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ARTIFICIAL NEURAL NETWORKS AND GENETIC ALGORITHM FOR TRANSFORMER WINDING/ INSULATION FAULTS

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ABSTRACT
This paper presents an application of Artificial Neural Network and Genetic Algorithm for transformer winding/insulation faults diagnosed using Dissolved Gas in Oil Analysis. A back propagation training method is applied in neural network to detect the faults without cellulose involvement. Genetic Algorithm is used to derive the optimal key gas ratios to enhance the accuracy of fault detection. The dissolved gas in oil analysis method is known to be an early fault detection method and enables to carry out diagnosis during online operation of the transformer. Besides, the condition of the transformer could be monitored continuously by time to time. The results are compared between the real and predicted faults to observe the accuracy rate of the system.

KEY WORDS
Artificial Neural Network, Genetic Algorithm, dissolved gas analysis, transformer fault detection and diagnosis

1. Introduction

Transformers are very vital equipment in the power distribution system as well as in the industrial field area. Maintenance of transformers performance during normal and abnormal conditions is important to avoid internal winding faults resulting from electrical and thermal stresses. Even though a transformer is provided with the protection devices and follows a maintenance routine schedule, early fault detection prevents any premature breakdown besides improving the system reliability.

Therefore, the studies on transformer faults help in predicting the fault behavior and are used to prevent and evaluate the same fault from reoccurring in the system. The breakdown of insulating materials leads to release of gaseous decomposition products. The dissolved gases analysis (DGA) in transformer insulation oil is a powerful tool to diagnose the faults [1]. This method enables an online inspection without having to isolate the transformer, and the condition of oil could be monitored time to time.

The detection of transformer winding/insulation faults is approached and analyzed by different methods. ANN based fault diagnosis through training process [2, 3] has been used for power transformers. Neural network modeling for winding faults of distribution transformers [4] is developed and a novel extension method is proposed [5] for fault diagnosis. Genetic programming [6] and genetically optimized neural network [7] are proposed for fault detection of power transformers. Expert system [8] and simulation by fuzzy-logic controller [9, 10] are proposed for diagnosis of transformer faults. Recently, for fault classification, the application of wavelet transform as a preprocessor for NN is proposed [11]. In this paper, the transformer faults are analyzed by using Neural Network and Genetic Algorithm.

2. Dissolved Gas Analysis

Dissolved Gas Analysis (DGA) is an online method of transformer oil testing. The process starts from oil sampling to gas identification where the dissolved gases in the oil will be extracted and identified. As the oil testing is monitored online, there is no need to shut down and disturb the transformer. From the immersed oil, the hydrocarbon gases extracted are hydrogen (H_2), methane (CH_4), ethane (C_2H_6), ethylene (C_2H_4), acetylene (C_2H_2), carbon dioxide (CO_2) and carbon monoxide (CO). These gases prompt to produce specific faults when the amount of gas being produced exceed their limit of existence in the transformer oil. It is observed that different gases generated in the oil did produce different intensities of energy which possibly produce various faults. The severity of faults caused by the hydrocarbon gases are different and are classified as partial discharge, overheating, arcing and also cellulose. The fault severity varies from arcing (most severe), overheating (moderate), and partial discharge (least severe). The two most popular methods that correctly diagnose the fault are key gas and Roger's ratio methods [2]

2.1 Key Gas Method

A particular fault is identified from the relationship between key gases and fault types as follows.

H_2: Corona
CH_4 and C_2H_6: Low temperature oil breakdown
C_2H_4: High temperature oil breakdown
C_2H_2: Arcing

2.2 Roger's Ratios

The Roger's ratio method is used by The Central Electric Generating Board (CEGB) of Great Britain [1] in which the magnitude of four hydrocarbon gas ratios is used to generate a four digit code. The gas ratios are allocated with different codes which determine the fault types.

3. Principle of ANN and GA

3.1 Artificial Neural Network and Back-propagation Structure

ANN is known as an intelligent system where the system recognizes a certain set of pattern and makes simple rules for complex problems having an excellent training capability. The ANN system requires an input, output, network architecture and weighted connection of nodes which are known as the hidden layer. Depending on the network, the output remains as an output or being an input to the next hidden layer. The back propagation structure provides training network for multi-layer feed-forward network. Back propagation allows self learning where all weighted values are adjusted in each training level and train the input data until it reaches the desired output.

In this paper, the simulation is performed using Neural Network MATLAB Toolbox [12]. Before applying the neural network coding, the basic coding on the key gas method needs to be created in order to produce the data and target values for each sample of the DGA data.

Five input data are inserted into the designed Neural Network. In the key gas method, the four outputs produced are normal, corona, overheating and arcing. The data trimming method is applied where the fault data is normalized to make it compatible with the target data over a range between 0 and 1. The process in the Neural Network will be more appropriate with the normalization equation:

$$f_{norm} = \frac{f_i - f_{\min}}{f_{\max} - f_{\min}} \qquad (1)$$

where f_i = the actual value of sample data
$f_{\min}$ = the minimum value of the sample data
$f_{\max}$ = the maximum value of the sample data

The back propagation of two layer network using Levenberg-Marquardt training with feed-forward structure is applied in this paper. The hidden layer is trained using 52 neurons while 4 neurons are at the output layer. The optimal value of neurons used in the hidden layer is obtained by trial and error technique as it depends on the complexity of the system itself.

In training mode, the neural network is trained by 52 training data and 10 test data collected from the research paper on the DGA [3], as shown in Table 1. The data is trained in the network so that the network could learn the characteristics of the data and produce the desired output.

Table 1
Test data

No.	H_2	CH_4	C_2H_2	C_2H_4	C_2H_6
1	48	43	81	75	3
2	318	337	641	583	57
3	338	32	50	32	1
4	114	1417	0	2096	296
5	2	4	0	4	3
6	21	34	62	47	5
7	37	75	0	5	126
8	59	339	1	392	42
9	13	10	0	13	4
10	800	1393	3000	2817	304

The data is trained continuously until the desired output is reached. Early stopping or validation is used to improve and determine the optimum value for the regularization parameters. This is achieved by dividing the training data into new training set and validation set, to avoid any over-fitting where the error starts to increase.

3.2 Genetic Algorithm Method

In this paper Genetic Algorithm (GA) approach is used to derive the optimal values of the key gases with Rogers ratios as the fitness functions. GA is a method for solving optimization problems based on natural selection, the process that drives biological evolution [13, 14]. The GA repeatedly modifies a population of initial solutions. At each step, it selects individuals at random from the current population to be the parents. It then uses the parents to produce children for the next generation. Crossover and mutation operators are applied to the parents to generate new children. Over successive generations, the population evolves toward an optimal solution. In contrast to more traditional numerical techniques, the parallel nature of the stochastic search done by GA often makes it very effective in locating the global optimum. GA is less susceptible to getting stuck at local optima like ANN and gradient search methods. Also, GA is much less sensitive to initial conditions and is widely used in various optimization problems [15]. Constrained evolutionary optimization (CEO) is one of the few GA techniques.

In order to optimize the dissolved gases, some design variables are to be selected and a suitable fitness function is to be formed. The hydrocarbon gases, hydrogen (H_2), methane (CH_4), acetylene (C_2H_2), ethylene (C_2H_4), ethane (C_2H_6), are considered as design variables x_1, x_2, x_3, x_4 and x_5 respectively. Based on the Roger's ratio method of interpretation, four fitness functions to be minimized are formed as follows:

i. Ratio of methane and hydrogen, $y_1 = \dfrac{x_2}{x_1}$ (2)

ii. Ratio of ethane and methane, $y_2 = \frac{x_5}{x_2}$ (3)

iii. Ratio of ethylene and ethane, $y_3 = \frac{x_4}{x_5}$ (4)

iv. Ratio of acetylene and ethylene, $y_4 = \frac{x_3}{x_4}$ (5)

A brief description of the GA parameters is listed as follows [13, 16]:

1. Number of variables: In GA approach, each design variable is represented as a binary string (chromosome) of fixed length. The chromosomes are evaluated by using a fitness function. The number of variables in each function is two as the fitness function created was a ratio of two hydrocarbon gases.
2. Population size: A population of chromosomes is created. GA provides solutions by generating a set of chromosomes referred to as a generation. If the search has to continue, the GA creates a new generation from the old one until a decision is made on the convergence. Increasing the population size enables the GA to search more points at each generation and obtain a better optimal value. However, the larger the population size, the longer the GA takes to compute each generation [16]. The fitness functions are tested with different number of population sizes starting from population size equal to 20 up to 140.
3. Probability of mutation: The mutation operator randomly selects an individual from the population and then chooses two elements in this individual to exchange positions. The mutation probability is set to the default rate of 0.05.
4. Probability of crossover: A crossover operator exchanges information contained in two parent individuals to produce two offspring and then replace the parents. The number of times the crossover operator is applied to the population is determined by the probability of crossover and the population size. The crossover probability is set to the default rate of 0.8.
5. Lower and upper bounds on the variables: Each of the hydrocarbon gases is constrained within a specific range of lower and upper values. This is to ensure that the ratio functions are optimized within the desired range. The key gas method guidelines published by California State University, Sacramento in co-operation with Pacific Gas & Electric Company, USA is referred [1] for choosing lower and upper bounds on the design variables.

4. Results and discussion

4.1 Artificial Neural Network

To enhance the accuracy of the network, a proper structure of the network need to be determined. In this paper, 2-hidden layer back-propagation training network was chosen with 5 inputs data and 4 output nodes. The input data are hydrogen (H_2), methane (CH_4), acetylene (C_2H_2), ethylene (C_2H_4), ethane (C_2H_6), while the outputs to be observed are normal, corona, overheating and arcing.

The network was trained using 52 samples of dissolved gas analysis data. In order to verify the network accuracy, the network is tested with 10 samples of dissolved gas analysis data from different transformers. Simulations of the network are experimented using three sets of data - 10 %, 20 % and 30 % validation data together with 90 %, 80 % and 70 % training data respectively. The test data output using 20 % validation and 80 % training data is presented in Table 2.

Table 2
Simulation results based on Key Gas method

Neurons	MAE	MSE	Performance
5	0.3052	0.2224	0.097534
10	0.2886	0.2616	0.065749
15	0.2539	0.2276	0.062585
20	0.2794	0.1737	0.037881
25	0.3171	0.2292	0.021494
30	**0.2035**	**0.1543**	**0.013611**
35	0.3019	0.2627	0.061985
40	0.1282	0.1254	0.136445

The mean square error which is obtained from the difference of the target and simulation values is 0.1543 as shown in Table 2 and is observed to be less compared to the results of other sets of test data. The characteristics of the performance of the validation data and test data are observed to be very close.

Based on the test data from Table 1, the simulation results of the faults are presented in Table 3. As observed from Table 3, eight of the simulation results prediction is correct, while two of the simulation results failed to produce the correct predicted fault.

Table 3
Predicted faults from ANN simulation

No	Actual	N	C	O	A	ANN Diagnosis
1	Arcing	0	0	1	1	Arcing, Overheating
2	Arcing	0	0	1	1	Arcing, Overheating
3	Corona	1	0	0	0	Normal
4	Overheating	0	0	1	0	Overheating
5	Normal	1	0	0	0	Normal
6	Arcing	0	0	1	1	Arcing, Overheating
7	Overheating	0	0	1	0	Overheating
8	Overheating	0	0	1	0	Overheating
9	Normal	0	1	1	0	Overheating
10	Arcing	0	0	1	1	Arcing, Overheating

N-normal, C-corona, O-over heating, A-arcing

It is observed from the results that the actual and the ANN diagnosis values are quite matching except in two cases (samples number 3 and 9) where the diagnosis are imprecisely predicting the transformer faults.

Overall, based on the simulation results, it is shown that the back-propagation ANN approach performed satisfactorily for transformer faults analysis even with limited and unrecognized sample data. Therefore, an improvement in network training is a must in order to overcome this insufficient available data. More test data enable to develop a system that is able to detect transformer winding and insulation faults using DGA.

4.2 Genetic Algorithm

The optimization on gas ratios is performed using the Genetic Algorithm Tool within the GADS Toolbox [16]. The default setting in the GA Toolbox is used to simulate each fitness function subject to the constraints. The GA technique for minimization of Roger's Gas ratio as fitness functions is applied and optimal parameters are derived. The simulation results of each Roger's Gas ratio function is obtained for mutation probability of 0.05, crossover probability of 0.8 and varying number of generations. Each fitness function is minimized for a particular population size after experimenting with the simulations for different combinations of GA parameters.

The Roger's Gas ratio function is minimized with the optimal population size obtained for each of the gases ratios varying the number of generations. Hence, the minimized output function could be observed in order to assess the condition of the hydrocarbon gas ratio whether the ratio falls under no fault or fault condition based on the Roger's Gas Ratio Diagnostics [1]. Figs. 1 to 4 show the minimized gas ratios for a set of GA parameters, varying the number of generations.

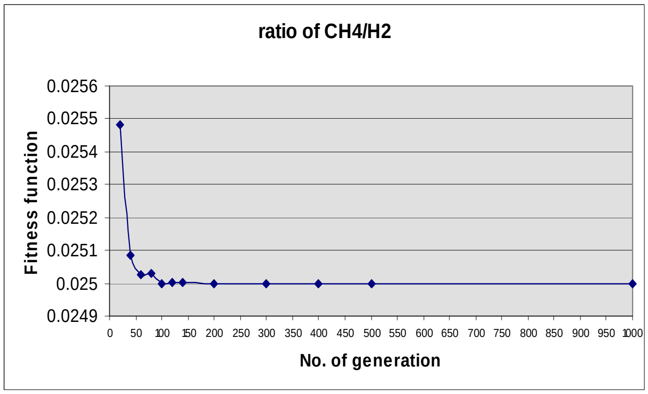

Figure 1. Minimized gas ratio of methane and hydrogen

The minimized gas ratio of methane and hydrogen is obtained for population size of 80 and is observed to be optimal after 100 generations, as shown in Fig. 1.

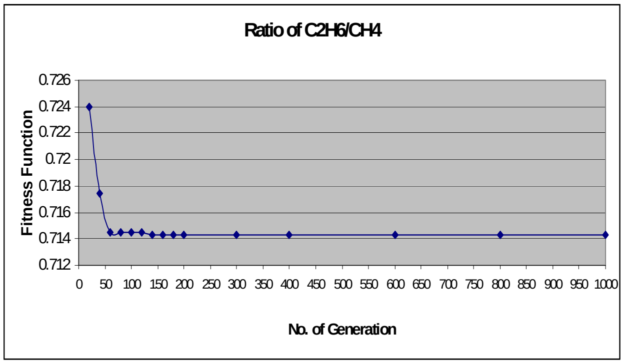

Figure 2. Minimized gas ratio of ethane and methane

Fig. 2 shows the minimized gas ratio of ethane and methane with a population size of 140. The optimal ratio is obtained after 150 generations.

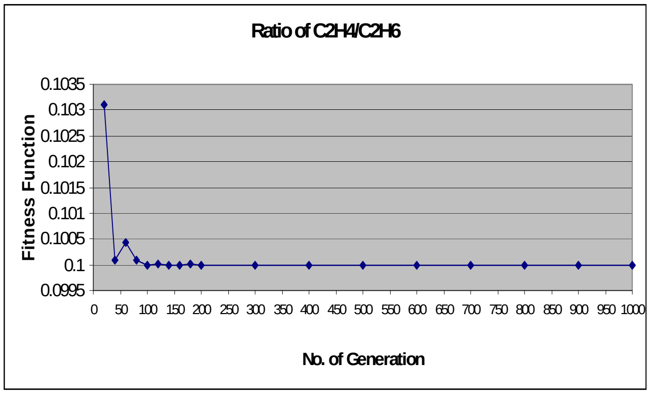

Figure 3. Minimized gas ratio of ethylene and ethane

The minimized gas ratio of ethylene and ethane is obtained with a population size of 60 and varying the number of generations. The optimal ratio becomes constant after 100 generations as shown in Fig. 3.

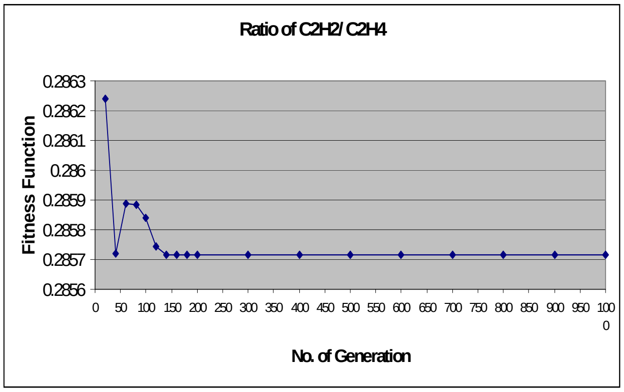

Figure 4. Minimized gas ratio of acetylene and ethylene

Fig. 4 shows the minimized gas ratio of acetylene and ethylene with a population size of 100. The optimal ratio is obtained after 150 generations.

The four optimum gas ratios from Figs. 1 to 4 are presented in Table 4.

Table 4
Minimum gas ratios

Ratio	CH_4/H_2	C_2H_6/CH_4	C_2H_4/C_2H_6	C_2H_2/C_2H_4
FVAL	0.025	0.714	0.100	0.286
CODE	5	0	0	0

If any of the gas ratios exceed the minimized function gained from the optimization technique, it is assumed that the gas ratios experience a fault. It is observed from Table 4 that the four optimal gas ratios correspond to partial discharge based on C. E. G. B. diagnostics [1]. Similarly the fault diagnosis interpretation from optimal gas ratios for other samples of test data can be derived by GA method.

The simulation results for transformer fault diagnosis from both ANN and GA methods are promising. It is observed that ANN can give an accurate fault prediction. Whereas for GA technique, an appropriate objective function need to be identified to achieve an optimal value.

5. Conclusion

It is shown in this paper that Artificial Neural Network (ANN) is capable of predicting transformer faults as its capability of producing relevant outputs by the simulation are proved. An attempt is made to predict the fault diagnosis using the Genetic Algorithm approach. The performance of GA for optimizing the gas ratios is encouraging. Further investigations are necessary to develop a closed form expression for the dissolved gases in the oil and co-ordinate the fault diagnosis for on-line monitoring. Continuous learning of the system could enhance the capability of the Artificial Neural Network.

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