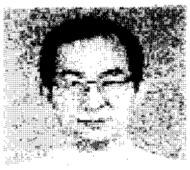

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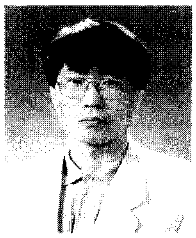

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